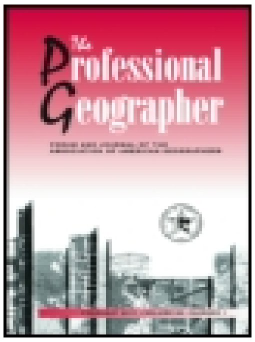

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Cyberbullying is an emerging social issue along with the prevalence of social media. Previous studies have used extensive surveys or firsthand data primarily from conventional social networks[1] (e.g., Twitter) to study cyberbullying, which often ignores the factor of anonymity and location. Considering the sensitive nature and contagious effect of cyberbullying, a better understanding of the spatiotemporal pattern in cyberbullying is sorely needed to develop effective policies to combat this toxic social behavior. Grounded in the dramaturgy theory and the emerging literature on technoself, this study aims to compare cyberbullying in the anonymous social media (Yik Yak) with the conventional social media (Twitter) and explore its spatiotemporal patterns. A support vector machine is used to help identify records with bullying content. Average nearest neighbor, kernel density, and Ripley's *K*-function are used to explore the spatiotemporal patterns of cyberbullying behavior. We have found that cyberbullying is more likely to occur in anonymous than conventional social media. We also detected a clustering pattern corresponding to the student population, which can be explained by the dramaturgy theory and recent studies on technoself. In addition to making suggestions to help reduce cyberbullying in the future, this article also sheds light on the need for future studies. **Key Words: cyberbullying, dramaturgy theory, GIS, spatiotemporal pattern, technoself.**

今日随着社群媒体的普及，网络霸凌成为浮现中的社会议题。过往的研究，主要运用大量的调研或来自传统社群网络的第一手信息 (例如推特) 来研究网络霸凌，却经常忽略了匿名性与地点的因素。考量网络霸凌的敏感本质与具传染性的效应，我们急需更佳地理解互联网霸凌中的时空模式理解， 以发展打击此一恶毒社会行为的有效政策。本研究植基于拟剧理论和逐渐兴起的科技自我之文献，旨在比较在匿名社群媒体 (Yik Yak) 中和传统社群媒体 (推特) 的网络霸凌，并探讨其时空脉络。本研究运用支持向量机来协助指认具有霸凌内容的纪录。平均最近邻里，核密度，以及雷普利的 K 函数，用来探讨网络霸凌行为的时空模式。我们发现，与传统社群媒体相较之下，网络霸凌更可能以匿名的方式出现。我们同时侦测符合学生人口的聚集模式，该模式可透过拟剧理论和晚进对于科技自我的研究进行解释。除了对协助减少未来的网络霸凌提出建议之外，本文同时揭示未来研究所需之处。 **关键词: 关键词, 网络霸凌, 拟剧理论, GIS, 时空模式, 科技自我。**

El ciberacoso es un problema social que ha emergido junto con la prevalencia de los medios sociales. Los estudios anteriores han utilizado exploraciones extensas o datos de primera mano, primariamente de redes sociales convencionales (e.g., Twitter) para estudiar el ciberacoso, que a menudo ignoran el factor de anonimato y localización. Tomando en cuenta la naturaleza sensible y el efecto contagioso del ciberacoso, una mejor comprensión del patrón espaciotemporal en el ciberacoso es extremadamente necesario para desarrollar políticas efectivas para combatir esta maligna conducta social. Con base en la teoría dramaturgia y en la emergente literatura sobre el tecno-personal [*technoself*], este estudio apunta a comparar el ciberacoso en los medios sociales anónimos (Yik Yak) con los medios sociales convencionales (Twitter) y explorar sus patrones espaciotemporales. Se usó una máquina vector de apoyo para ayudar a identificar los registros con contenido ciberacosante. Se usaron promedios de vecino más cercano, densidad kernel y función *K* de Ripley para explorar los patrones espaciotemporales del comportamiento ciberacosante. Hemos hallado que el ciberacoso ocurre con mayor probabilidad en los medios sociales anónimos que en los convencionales. Detectamos también un patrón de agrupamiento correspondiente con la población estudiantil, lo cual puede explicarse con la teoría dramaturgia y estudios recientes sobre el tecno-personal. Además de hacer sugerencias para ayudar a reducir el ciberacoso en el futuro, este artículo también arroja luz sobre la necesidad de más estudios. **Palabras clave: ciberacoso, teoría dramaturgia, SIG, patrón espaciotemporal, tecno-personal.**

Cyberbullying is an emerging social problem drawing increasingly keen attention from both academia as well as mass media today. Stirred up by several teenage suicides (e.g., Ryan Halligan 2003; Megan Meier 2006; Tyler Clementi 2010) across the United States that are believed to be at least partially attributed to cyberbullying, both professional educators and the general public have started to recognize the severity of this burgeoning issue. As a result of the prevalence of Web 2.0 technologies and the mushrooming of various social media among the younger generation, we have witnessed the evolution of cyberbullying in different styles and their multifaceted impacts. Among the many characteristics of cyberbullying, anonymity and spatiality are distinctive in that they have a large impact on the spread of bullying messages (Patchin and Hinduja 2006; Walker, Sockman, and Koehn 2011; Sticca and Perren 2013;

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Hinduja and Patchin 2015). Although previous studies have probed cyberbullying with great effort (Bauman and Bellmore 2014; Whittaker and Kowalski 2015), empirical support for these two features is still lacking. To fill in this gap in the literature, we report an innovative study of cyberbullying from both theoretical and empirical perspectives. This article summarizes our analysis of cyberbullying through a geographic lens with anonymous social media data. Specifically, it is the first empirical study that delineates a spatiotemporal pattern of the abusive content from Yik Yak, a popular anonymous online social network (AOSN). Furthermore, our study is conceptually grounded in the classic dramaturgy theory as well as the literature from the technoself studies to contextualize the empirical results.

The article is organized as follows: First, it reviews current literature on cyberbullying; second, it discusses the characteristics of AOSNs and provides a theoretical background for this study; third, it presents a case study on the spatiotemporal patterns of cyberbullying using data harvested from Yik Yak; finally, it discusses the findings and future directions of cyberbullying research.

Cyberbullying

Smith et al. (2008) defined *cyberbullying* as "an aggressive, intentional act carried out by a group or individual, using electronic forms of contact, repeatedly and over time against a victim who cannot easily defend him or herself" (376). Traditionally, cyberbullying occurred mostly via text message and e-mail among teenagers. Nowadays, as social media have become more and more prevalent, they have enabled cyberbullying to evolve from limited platforms into a plethora of online networks.

In the comprehensive book *Bullying beyond the Schoolyard*, Hinduja and Patchin (2015) introduced several key elements that pertain to cyberbullying, of which anonymity, deindividuation, and limitless victimization risk are the ones distinguishing cyberbullying from traditional bullying. Anonymity, or pseudonymity, makes it difficult to directly identify online aggressors, which might embolden them to express very harmful words they dare not say in public or normal social settings. Facts can be distorted and no one might ever be found responsible. *Deindividuation*, briefly defined as "a subjective state in which people lose their self-consciousness" (Singer, Brush, and Lublin 1965, 356), denotes the idea that one loses his or her self-awareness in an online setting due to the unconventional ways of communication. Last but not least, compared to traditional bullying, bullying messages in cyberspace are spatially and temporally ubiquitous as they can be circulated repetitively among people who might not even know the victim, which results in a limitless victimization risk.

Although cyberbullying has been carefully studied, only limited progress has been made in terms of methodology for conducting empirical studies. As of today, cyberbullying studies have primarily used extensive surveys among high school students (Hinduja and Patchin 2008; Aoyama, Barnard-Brak, and Talbert 2012; Kernaghan and Elwood 2013; Kwan and Skoric 2013) and undergraduate students (Kraft and Wang 2010; Walker, Sockman, and Koehn 2011; Minor, Smith, and Brashen 2013), and their results have undoubtedly revealed important facts of cyberbullying. Although online surveys provide a remarkable amount of both qualitative and quantitative data on cyberbullying for researchers, they are also constrained in multiple ways. One of the major limitations of an online cyberbullying survey is that the data it collects are essentially secondhand, which can be distorted and inadequate compared to the original data. In other words, the concept of cyberbullying is hard to standardize among individual participants. It is possible that some subjects consider the undesirable and obsessive communication instances to be tolerable norms instead of bullying in cyberspace (Walker, Sockman, and Koehn 2011). In addition, because of the sensitive nature of this topic, it is very possible for both the bully and the victim to hide their true opinions on the questions even if their anonymity is guaranteed. Another limitation of survey is the scale of data. As noted by Xu et al. (2012), the sample size of surveys is typically on the scale of hundreds and such a small sample can be hardly generalizable over extensive time, space, and population.

Although these limitations are still present, there has recently been more interest in using large-scale, firsthand data of social media (e.g., Facebook, Twitter, etc.) to study cyberbullying thanks to developments in text mining and machine learning technologies (Yin et al. 2009; Kontostathis, Edwards, and Leatherman 2010; Bosse and Stam 2011; Dinakar, Reichart, and Lieberman 2011; Kouloumpis, Wilson, and Moore 2011; Lieberman, Dinakar, and Jones 2011; Xu, Zhu, and Bellmore 2012; Nandhini and Sheeba 2015). Many of these studies have provided valuable insights to cyberbullying. For example, Dadvar et al. (2012) used a support vector machine (SVM) model and found that a gender-specific text classifier can improve the capacity of a classifier to detect cyberbullying. With the traditional survey method, it would be hard to acquire the firsthand data from massive data sets and analyze cyberbullying content in a broad scope. In fact, the *Journal of School Violence* recently published a special issue exploring new directions in cyberbullying research, in which Bauman and Bellmore (2014) demonstrated the importance of online technologies, as they argued, "It will be critical that scholars stay informed not only of usage trends in the most popular forums but also of usage of niche forums that may present different types of risks for those involved with cyberbullying" (6).

Having reviewed the current status of cyberbullying research, we notice that previous studies have presented different perspectives toward cyberbullying. Specifically, research using the traditional survey method tends to investigate the association between cyberbullying behaviors and social or demographic factors, whereas research using text mining technologies focuses more on ontological questions regarding cyberbullying. Surprisingly, few studies have touched on the spatiotemporal pattern of cyberbullying regardless of a large amount of studies using spatiotemporal information in other areas. This article fills in the gap of cyberbullying research. In light of the spatial and temporal ubiquity of cyberbullying, it is important to examine the spatiotemporal patterns of cyberbullying to provide researchers, educators, and parents with a guidance on when, where, and what kind of cyberbullying events happen so that precaution and prevention programs can be implemented more effectively. Furthermore, with the increasing popularity of mobile devices and location-based services (LBS) nowadays, it is no longer a technological barrier to acquire the time and location of individual messages.

Anonymous Online Social Networks

Theoretical Perspectives

AOSNs are widespread today among social media users and this phenomenon can be understood and analyzed from a dramaturgical perspective. The dramaturgy theory put forward by Goffman (1959) in his book *The Presentation of Self in Everyday Life* is one of the most insightful theories describing people's social interactions. Goffman viewed human behaviors essentially as performances in a theater setting. Specifically, he distinguished people's performances in the front stage and the back stage, where the front stage is "where the actor formally performs and adheres to conventions that have meaning to the audience" and the back stage is "where performers are present but audience is not, and the performers can step out of character without fear of disrupting the performance" (Goffman 1959, 29). It should be noted that as a socially accepted norm, the performers and the audience have reached a consensus to let the performance run smoothly most of time. In other words, we interact in a "cozy conspiracy" in which it appears as if everyone knows what they are talking about, can remember the names of those to whom they are talking, and has an appearance and presence that is pleasant and unexceptionable. In this sense, our "selves" are presented for the purpose of interacting with others and are developed and maintained with the cooperation of others through the interaction (Miller 1995). Therefore, Goffman would see anonymity as an important protection or lubrication when people present themselves in ways that are usually socially unacceptable such as bullying. This is because people would anticipate limited consequences, whether positive or negative, when the partners of their interaction are remote, unfamiliar, and irrelevant to them. Being anonymous to others, people need not fear the potential loss of dignity or reputation, hence not experiencing the awkwardness when they fail to embellish their performance.

Based on Goffman's dramaturgy theory, recent researchers have investigated how people represent themselves in the online world and coined the term *technoself.* As the technoself studies (TSS) covers a broad concern addressing "the changing state of human identity in society resulting from the adoption of new technologies" (Luppicini 2012, 2), it provides a new and systematic perspective for us to view cyberbullying as a deindividuation phenomenon. As one of the pioneers in TSS, Turkle has written abundantly regarding human identities in cyberspace. In her classic *Life on the Screen: Identity in the Age of the Internet*, Turkle (1995) brought up the idea of fragmented selves that denotes an identity problem of a technology-driven world that "one cannot summon the correct self at the appropriate time, or cannot figure out how to enable the fractious selves to work together" (178). This coheres with the deindividuation process in which people under certain circumstances lose their self-consciousness, which is most evident in an anonymous environment. Being made up of fragmented selves, it is difficult for one to construct one's identity and behave as expected by social norms. Therefore, in such a situation, we might expect to see a higher occurrence of abnormal or immoral behaviors such as cyberbullying.

In addition to fragmented selves, TSS scholars have observed another phenomenon that is tightly tied to AOSN. Konrath (2012) noted that although online social media has expedited our communication and created effective and creative ways for people to express themselves, the connections it establishes are superficial. She summarized empirical studies that indirectly suggest that people are becoming increasingly more narcissistic and indifferent toward other people, which essentially evokes social disconnection instead of connection (Twenge and Campbell 2009). In an anonymous setting, such a phenomenon is more exemplified as people's dialogues with each other are instantaneous and untraceable, which further diminishes people's need and desire to establish long-term connections with empathetic attitudes. For most users, AOSNs are platforms for people to experience excitement via a temporary connection with someone they do not know. The topics might seem to be deep and personal, but the relationships formed are generally unilateral instead of reciprocal.

AOSNs and Yik Yak

AOSNs first appeared as chatrooms in the early 1970s. Although the idea of communication with hidden identities is by no means new, it is vastly enabled today thanks to widely available smart phones and Web 2.0 technologies. As online social networking becomes the norm in the twenty-first century, a plethora of anonymous and pseudonymous mobile applications have mushroomed on the

Table 1 *An overview of Yik Yak*

Synchronization	Spatiality	Privacy	Anonymity	Culture
Asynchronous	Location-based	Public	Completely anonymous	Casual, funky, college setting

market, including Secret, Whisper, Snapchat, Tinder, Yik Yak, Ether, Wickr, and so on. Although specific functions and aims might vary, all of these online social networks allow users to share information that is more preferable if shared anonymously, sometimes with various levels of anonymity. Alongside conventional online social networks such as Facebook and Twitter, these AOSNs have catered to users in an important, private aspect. The quantity of literature on AOSNs in particular is limited, however, as they are more often included in the broader genre of social networks (Friedman, Khan, and Howe 2000; Postmes and Spears 2002). In the literature, some studies from the algorithmic perspective focus on how to anonymize and deanonymize within a social network (Narayanan and Shmatikov 2009); some focus on user behaviors in the private setting (Lewis, Kaufman, and Christakis 2008). In Wang et al. (2014), which summarizes the first large-scale empirical study of an online anonymous social network, the researchers collected millions of posts from Whisper over three months and analyzed the structure of user interactions, user engagement, content moderation, and so on. It is notable that no previous study has expressed the concern of the spatiotemporal characteristics of AOSN specifically.

For our study, we used data from Yik Yak, which is a typical AOSN that is active today. Yik Yak functions like a bulletin board to local communities. Compared to other forms of online social networks, Yik Yak is unique in several ways (Table 1). It highlights its combination of hyperlocality and complete anonymity, which had not been sought after by other online social networks. Within a year and a half, this new and apparently simple application became widely used on 1,600 campuses by millions of monthly active users. Launched from Furman University, Yik Yak has never deviated from its most faithful and active user group, students. The founders realize that university campuses are ideal venues for a hyperlocal bulletin board like Yik Yak to thrive because of the high density of a young and creative population who share various concerns and interests.

Despite the popularity of Yik Yak, there have been concerns about cyberbullying or inappropriate content on Yik Yak since the very early days after its launch. Because of its complete anonymity and geographic vicinity, Yik Yak has become a convenient platform on which people can easily target someone without fear of being traced. Furthermore, some people have even used it to spread threatening messages to the public. For example, on 24 November 2014, a nineteen-year-old student at Michigan State University announced that he would start a shooting on campus, which caused great disturbance. The student was eventually tracked via his Internet Protocol address and was arrested.

A Case Study of Cyberbullying

Study Area and Data

The study was conducted around the main campus of Ohio State University (OSU) in Columbus, Ohio, which covers area of approximately 25 square miles. As of Fall 2015, OSU had an enrollment of 58,663. Although the exact number of Yik Yak users is hard to estimate, Yik Yak is actively used in this area thanks to a large student body. The data were collected from 1 September 2015 to 28 September 2015 on a daily basis.

The yaks were collected via a Yik Yak application programming interface (API), which only allows users to download the 100 most updated yaks each time it refreshes. Considering the user base and our own experience with Yik Yak, the refresh interval of the downloading process was set to two hours. Each yak contains a time stamp, information about where it is posted (longitude/latitude with an accuracy level of two decimal places), and the textual content. After that, an exhaustive list of tweets posted during the same time span (1 September 2015 to 28 September 2015) and location (approximately two miles from OSU) was accessed through Twitter's advanced search tool and then downloaded using jQuery. The Twitter data need to be compared with Yik Yak data. As a limiting factor, detailed spatiotemporal information on individual tweets is missing due to the restriction Twitter imposes on its search results. After the data are downloaded, they are processed to remove blank, meaningless (e.g., "llllllllll" or "&22%dfsjhfal"), or duplicate content.

Method

How to define bullying content in social media is probably the most important question in cyberbullying studies. Traditionally, researchers describe the characteristics of the bullying behavior and people's expected emotion or reaction in detail so that the subjects are clear about whether bullying has occurred. Using primarily firsthand data from social media, however, sentiment analysis is a more viable and effective sine qua non. Therefore, it requires us to give an accurate definition of posts that can be considered abusive. Based on previous studies and our own experience, we consider an

Table 2 *Accuracy of support vector machine training*

Total no.	No. of abusive	Correct no.	Correct %	Correct no.	Correct %
500	45	27	60	420	92

abusive post to possess one or more of the following characteristics:

- Contains both foul words and (a) pronoun(s) (e.g., "Wanna tell the guy sitting in front of the classroom to f**k himself").
- Contains both foul words and an individual name (e.g., "f**k XXX," "XXX is an idiot," "XXX smells like sh*t").
- Contains a discriminating statement regarding race or gender (e.g., "Asians don't hold door for people").

The list of foul words was acquired from http://www.noswearing.com/. In our study, foul language is not considered to be bullying or abusive by itself, as it only does limited emotional harm if not aimed at specific individuals or groups. In a previous study, researchers have developed a model to detect cyberbullying in which a combination of pronouns and foul language is used to identify "harassment" online (Yin et al. 2009). This study primarily adopts this method while making several modifications. First, it includes specific names that appeared in the yaks combined with foul language. As the data collection time intersects with the college football season, the name of a famous former football player appeared frequently along with cussing words in our data set. Despite the absence of pronouns, we consider such yaks as abusive nonetheless. Second, racially and sexually abusive information is taken into consideration as well. This is adopted from a later study where researchers targeted video comments insulting other people's sexuality, race or ethnicity, and intelligence (Dinakar, Reichart, and Lieberman 2011). We made this modification because considering the anonymous nature of yaks, we found it more likely to see yaks insulting a gender or racial group than a specific individual. It should also be noted that as the data are collected during the college football season, we frequently observed foul or discriminating language associated with geographic names or school names (e.g., "f**k Michigan!"). This is not considered abusive because such statements are more culturally acceptable.

As we defined what bullying content is, we manually labeled a random sample of 2,000 yaks as 0 or 1 to indicate whether each of them contains abusive information. Then, we adopted the commonly used Term Frequency/Inverse Document Frequency (TFIDF) value to tokenize each feature in the text corpus via scikit-learn, a machine learning toolkit for Python. TFIDF was first invented by Salton, Wong, and Yang (1975) to measure term frequency, which is offset by its occurrence in the corpus to adjust for the fact that some words generally appear more frequently than others. It is a technique widely used in text classification. After the features are tokenized using TFIDF values, stop words are removed based on a percentage of 0.08. After that, a truncated singular value decomposition (SVD) method is applied to reduce the dimension of the tokenized features ($n = 75$) to enhance the accuracy and efficiency of the prediction later. Truncated SVD is a widely adopted method in textual dimension reduction (Yang 1995; Husbands, Simon, and Ding 2001; Kim, Howland, and Park 2005). Finally, splitting the labeled yaks into a 1,500-instance training set and a 500-instance testing set, an SVM classifier is trained, tested, and applied to help determine whether the remaining yaks and tweets in the corpus contain abusive content.

As the yaks are labeled with bullying indicators, we implemented an average nearest neighbor analysis to detect whether spatial clustering is present with the yak distribution. After that, we ran a kernel density analysis as well as a Ripley's *K*-function to examine the characteristics of the detected spatial clusters in ArcMap 10.2 (ArcGIS Desktop, Release 10.2, Esri, Redlands, CA, USA). For temporal analysis, we extracted the hour and the day in a week when each yak is posted. Then, we counted the time occurrence of both abusive yaks and total yaks and made combined graphs.

Results

A total of 12,349 yaks and 21,708 tweets were downloaded, out of which 11,673 and 18,252 unique ones were identified, respectively. The same SVM classifier was trained and applied to both yaks and tweets to identify abusive contents. Within the testing data set of 500 instances, 27 out of 45 abusive instances and 420 out of 455 nonabusive instances were correctly identified by the SVM classifier (Table 2).

Table 3 *Comparison between Yik Yak and Twitter*

Social network	Bully no.	Nonbully no.	Total no.	Bully %
Yik Yak	1,567	10,106	11,673	13.4
Twitter	1,990	16,262	18,252	10.9
Total	3,557	26,368	29,925	11.9

Among the 11,673 yaks entered for analysis, 13.4 percent were identified as abusive, which contrasts with the 10.9 percent of tweets out of the total of 18,252 (Table 3). These figures are slightly larger than the result shown in the testing data set (9 percent), mainly due to a relatively small sample size. This preliminary result supports the hypothesis that an AOSN contains more abusive content than a conventional online social network, although not remarkably. A two-tailed chi-square test was then implemented, and the calculated p value was less than 0.0001, which suggests that the result is statistically significant. In terms of the actual abusive content, based on our visual estimation, yaks can be observed more on specific topics, whereas tweets appear to be mentioned more ubiquitously, which we believe is largely due to the different user base and cultural setting of these two social media.

In terms of the spatial distribution of yaks, we found some interesting patterns. The ratio between the observed average nearest neighbor distance and the hypothetical average nearest neighbor distance is

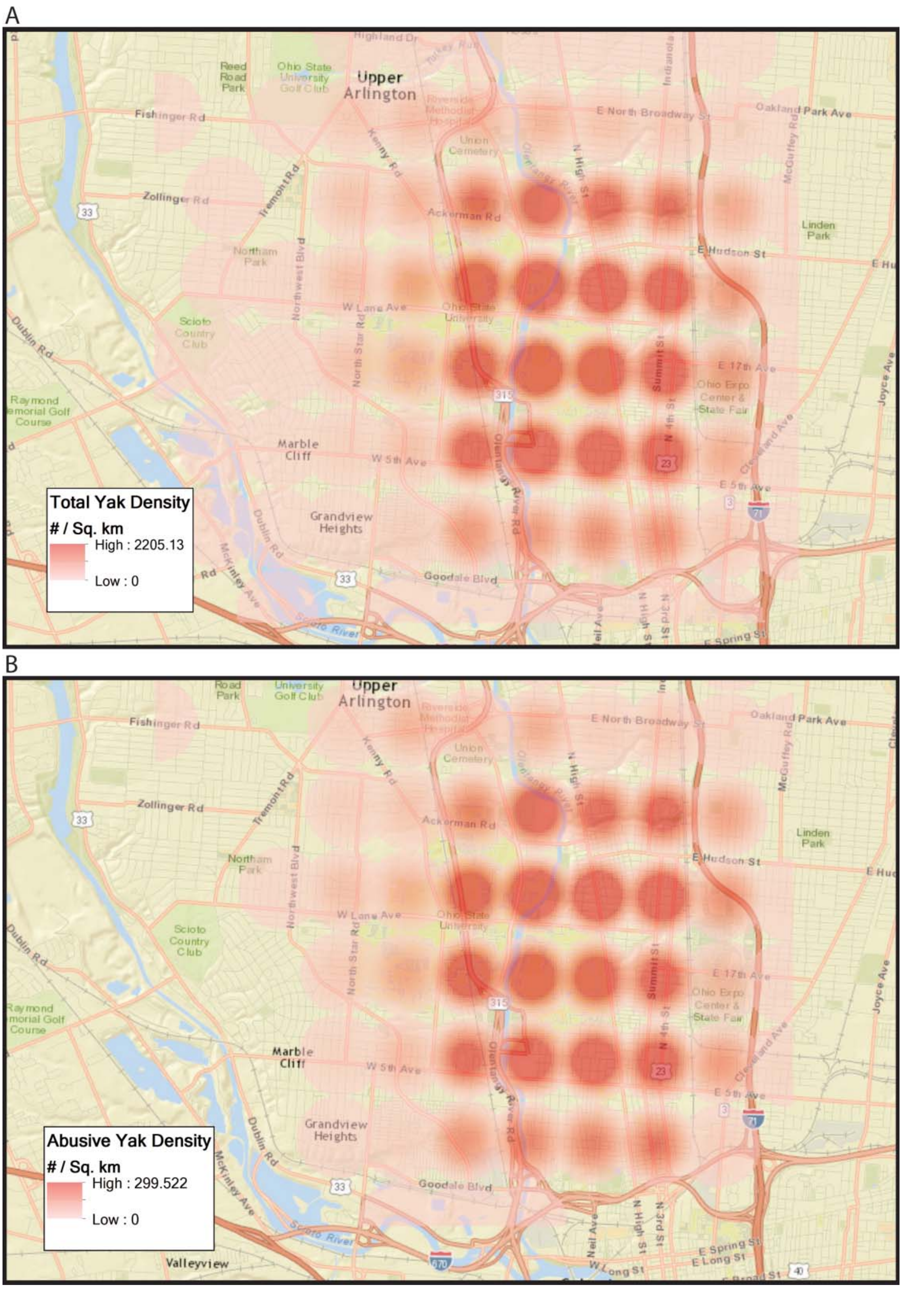

Figure 1 *Density of total yaks and abusive yaks near Ohio State University. Base map source: ESRI World Street Map. (Color figure available online.)*

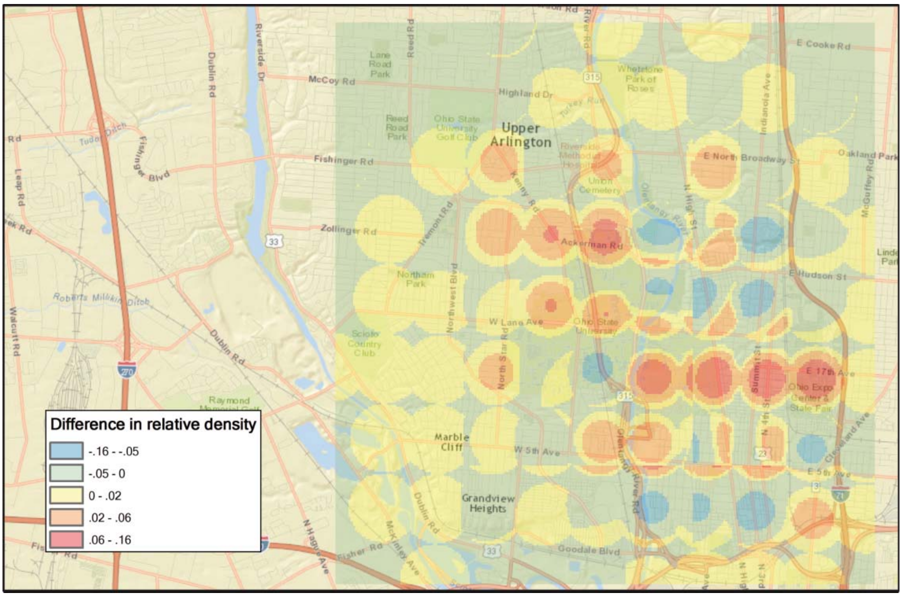

Figure 2 *Density difference between total yaks and abusive yaks near Ohio State University. Base map source: ESRI World Street Map. (Color figure available online.)*

0.017 for total yaks and 0.078 for abusive yaks. Both indexes are statistically significant, suggesting that spatial clustering is evident in both cases. The kernel density maps show that both total yaks and abusive yaks are clustered around the campus area (Figure 1). Figure 2 shows the difference between the row-standardized density of total yaks and abusive yaks. The hue of the color indicates whether the distribution of abusive yaks is denser than the distribution of total yaks (warm color) or the opposite (cold color). As Figure 2 illustrates, a higher density for abusive yaks is visible at the core campus, the eastern residential area, and the University Village/Buckeye village residential area in the northwest, and all these areas have a dense student population.

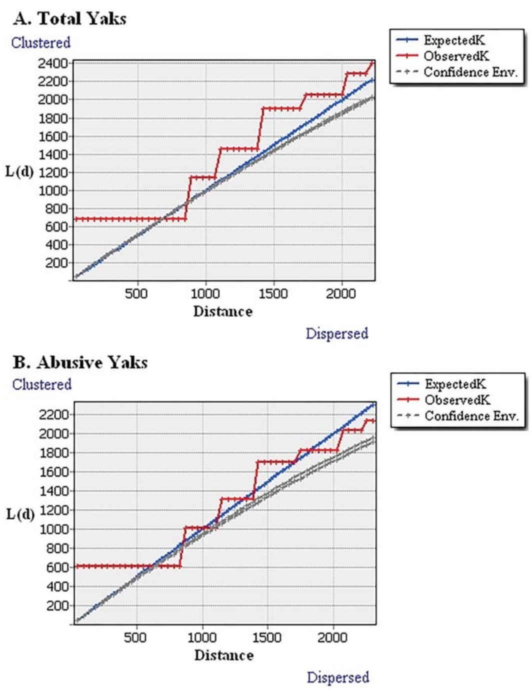

Figure 3 *Comparing K-function graphs of total yaks and abusive yaks. (Color figure available online.)*

Although constrained by coarse data resolution, we can identify clusters around several spots located on the core campus. The Ripley's *K*-function result suggests that total yaks are clustered at approximate radiuses of 0 to 600 m and 800 m and above, whereas abusive yaks are distinctively clustered at approximate radiuses of 0 to 550 m, 800 to 1,000 m, 1,200 to 1,300 m, and 1,400 to 1,700 m (Figure 3). These patterns indicate that abusive yaks are more locally concentrated than total yaks, which depicts a cluster across the space. These clusters can be explained by the infectious or viral nature of cyberbullying, which is usually not confined by physical boundaries (Hinduja and Patchin 2015). As Yik Yak functions as a hyperlocal online bulletin board, however, favored yaks are likely centered at common topics relevant to the locality (i.e., OSU campus). Therefore, when a student posts about something on Yik Yak, students at other proximate locations might resonate with the post and post on the same thing as well. This can be considered a spatial spillover phenomenon occurring in both physical space and cyberspace. The most evident example of this phenomenon happened during a football game when some initial abusive yaks targeted at a football player were soon echoed by a large amount of yaks.

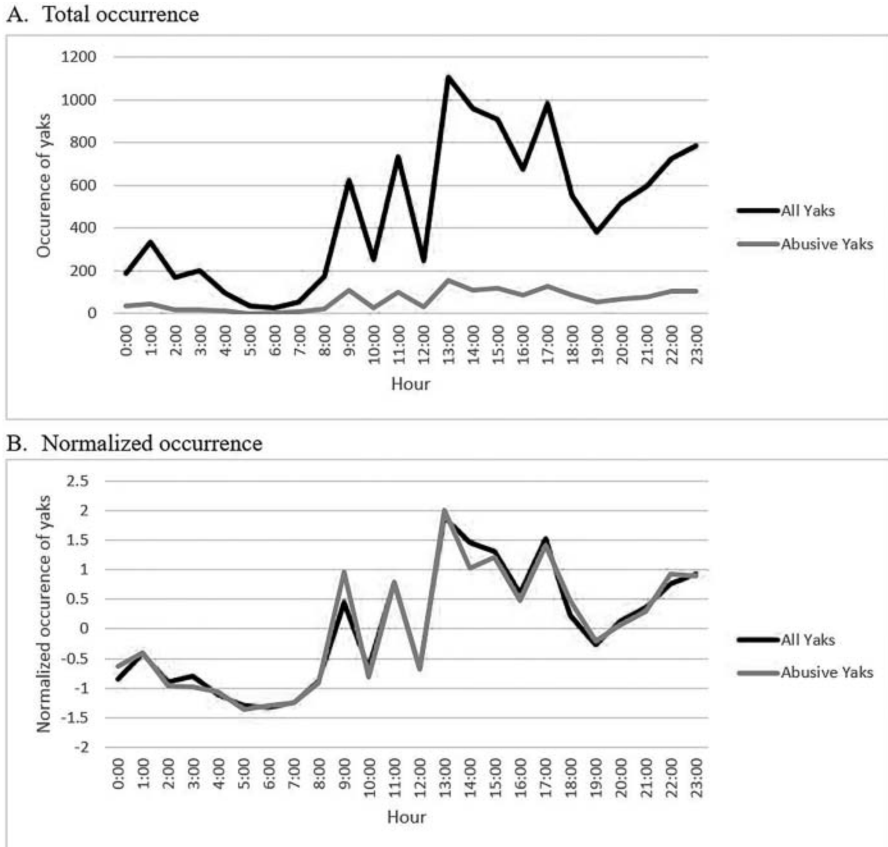

Figure 4 *Occurrence of yaks in accordance with time in a day.*

The result of temporal analysis meets our expectation. As shown in Figure 4A and 4B, Yik Yak users are most active in the afternoon (peak at 1:00 p.m.) and most inactive at dawn (dip at 6:00 a.m.). The abusive yaks follow a similar trend of total yaks, with the exception of 9:00 a.m., when abusive yaks are posted more intensely, and 2:00 p.m., when they encounter a precipitous drop. We think this pattern coheres well with students' activity cycle in a day: As classes start in the morning, students tend to post grumpy yaks to express their reluctance to go to class. Such posting activity goes along with the class schedule and peaks after lunch. In the afternoon, students are busier with an increasing amount of various activities and are less active in terms of yak posting. In the evening, students have more time to use Yik Yak to post what they have done and seen in the day and we observe an increase of yaks until midnight. Figures 5A and 5B show that numbers of both total yaks and abusive yaks remains generally stable over the week. The count for total yaks encounters a sudden decline on Wednesdays but then soon resumes to the normal slowly rising trend on Thursdays. The reason for such a drop remains unknown, and more data over a longer time span would be necessary to detect whether such a sudden drop occurs by chance.

Discussion

Based on the case study results, the following points have become apparent. First, a comparison between Yik Yak and Twitter illustrates a higher occurrence of abusive content in AOSN than in conventional social networks. Such a finding is consistent with the dramaturgy theory and major findings of TSS, which suggest that an anonymous atmosphere is a catalyst to the deindividuation process often involved in cyberbullying. From the dramaturgical perspective, as Goffman (1959) contended, the back stage provides performers with an environment to rest and prepare for front-stage performances. Therefore, it is possible that Yik Yak users utilize this social media as a channel to release their stress accumulated from real life, and some of them do so via posting abusive content. Unlike Twitter, Yik Yak's users need not worry about the yaks being traced and identified with their real identity due to its anonymous nature. From the perspective of social disconnection in cyberspace (Konrath 2012), it is also expected to see more abusive content on the anonymous social media. A possible explanation is that the lack of acknowledged identity will result in the lack of conversational context, which further leads to a higher probability of

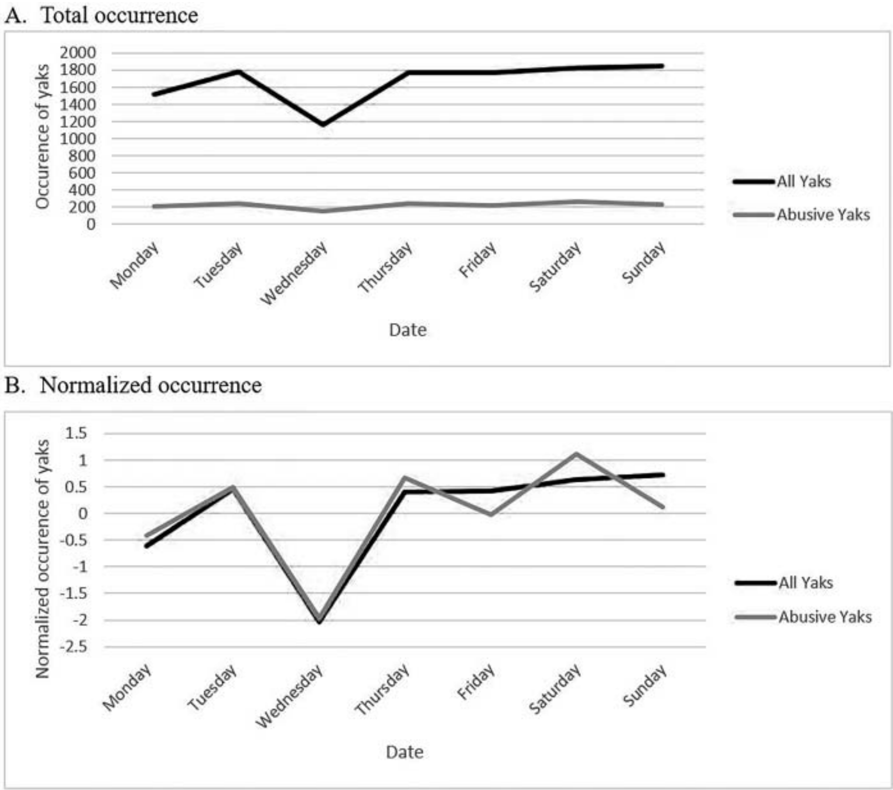

Figure 5 *Occurrence of yaks in accordance with days in a week.*

miscommunication between the users. Therefore, most yaks are unilateral and focused on expressing emotions, which in many cases include abusive or discriminative information. An example is "Asian students don't hold doors for people," which is race targeting, overgeneralizing, and decontextualized.

Second, the kernel density analysis reveals that there does exist a spatial pattern showing how yaks are distributed. Both total yaks and abusive yaks are clustered around the core campus area, although abusive yaks are more concentrated than total yaks. In other words, there is a positive correspondence between the occurrence of abusive yaks and the density of student population. Explanations of such phenomena can be inferred based on the temporal pattern, which, as discussed earlier, matches well with the daily schedule of a typical college student. Interestingly, such observation coheres with the dramaturgy theory (Goffman 1959) in that it showed a contrast between the "front stage" identity and the "back stage" identity of students. As indicated by the temporal graph and the content of some yaks (e.g., "It's a nightmare listening to Prof. X. I wanna hang myself now!"), some students actually post yaks during class time, which can be regarded as an escape from the nerve-wracking "front stage" (a bored student in a classroom) to the restful "back stage" (a cynical and humorous yakker). Our observation can also be explained by the concept of fragmented selves from TSS (Turkle 1999). As Turkle addressed, our everyday life is essentially a set of multiple personas, whereas cyberspace takes the fluidity of identities and raises it to a higher power: People come to see themselves as being the sum of their distributed presence in all of the windows they open on the screen. As the majority of students are relatively young, their personas are still being shaped and absorbed by themselves. Therefore, it is more unlikely for them to summon the entirety of their identities when being online, which would result in deindividuation and a lack of responsible behaviors. For example, when a student posts abusive language toward people of a different race, his or her racial identity is exaggerated and other identities are shrunken (e.g., occupation, gender, age, life experience, etc.). Those with higher levels of maturity can recognize all of their personas and behave with a balance among them more easily. Limited by the anonymous nature of Yik Yak, we could not retrieve personal data of individual users or trace their activities over time. We also noticed that content on Yik Yak is highly cohesive to the latest news at local, national, or international levels. For example, the majority of yaks can be focused on a football match between OSU and the University of Alabama on game day. Such ad hoc events can significantly, although often temporarily, affect the language use on Yik Yak.

Cyberbullying has been regarded more often as a personal offense than collective abuse (Smith et al. 2008; Hinduja and Patchin 2015). With the burgeoning of AOSNs such as Yik Yak, however, we might need to reconsider what symbolizes bullying behavior where both the bully and the victim could be many. Cyberbullying undoubtedly has a contagious effect in the community. Although abusive messages are usually few in number, their content is often targeted at large populations and can cause traumatizing reactions for the masses, which is, intriguingly, a manifestation of the Pareto principle (Brynjolfsson, Hu, and Simester 2011). As cyberbullying is becoming an increasingly severe problem, it is the responsibility of both social media companies such as Yik Yak and universities to avoid further harm done by it. It is gratifying to see that Yik Yak has already implemented various methods to prevent cyberbullying, including geofencing out its accessibility base on school location, content filtering through user collaboration, a bullying report center, and so on. From the school's perspective, teachers and administrators need to be more aware of the characteristics and usage of AOSNs on campus. Moreover, it would be beneficial for teachers themselves to be active on AOSN and post positive and contributing messages to influence the culture in general (Hinduja and Patchin 2015). We look forward to seeing future studies continue the research of characteristics and impacts of cyberbullying in AOSNs at a larger scale.

Conclusions and Future Work

Being the first effort examining the spatiotemporal pattern of cyberbullying in AOSNs, our research has made new contributions to cyberbullying studies in both conceptual and empirical perspectives. Conceptually, we probed Goffman's dramaturgy theory as well as the TSS and linked them with the deindividuation process of cyberbullying. By comparing theories, key concepts, and applications of both fields, we contend that the fragmented selves and the increasing social disconnections at a deep level, both of which are tightly related to the inundation of social media today, contribute to people's loss of self-awareness and eventually bullying behavior online. Empirically, using data acquired from Yik Yak and Twitter and with help from machine learning techniques (SVM), we found statistical evidence supporting a positive correlation between abusive content and the user's anonymity online. Based on previous studies on sentiment analysis regarding abusive content, we also tailored the criteria of abusive content detection specifically to the Yik Yak environment, including combinations of (1) foul words and pronouns; (2) foul words and names; and (3) racial or gender discrimination. Finally, we implemented a spatial analysis that indicated a stronger tendency of AOSN users who are closer to campus to post abusive content than those who are further from campus and used a temporal analysis to explain our observation.

We are fully aware of the limitations of the work reported here, which also point to a few directions for future work. First, the Yik Yak data are primarily acquired through Yik Yak's undisclosed API and strict restrictions are imposed by the company, such as downloading rate, spatial resolution, number of accounts, and so on. Future studies need to be conducted at a larger spatiotemporal scale to acquire higher quality data. Second, although already improving on the detection of bullying posts compared with a limited number of previous studies, more adequate definitions and effective classifying methods are required to specify the cyberbullying issue. For example, bullying can be further categorized into subtypes such as sexual bullying, racial bullying, intelligence bullying, and so on, and people's emotions can be described as more than a dichotomy (Roberts et al. 2012). To achieve this, advanced methods of sentiment analysis should be incorporated into future research efforts (Nahar, Li and Pang 2013; Nandhini and Sheeba 2015). Third, the analysis of tweets is limited in this study due to lack of spatial information. An in-depth comparative study between anonymous and identified online social networks will be carried out in the future with data of the same quality. We believe that such comparative studies can provide valuable insights to help us further understand people's perceptions and involvement in social media across space. ■

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Note

[1] Social media whose users primarily use their real name and provide identifiable information, although some might use pseudonyms (e.g., Facebook and Twitter).

Literature Cited

Aoyama, I., L. Barnard-Brak, and T. Talbert. 2012. Cyberbullying among high school students: Cluster analysis of sex and age. In *Evolving psychological and educational perspectives on cyber behavior*, ed. R. Z. Zheng, 246–57. Hershey, PA: IGI Global.

Bauman, S., and A. Bellmore. 2014. New directions in cyberbullying research. *Journal of School Violence* 14:1–10.

Bosse, T., and S. Stam. 2011. A normative agent system to prevent cyberbullying. In *International conference on Web intelligence and intelligent agent technology (WI-IAT), 2011 IEEE/WIC/ACM*, ed. S. Calabretto, 425–30. Piscataway, NJ: IEEE.

Brynjolfsson, E., Y. Hu, and D. Simester. 2011. Goodbye Pareto principle, hello long tail: The effect of search costs on the concentration of product sales. *Management Science* 57:1373–86.

Dadvar, M., F. M. G. de Jong, R. J. F. Ordelman, and R. B. Trieschnigg. 2012. Improved cyberbullying detection using gender information. In *Proceedings of the Twelfth Dutch-Belgian Information Retrieval Workshop (DIR 2012)*, 23–25. 23–24 February, Ghent, Belgium

Dinakar, K., R. Reichart, and H. Lieberman. 2011. Modeling the detection of textual cyberbullying. Paper presented at the International AAAI Conference on Web and Social Media, North America, July. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/3841/4384 (last accessed 14 November 2016).

Friedman, B., P. H. Khan, Jr., and D. C. Howe. 2000. Trust online. *Communications of the ACM* 43:34–40.

Goffman, E. 1959. *The presentation of self in everyday life*. New York: Random House.

Hinduja, S., and J. W. Patchin. 2008. Cyberbullying: An exploratory analysis of factors related to offending and victimization. *Deviant Behavior* 29:129–56.

———. 2015. *Bullying beyond the schoolyard: Preventing and responding to cyberbullying*. Thousand Oaks, CA: Corwin.

Husbands, P., H. Simon, and C. H. Ding. 2001. On the use of the singular value decomposition for text retrieval. *Computational Information Retrieval* 5:145–56.

Kernaghan, D., and J. Elwood. 2013. All the (cyber) world's a stage: Framing cyberbullying as a performance. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace* 7:1–11.

Kim, H., P. Howland, and H. Park. 2005. Dimension reduction in text classification with support vector machines. *Journal of Machine Learning Research* 6:37–53.

Konrath, S. 2012. The empathy paradox: Increasing disconnection in the age of increasing connnection. In *Handbook of research on technoself*, ed. R. Luppicini, 204–28. IGI Global.

Kontostathis, A., L. Edwards, and A. Leatherman. 2010. Text mining and cybercrime. In *Text mining: Applications and theory* ed. M. W. Berry and J. Kogan, 149–64. Chichester, UK: Wiley.

Kouloumpis, E., T. Wilson, and J. Moore. 2011. Twitter sentiment analysis: The good the bad and the omg! *ICWSM* 11:538–41.

Kraft, E., and J. Wang. 2010. An exploratory study of the cyberbullying and cyberstalking experiences and factors related to victimization of students at a public liberal arts college. *International Journal of Technoethics* 1 (4): 74–91.

Kwan, G. C. E., and M. M. Skoric. 2013. Facebook bullying: An extension of battles in school. *Computers in Human Behavior* 29:16–25.

Lewis, K., J. Kaufman, and N. Christakis. 2008. The taste for privacy: An analysis of college student privacy settings in an online social network. *Journal of Computer-Mediated Communication* 14:79–100.

Lieberman, H., K. Dinakar, and B. Jones. 2011. Let's gang up on cyberbullying. *Computer* 44:93–96.

Luppicini, R. 2012. The emerging field of technoself studies (TSS). In *Handbook of research on technoself: Identity in a technological society*, ed. R. Luppicini, 1. IGI Global.

Miller, H. 1995. The presentation of self in electronic life: Goffman on the Internet. Paper presented at the Embodied knowledge and virtual space conference, Goldsmiths' College, University of London, June.

Minor, M. A., G. S. Smith, and H. Brashen. 2013. Cyberbullying in higher education. *Journal of Educational Research and Practice* 3 (1): 2.

Nahar, V., X. Li, and C. Pang. 2013. An effective approach for cyberbullying detection. *Communications in Information Science and Management Engineering* 3:238.

Nandhini, B. S., and J. Sheeba. 2015. Online social network bullying detection using intelligence techniques. *Procedia Computer Science* 45:485–92.

Narayanan, A., and V. Shmatikov. 2009. De-anonymizing social networks. In *30th IEEE Symposium on security and privacy*, ed. C. Gates, 173–87. Piscataway, NJ: IEEE.

Patchin, J. W., and S. Hinduja. 2006. Bullies move beyond the schoolyard: A preliminary look at cyberbullying. *Youth Violence and Juvenile Justice* 4:148–69.

Postmes, T., and R. Spears. 2002. Behavior online: Does anonymous computer communication reduce gender inequality? *Personality and Social Psychology Bulletin* 28:1073–83.

Roberts, K., M. A. Roach, J. Johnson, J. Guthrie, and S. M. Harabagiu. 2012. EmpaTweet: Annotating and detecting emotions on Twitter. In *Proceedings of the Eight International Conference on Language Resources and Evaluation, European Language Resources Association (ELRA)*, ed. N. Calzolari, 3806–13. Istanbul.

Salton, G., A. Wong, and C. S. Yang. 1975. A vector space model for automatic indexing. *Communications of the ACM* 18:613–20.

Singer, J. E., C. A. Brush, and S. C. Lublin. 1965. Some aspects of deindividuation: Identification and conformity. *Journal of Experimental Social Psychology* 1:356–78.

Smith, P. K., J. Mahdavi, M. Carvalho, S. Fisher, S. Russell, and N. Tippett. 2008. Cyberbullying: Its nature and impact in secondary school pupils. *Journal of Child Psychology and Psychiatry* 49:376–85.

Sticca, F., and S. Perren. 2013. Is cyberbullying worse than traditional bullying? Examining the differential roles of medium, publicity, and anonymity for the perceived severity of bullying. *Journal of Youth and Adolescence* 42:739–50.

Turkle, S. 1995. *Life on the screen: Identity in the age of the Internet*. New York: Simon & Schuster.

———. 1999. Cyberspace and identity. *Contemporary Sociology* 28:643–48.

Twenge, J. M., and W. K. Campbell. 2009. *The narcissism epidemic: Living in the age of entitlement*. New York: Simon & Schuster.

Walker, C. M., B. R. Sockman, and S. Koehn. 2011. An exploratory study of cyberbullying with undergraduate university students. *TechTrends* 55:31–38.

Wang, G., B. Wang, T. Wang, A. Nika, H. Zheng, and B. Y. Zhao. 2014. Whispers in the dark: Analysis of an anonymous social network. In *Proceedings of the 2014 Conference on Internet measurement*, ed. Z. Li, 137–50. Vancouver: ACM.

Whittaker, E., and R. M. Kowalski. 2015. Cyberbullying via social media. *Journal of School Violence* 14 (1): 11–29.

Xu, J.-M., K.-S. Jun, X. Zhu, and A. Bellmore. 2012. Learning from bullying traces in social media. In

Proceedings of the 2012 conference of the North American chapter of the Association for Computational Linguistics: Human language technologies, ed. J. Chu-Carroll, 656–66. Montreal: Association for Computational Linguistics.

Xu, J.-M., X. Zhu, and A. Bellmore. 2012. Fast learning for sentiment analysis on bullying. In *Proceedings of the first international workshop on issues of sentiment discovery and opinion mining*, ed. E. Cambria, 10. Beijing: ACM.

Yang, Y. 1995. Noise reduction in a statistical approach to text categorization. In *Proceedings of the 18th annual international ACM SIGIR conference on research and development in information retrieval*, ed. E. A. Fox, P. Ingwersen, and R. Fidel, 256–63. Seattle: ACM.

Yin, D., Z. Xue, L. Hong, B. D. Davison, A. Kontostathis, and L. Edwards. 2009. Detection of harassment on Web 2.0. *Proceedings of the Content Analysis in the WEB* 2:1–7.

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