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Contents and Contexts of Cyberbullying: An Epidemiologic Study using Electronic Detection and Social Network Analysis

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ABSTRACT

Most of what is known about cyberbullying – its prevalence, risk factors, and links with offline bullying, violence and delinquency – draws heavily on single surveys, which limit researchers' ability to examine actual cyberbullying communications or the peer group contexts of the behavior. Using a multi-methods research design, we classified the contents of cyberbullying messages, measured their frequency and associations with offline bullying, and examined how social networks are associated with these behaviors. Beginning in January 2015, we surveyed 164 adolescents, grades 6 through 8, from two Iowa middle schools. Two surveys, one at the start of the spring semester and one at the end of spring 2015, gathered self-reported information on perpetration, victimization, and witnessing of online and offline bullying and the structure of peer networks. Of the 164 participants, a total of 77 participated in an electronic capture period from January through May 2015. We equipped participant smartphones with an application that collected incoming and outgoing text messages and Facebook and Twitter activity, and also surveyed them weekly about their bullying experiences. Approximately 21 per 1000 messages among youth in this sample were found to be aggressive in nature. Most aggression centered on topics about personality traits, sexual activity, harassment, jealousy, and appearance, and in peer-about-peer, peer-to-peer, and dating partners' communications. Messages with negative sentiment were found in specific participants, do not occur in mutual communications, and appear in gossip (i.e., discussed a third party). Findings form a scientific foundation for future studies of cyberbullying and more widely cyberaggresion. Our research also has practical implications for antibullying policies and practices, by providing by increasing knowledge about actual cyber aggressive communications and the social contexts in which they are embedded.

Purpose

Today's youth are the most technologically connected generation: 95% of US teens age 12 to 17 are "online" using email, social-networking websites, or texting services (Madden et al., 2013). About 78% of teens have cell phones, of which half are smartphones (pewinternet.org). With this explosion of electronic communications, cyberbullying has emerged as a new form of interpersonal aggression delivered electronically through online social networks, text messages, emails, and photo and video sharing. Cyberspace as an avenue for receiving or delivering acts of aggression is not well understood. The extant literature, almost exclusively cross-sectional surveys, indicates that cyberbullying is frequently delivered via social-media websites and cell phones, has a high percentage of "bully-victims," and is correlated with "offline" bullying (Wang et al., 2012; Smith et al., 2008). A significant limitation of these cross-sectional designs is that data are not gathered on the actual cyberbullying content of electronic communications and the larger peer contexts of these behaviors. This foundational information is needed to develop evidence-based intervention strategies to prevent cyberbullying. For this study, a longitudinal cohort of middle school students was followed over five months to capture cyber communications from smartphones. In addition, self-reported experiences of online and offline bullying were collected. Our objectives were to: 1) Classify the contents of cyberbullying messages and measure the frequency of various content themes in electronic communications. 2) Estimate associations between cyberbullying and offline bullying. 3) Examine associations between cyberbullying and social-network positions and composition.

Project Subjects

<u>Study sample and recruitment</u>. The study sample is comprised of students (grades 6-8) enrolled in two middle schools in Iowa during the 2014-15 school year. A total of 933 students were invited to participate in the study between December 2014 and May 2015. Members of the research team attended five in-person recruitment events (three at one school and two at another). Recruitment packets which contained an information sheet, consent and assent forms, survey documents and paid self-addressed envelopes were distributed either by mail (at one school) or through school distribution to parents (at the second school). At least four additional follow-

up rounds of follow-up recruitment packages were delivered to eligible participants. Of the 933, 164 (17.6%) consented to participation and completed at least one of the two participation surveys (see below). All students who reported being the primary user of 1) an Android, or 2) iPhone and Facebook user were eligible for an electronic capture phase. A total of 77 (47.0%) enrolled in the electronic capture phase.

See Table 1 in appendix for demographics of participants. Of the 167 survey participants, 65 were boys and 101 were girls. About 36% were in 6th grade, 32% in 7th grade and 32% in 8th grade. Ten percent identified as Hispanic or Latino, 7% were black, 7% were Native American, 7% were other and 86% were white. The majority (86.2%) received all A's, or a combination of A's and B's on last year's report card. Twelve percent had never been absent from school in the previous year, while the majority were absent either once (35%) or several times (34%). The smartphone sample had some differences in demographic and school characteristics, with slightly more girls (69% vs. 60%), more Latino/Hispanic (15% vs. 9%) and whites (93 vs. 86%) and more absenteeism (93.4% vs. 88.5% were absent at least once).

Project Design and Methods

Definitions. ***Bullying*** is defined as aggressive behavior that is repetitive and results in a power differential (Madden et al., 2013). One of our aims was to identify the types of ***aggressive behaviors*** that constitute cyberbullying. Thus, our measures of bullying were focused on specific behaviors that occurred repeatedly in the last two months. These behaviors were further classified according to the ***form in which the aggression occurred*** either physical (hit, kick), verbal, psychological (spreading rumors, exclusion), property damage, and cyber (posting of hurtful messages, threats online, or exclusion from online communities). Finally, we described ***role of the student experiencing aggression*** as victim/target, perpetrator, or witness.

Surveys. Middle school participants enrolled between December 2014 and March 2015 were invited to complete two surveys, one at baseline upon enrollment and one at follow-up in May 2015. Of the 164 students completed a Wave I survey, 152 completed a Wave II survey for a retention rate of 92.6%. An additional three participants who enrolled into the study in April and May 2015 only completed the Wave II survey instrument.

Wave I and II participants had comparable demographics. Both surveys contained questions about demographics (age, grade, gender, ethnicity, parents' marital status, household composition, religiosity, and socioeconomic status), daily activities, health, academics, attachment to parents, dating experiences, electronic communications, experiences of aggressive behavior, delinquency, and alcohol/drug use. Table 2 in the appendix shows the items used to create our bullying exposure variable. The survey also included a social network component, which asked subjects to provide the names of their friends, students they don't get along with, and those that others want to be friends with. All names provided were replaced with study-generated identifiers. Surveys were completed either online in Qualtrics or by self-administered hard copy form and took approximately 15-20 minutes to complete. Participants were compensated $15 for completing each survey. Smartphone Data Collection. Android users or Facebook or Twitter users were eligible for participation in the electronic capture phase. For this phase, 77 participants uploaded an application onto their smartphone for registration into the study. For Android users, the application collected all text, Facebook and Twitter messages from January-May 2015. For iPhone users, the application captured Facebook and Twitter posts. No text messages were captured from iPhone users; the smartphone text capture could not be programmed into the iPhone operating systems.

Participants of the electronic capture phases also received weekly queries by texts requesting them to answer questions about bullying experiences. The first question was “ During the past week, did you observe any of the following: a) Hurtful information about another student posted on the internet; b) An email threatened or insulted to another student; c) An instant message that threatened or insulted another student; d) A text message that threatened or insulted another student; or e) Threat or insult of another student through online gaming, example, while playing a game, through Second Life, or through XBOX.” A checked box to any of these questions prompted the following to appear: “Did you send, post, or share this information with others?”. Third, we asked “During the past week, did you observe any of the following: a) Hurtful information about you posted on the internet; b) An email threatened or insulted you; c) An instant message that threatened or insulted you; d) Threat or insult of you through online gaming, example, while playing a game, through Second Life, or through XBOX.”

Participants were compensated $40 per month during the electronic capture period.

Data Cleaning. Extensive data cleaning procedures were completed to de-identify data, as required by our Human Subjects Protection Committee, and to correct for misspellings. We conducted computer-automated cleaning using a Social Security file of first names and English language lexicons, and hand inspection of terms that matched neither names nor words.

Data Analysis

Aim 1. Classification of contents of messages, and measurement of prevalence of cyberaggression.

<u>Content Analysis</u>. Samples of messages were drawn using the weekly queries of smartphone users. The week of, one week before and one week after participants reported being a victim or witness or cyberaggression were pulled into a "case sample." A "control sample" was generated from participants who reported no cyberaggression; a three week random sample of 21 consecutive days of communication were randomly selected from control participants. Using content analyses, these samples were first coded independently by two members of the research team for aggression (yes or no), reasons for aggression (i.e., appearance, race/ethnicity, religion, gender and sexual orientation); and role of participant (e.g., victim, perpetrator, bystander). Discrepancies in codes were resolved by the two coders. Unresolved codes were arbitrated by one of the Principal Investigators.

<u>Natural Language Processing</u>. Natural Language Processing methods for text parsing and cleaning, syntactic and semantic normalization, and concept and relationship extraction were employed with the full sample of SMS, Facebook and Twitter messages.

<u>Machine Language Procedures</u>. Machine-learning procedures were implemented on conversations between pairs (e.g., A and B) who had at least 100 messages exchanged between them (n=110,040). Our classifier was based on: conversation features (minimum and maximum number of the words exchanged, the total number of words in a conversation, the difference of the words sent by A and B, and the ratio of the words sent by A and B); text features (term frequency-inverse document frequency); and sentiment score (positive or negative).

Cyberaggression rate. We calculated the frequency in which cyberaggression occurs as follows: # cyber-aggression messages/# students, and # messages per 100 students per week, and # messages per 1000 messages.

Aim 2. Estimate associations between cyberbullying and offline bullying.

Through our surveys, we captured offline bullying (relational, verbal, physical), cyberbullying, and role in exposure (victim, perpetrator, witness/bystander). To estimate associations between on- and offline bullying from self-reports, we fit Generalized Linear Models (GLM) using a logit link function to estimate odds ratios. To estimate associations using self-reported offline bullying at baseline and on-line bullying reported during weekly electronic queries, we fit a GLM using a log link function and Poisson distribution to estimate rate ratios.

Aim 3. Examine associations between cyberbullying and social-network positions and composition.

Social network data were drawn from survey responses about friendships and from electronic communications sent through social media platforms and text messages. We employed a hash function, which automatically encoded sender and receiver identifiers with platform-specific study identifiers. Thus, in the survey data, nodes consisted of in-school peers with ties representing friendships. In the electronic communications, nodes included participants and those entities who communicated with the former. Edges consisted of individual messages collected during the observation period. Using sentiment analysis and topic modeling, we labeled contents of edges based on their sentiment and topics, respectively. We then conducted preliminary analyses of patterns between social networks and negative sentiments and topics.

Findings

Aim 1 Content Analysis and Measures of Frequency. A total of 159,473 messages were collected (54,825 smartphone messages; 101,332 Facebook posts and 3,316 Twitter posts) from the 77 smartphone participants during the study period. Of the 77 participants, 73 participated in at least one weekly survey. Of these, 35 reported through realtime weekly queries either being a witness or victim of cyberaggression during follow-up.

A total of 35,566 messages were sampled for qualitative coding; these messages were captured during a 3-week window of time (the week of the report, the week prior to the report and the week after the report). Of these, 2883 messages (8.1%) were coded as aggressive in content. The most common topics of aggressive conversations involved fighting between parties (36.4%), aggressive language about personality traits (23.0%), sexual activity (16.6%), harassment (14.2%), jealousy (13.6%) and appearance (12.2%) (Table 2). Most aggressive language involved peers communicating about other peers (i.e., gossip) (42.3%), peers communicating aggressively to each other (peer-to-peer) (22.2%), and dating partners (11.1%). Messages that discussed verbal or physical disputes that escalated to using aggressive language or personal attacks were coded as fighting. Messages that expressed negativity about how a person acts were coded as personality. Messages that involve name-calling because of sexual behavior or unwanted sexual messages sent to a peer are coded as sexual activity. Messages that persisted after a victim asked an individual to stop messaging them or after they stop responding for long periods of time were coded as harassment. Messages that use negative language to reference the way a person looks are coded as appearance.

Using machine learning procedures in a sample of 110,040 messages, 2% (n=2323) of messages were coded as aggressive in nature. This is equivalent to a prevalence of 21 incidents of aggression per 1000 messages over the five month study period.

<u>Aim 2. Associations between face to face and cyberbullying</u>.

Survey Sample (N=164). A total of 21 (15.3%) students reported being a victim of face-to-face bullying, 5.1% a victim of cyberaggression at baseline, and 5.4% a victim of cyberaggression at follow-up (Table 3). Students who reported face-to-face victimization had 7.31 times the odds of being cyberbullied at follow-up compared with students who didn't experience face-to-face victimization (OR: 7.31; CI: 3.00, 17.80), and 3.26 times the odds of witnessing bullying (OR: 3.26; CI: 1.44, 7.39) (Table 5).

Smartphone Sample (N=77). In the smartphone sample, based on weekly queries, we found a cyberagression witness rate of 14.2 reports per 100 student-weeks, and a victimization rate of 5.4 reports per 100 person-weeks (Table 4). In the smartphone subsample, students who were bullied face-to-face at baseline had about 3.7 times the rate of cyberbullying victimization than students who were not bullied face-to-face (IRR: 3.73; CI: 1.80, 7.71) (Table 5).

Aim 3. Social network analyses

Survey network data. We first examined whether self-reported cyberaggression victimization was clustered in the social network of middle school students. Figure 1 presents a network visualization of cyberagression victimization at Wave I in one school. There are two larger clusters of cyberaggression victimization – one on the left and another on the bottom right. This visualization suggests that cyberagression victimization is clustered among participants who are close to central nodes, but are not central themselves in friendship networks. Future analyses will examine correlates of cyberaggression victimization, including the attributes of middle-school students and measures of network structure.

Negative topics in text message networks. We examined the types of conversations middle schoolers engage in through electronic communication and sought to identify and quantify to presence of negative topics, which we expected were correlated with cyberaggression. We estimated a series of topic models using latent drichelet allocation on 159,669 messages between middle-school participants and their contacts. We aggregated these messages into 3,688 unique conversations over a five-month period. Based on goodness-of-fit statistics, we estimated a topic model with 25 topics. One topic loaded heavily with negative terms – specifically in terms of the most frequent terms in the topic. Future analyses will examine correlations between this topic and other topics as well as with individual characteristics.

Negative sentiments in text message networks. Finally, we examined the sentiment of text messages. As shown in red in Figure 2, text messages with negative sentiment tended to be clustered in specific participants. We estimated whether the polarity of daily conversations was correlated with the directionality of test messages. Compared to daily text message conversations with positive valence, those with negative valence were only half (odds ratio=.57) as likely to occur in mutual communications; this suggests that negative conversations are more likely to be asymmetric. Preliminary regression results indicate that messages with negative sentiments were highly associated (OR=4.55) when discussing a person’s name, which appears to be a form of gossip (Table 6).

Implications for criminal justice policy and practice

This research has resulted in a number of key outputs that advance the scientific understanding of cyberbullying and more widely, cyberaggression. From a scientific standpoint, we have identified some key trends and relationships.

Our research provided multiple measures of cyberbullying frequency obtained from survey self-report, smartphone weekly queries and machine learning procedures. Teens engage in a tremendous amount of cyber communications – about 2000 messages per participant over one school semester in our study. From self-reports, we found a cyberbullying prevalence of about 5%, or we expect 5 per 100 students to have experienced cyberbullying in the last two months. From our weekly smartphone queries, we estimated a rate of 14/100 student-weeks, or that approximately 14 out of 100 students who use smartphones per week are victims or witnesses of cyberbullying. From our machine-learning sample, we were able to estimate a prevalence per message and found that about 21 per 1000 messages captured from teens contain cyber aggressive language. Measuring bullying multiple ways and with different denominators (i.e., exposure units) allows us to triangulate the burden of cyberbullying.

Classifying the aggressive content of middle school cyberbullying communications supports school efforts in management and response to bullying. All 50 states in the country have school anti-bullying laws, of which most do not specifically address cyberbullying. Yet, our prior research (Bruening et al., 2017; Young et al., 2017) identifies cyberbullying as one of the major challenges faced by schools. Schools report struggling specifically in understanding if incidents meet definitions of bullying and in investigating incidents. Our research provides specific language and content that constitutes cyberbullying and more widely aggression in the communications of youth.

Offline bullying is strongly associated with subsequent online bullying – key information that also will support efforts to respond to bullying and prevent escalation to cyberbullying. Anti-bullying policies also require that schools investigate bullying incidents, and develop safety and response plans for victims/targets. To protect children who are bullied face-to-face against becoming targets/victims online, investigations must be comprehensive with special attention to both off and online avenues for aggressive behaviors. Safety measures must be put into place that protect targets and victims both on school grounds and in cyberspace.

Messages with negative sentiment were found in specific participants, less likely in mutual communications, and appear in gossip (i.e., discussed a third party). This project's focus on the linguistic and relationship contexts of identified several relational dimensions of cyberaggression. Electronic communications with negative sentiment were clustered, suggesting that specific adolescents play key roles in nurturing negative sentiment across their contacts. In contrast to the notion that cyberaggression emerges randomly across various pairs of individuals, we found that negative language by specific individuals tended to be spread across their relationships. The fact that negative sentiments were more likely to be asymmetric communications appears to be consistent with the notion that cyberaggression is more likely to be targeted at specific individuals as opposed to reflecting a process of mutual conflict. Finally, the fact that negative sentiment is associated strongly with discussion about third parties highlights the role of gossip as a major dimension of cyberaggression. A direct implication of this finding is the development of interventions discouraging posts or messages about third parties in electronic communications.

Our research team developed new technology for coding the aggressive nature of cyber communications. Trolling through thousands of messages is a great challenge for investigations of potential cyberbullying cases. New software developed to organize, code and identify aggression in cyber messages has future practical implications for criminal justice response and management of "big data".

Implication for Practice. Our study informs specific next steps for youth violence prevention practices and the development of interventions. For the public, parents, and adolescents, our findings provide opportunity to increase awareness about the types of messages that are harmful. Second, our research indicates that peer networks play a significant role as an avenue for intervention to promote pro-social norms. We found that bullying victims were located close to central nodes of peer networks but not central themselves. This interestingly suggests a new focus to intervene on individuals who are well integrated into their networks.

While schools across the country anti-bullying curricula, few evidence-based approaches specifically address cyberbullying with one program (KiVa) showing some short-term but not long-term effects mostly in elementary school students (see review by Cantone et al., 2015). Our work informs the development of future interventions. First, we provide specific language that informs all educational components of intervention programs that include cyberaggression. This can improve upon existing curricula that need realistic examples of what constitutes cyberbullying. Second, bystanders can play a critical role in the prevention of cyberaggression. We encountered several bystanders in our qualitative analysis; they witnessed aggressive language that occurs in their networks. As we conceptualize new strategies for prevention and intervention, we see bystanders play positive roles in networks where aggression occurs. Positive sentiment and supportive language content identified from this study that can furthermore be used for bystander intervention training and programming. Third, we will refine the technology that we have developed to monitor electronic messages for aggressive content, that ultimately can be used for future interventions used by parents, schools and law enforcement.

Conclusions

This in-depth study of the cyberbullying communications in a cohort of middle school youth used multiple rigorous methods including self-reports, electronic capture of communications, electronic weekly queries, machine learning, social networks analysis, and mixed methods. In summary, while cyberbullying victimization was self-reported by 5% of youth, cyberbullying was witnessed by about 14 of 100 students per week, and aggressive language was found in about 21/1000 smartphone messages. Victims of face-to-face bullying are much more likely to become victims of cyberbullying. Negative language occurs in certain social networks, and the most common topics of cyberaggression are personality traits, sexual activity, harassment, jealousy, and appearance. Although findings are limited to our study sample, the methods and findings set the stage for future larger studies.

Table 1. Demographics of Participants (Survey Phase N=167; Electronic Capture Phase N=75*)

	Survey	Electronic Capture
	n (%)	n (%)
Gender		
Male	65 (39.2)	23 (30.7)
Female	101 (60.8)	52 (69.3)
Grade		
6^{th}	59 (36.0)	20 (26.7)
7^{th}	52 (31.7)	28 (37.3)
8^{th}	52 (31.7)	27 (36.0)
Hispanic/Latino		
Yes	16 (9.6)	11 (14.7)
No	150 (90.4)	64 (85.3)
Race/ethnicity		
Asian	1 (1)	0
Black	12 (7.2)	7 (9.3)
Hispanic/Latino	16 (9.6)	11 (14.7)
Native American	12 (7.2)	3 (4.0)
White	144 (86.2)	70 (93.3)
Other	11 (6.6)	4 (5.3)
Academic Performance Last Year		
All A's	52 (31.3)	25 (33.3)
A's and B's	82 (49.4)	40 (53.3)
Mostly B's	9 (5.4)	1 (1.3)
B's and C's/Mostly C's	23 (13.9)	9 (12.0)
Absenteeism Last Year		
Never	19 (11.5)	5 (6.7)
Once	58 (35.2)	24 (32.0)
Several Times	55 (33.3)	26 (34.7)
1x or more times/month	33 (19.9)	20 (26.7)

*Excludes 2 students who did not complete surveys; N's do not add up to 167 due to missing data

Table 2. Content Analysis of Messages captured 3 week windows of reported cyber-aggression (N=2883)[a]

	n (%)
Topic	
Hygiene	30 (1.0)
Appearance	352 (12.2)
Fighting	1049 (36.4)
Jealousy	393 (13.6)
Race/Ethnicity	87 (3.0)
Sexual Orientation	21 (0.7)
Sexual Activity	478 (16.6)
Socioeconomic Status	16 (0.6)
Personality	662 (23.0)
Manipulation	119 (4.1)
Intellect	42 (1.5)
Harassment	408 (14.2)
Cannot Determine Topic [b]	261 (9.1)
Target	
Peer to Peer	
Peer About Peer	639 (22.2)
Dating Partner	1220 (42.3)
Parent	321 (11.1)
Other Adult	73 (2.5)
Self [c]	107 (3.7)
Cannot Determine [d]	165 (5.7)
	649 (22.5)

[a]Messages may have multiple topics and targets.
[b]Aggression was apparent in communications, but topic of aggression was unclear. Examples are cases such as pictures being sent; vague references to incidents not clearly described; exclusion of a peer but reason for exclusion not expressed. Note that pictures were not collected as part of this study.
[c]Negative comments (aggression) directed towards oneself.
[d]Aggression was expressed but the target's relationship with those involved in the communications was unclear.

Table 3. Aggressive and bullying experiences by form and frequency

Aggression in Wave I	**Frequency**					
	Never	Once or Twice	2-3 per month	1 per week	Several times per week	Everyday or more
Form of Aggression						
Hit, kicked, pushed, shoved around, locked indoors by other	118 (72.4)	35 (21.5)	7 (4.3)	0	1 (0.6)	2 (1.2)
Called mean names, made fun of, teased by other	90 (55.2)	44 (27.0)	9 (5.5)	8 (4.9)	8 (4.9)	4 (2.5)
Targeted with rumors or lies by other	103 (63.2)	39 (23.9)	10 (6.1)	8 (4.9)	2 (1.2)	1 (0.6)
Had property stolen or damaged by other	126 (77.8)	29 (17.9)	2 (1.2)	2 (1.2)	2 (1.2.)	1 (0.6)
Kept out of things, excluded, completely ignored by other	109 (67.3)	29 (17.9)	14 (8.6)	4 (2.5)	2 (1.2)	4 (2.5)
Received sexual jokes, comments, gestures towards you fr. other	139 (85.3)	17 (10.4)	4 (2.5)	1 (0.6)	0	2 (1.3)
Targeted by hurtful information posted on the internet	148 (90.8)	11 (6.8)	3 (1.8)	1 (0.6)	0	0
Threatened/insulted by other student through email?	158 (96.9)	3 (1.8)	2 (1.2)	0	0	0
Threatened/insulted by other student through text/instant messaging	140 (85.9)	19 (11.7)	4 (2.5)	0	0	0
Threatened/insulted through online gaming or through XBOX	145 (89.5)	13 (8.0)	1 (0.6)	1 (0.6)	0	2 (1.2)
Purposely excluded from online community	143 (87.7)	12 (7.4)	6 (3.7)	1 (0.6)	1 (0.6)	0
	No	Yes				
Experienced any physical aggression	118 (72.4)	45 (27.6)				
Experienced any verbal aggression[1]	83 (50.9)	80 (49.1)				
Experienced any psychological aggression[2]	83 (50.9)	80 (49.1)				
Experienced any property-related aggression	126 (77.8)	36 (22.2)				
Experienced any face to face aggression[3]	53 (31.7)	114 (68.3)				
Experienced any online aggression[4]	117 (70.1)	50 (29.9)				
Experienced physical bullying*	153 (93.9)	10 (6.1)				
Experienced verbal bullying*[1]	131 (80.4)	32 (19.6)				
Experienced psychological bullying*[2]	128 (79.0)	34 (21.0)				
Experienced property-related bullying*	155 (95.7)	7 (4.3)				
Experienced face to face bullying*[3]	116 (71.6)	46 (28.4)				
Experienced online bullying*[4]	150 (92.6)	12 (7.4)				

Aggression in Wave II	**Frequency**					
	Never	Once or Twice	2-3 per month	1 per week	Several times per week	Everyday or more
Form of Aggression						
Hit, kicked, pushed, shoved around, locked indoors by other	122 (79.2)	25 (16.2)	2 (1.3)	4 (2.6)	1 (0.7)	0
Called mean names, made fun of, teased by other	87 (56.9)	35 (22.9)	14 (9.2)	8 (5.2)	4 (2.6)	5 (3.3)
Targeted with rumors or lies by other	105 (68.2)	30 (19.5)	9 (5.8)	3 (2.0)	6 (3.9)	1 (0.7)
Had property stolen or damaged by other	125 (81.2)	19 (12.3)	7 (4.6)	2 (1.3)	0	1 (0.7)
Kept out of things, excluded, completely ignored by other	99 (65.1)	32 (21.1)	6 (4.0)	5 (3.3)	8 (5.3)	2 (1.3)
Received sexual jokes, comments, gestures towards you fr. other	126 (82.9)	16 (10.5)	4 (2.6)	1 (0.7)	4 (2.6)	1 (0.7)
Targeted by hurtful information posted on the internet	141 (92.8)	5 (3.3)	3 (2.0)	1 (0.7)	1 (0.7)	1 (0.7)
Threatened/insulted by other student through email?	146 (97.3)	1 (0.7)	0	1 (0.7)	2 (1.3)	0
Threatened/insulted by other student through text/instant messaging	129 (84.9)	17 (11.2)	0	1 (0.7)	3 (2.0)	2 (1.3)
Threatened/insulted through online gaming or through XBOX	141 (92.8)	8 (5.3)	1 (0.7)	0	0	2 (1.3)
Purposely excluded from online community	137 (89.5)	11 (7.2)	1 (0.7)	1 (0.7)	2 (1.3)	1 (0.7)
	No	Yes				
Experienced any physical aggression	122 (79.2)	32 (20.8)				
Experienced any verbal aggression[1]	80 (52.3)	73 (47.7)				

Experienced any psychological aggression[2]	83 (54.3)	70 (45.8)
Experienced any property-related aggression	125 (81.2)	29 (18.8)
Experienced any face to face aggression[3]	62 (37.1)	105 (62.9)
Experienced any online aggression[4]	115 (68.9)	52 (31.1)
Experienced physical bullying*	147 (95.5)	7 (4.6)
Experienced verbal bullying*[1]	119 (77.8)	34 (22.2)
Experienced psychological bullying*[2]	122 (80.3)	30 (19.7)
Experienced property-related bullying*	144 (93.5)	10 (6.5)
Experienced face to face bullying*[3]	107 (69.9)	46 (30.1)
Experienced online bullying*[4]	140 (92.7)	11 (7.3)

* These are for incidents that occurred at least 2-3 times a month.

[1] This variable was created by referring to both “Called mean names, made fun of, teased by other” and “Received sexual jokes, comments, gestures towards you from other.”

[2] This variable was created by referring to both “Targeted with rumors or lies by other “and “Kept out of things, excluded, completely ignored by other.”

[3] This variable was created from the physical, verbal, psychological, and property-related bullying variables.

[4] This variable was created by referring to all of the following: “Targeted by hurtful information posted on the internet”, “Threatened/insulted by other student through email”, ”Threatened/insulted by other student through text/instant messaging”, “Threatened/insulted by other student through text/instant messaging”, “Threatened/insulted through online gaming or through XBOX”, and “Purposely excluded from online community.”

Table 4. Rate of cyberbullying in smartphone sample overall and by face-to-face baseline experiences of bullying (N=75)

	N (%)	Rate of cyberbullying at follow-up (per 100 student-weeks)	
		Cyber victimization	Cyber witnessing
Face-to-face victimization at baseline			
Yes	20 (27)	8.9/100	20.3/100
No	53 (73)	3.9/100	11.6/100
Overall	73 (100)	5.4/100	14.2/100

Table 5. Measures of association between face-to-face bullying and cyberbullying

Survey sample	Odds Ratio	Standard Error	P-value	Conf. Interval
Face-to-face bullying	7.31	3.32	<0.001	3.00, 17.80
Gender (Male vs. Female)	1.41	0.71	0.49	0.52, 3.82
Grade level (ref. is 6th grade)				
7th grade	1.58	0.89	0.37	0.58, 4.28
8th grade	0.57	0.34	0.34	0.18, 1.81
School	1.52	0.74	0.39	0.58, 3.95
Number of text or instant messages received	0.93	0.07	0.61	0.70, 1.23

Smartphone subsample	Incidence Rate Ratio	Standard Error	P-value	Conf. Interval
Face-to-face bullying	3.73	1.38	<0.001	1.8, 7.71
Gender (Male vs. Female)	0.18	0.13	0.015	0.05, 0.72
Grade level (ref. is 6th grade)				
7th grade	0.35	0.22	0.092	1.0, 1.19
8th grade	0.14	0.08	<0.001	0.05, 0.41
School	0.25	0.1	<0.001	0.12, 0.54

Table 6.

Mixed Effect Logistic Regression of Any Negativity

Variables	Odds ratio	
Male	0.42	**
Age	0.92	
African American	2.76	
Latino	0.95	
Native American	0.54	
# of types of victimizations	1.12	
# of types of witnessed aggressions	0.93	
Perpetration of any relational aggression	1.38	
# of friends nominated	1.04	
Discussed third party	4.55	***
Constant	0.94	
nodes	56	
dyads	923	
conversations	4276	
node: sd	0.67	
alter: sd	0.79	

LR test vs. logistic regression: chi2(2) = 337.53 Prob > chi2 = 0.0000

** <.01

***<.001

Figure 1. Network Visualization of middle school students

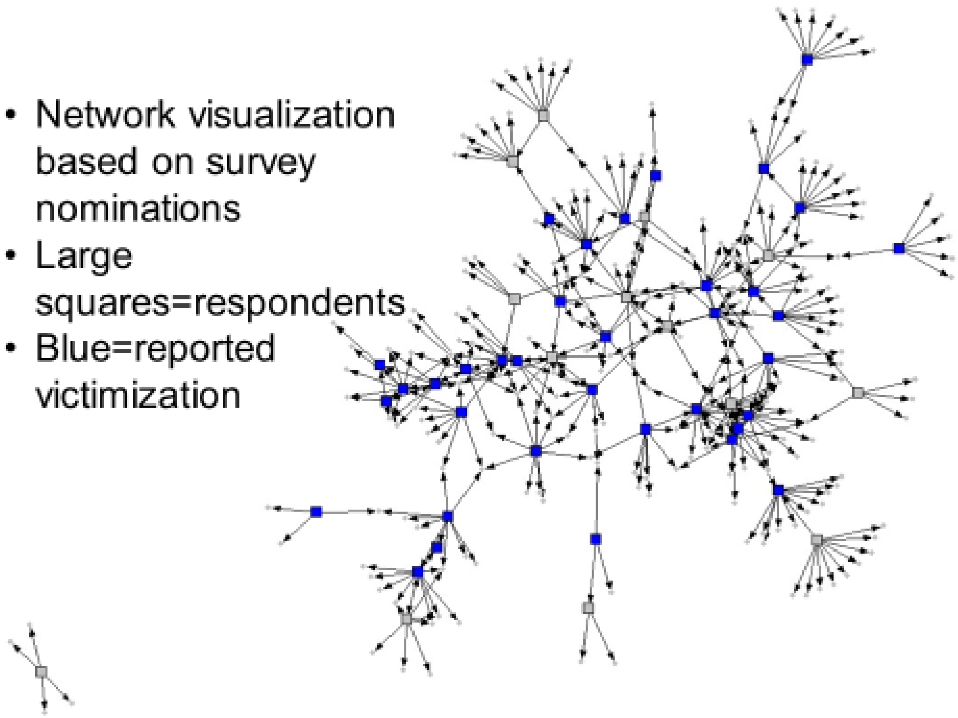
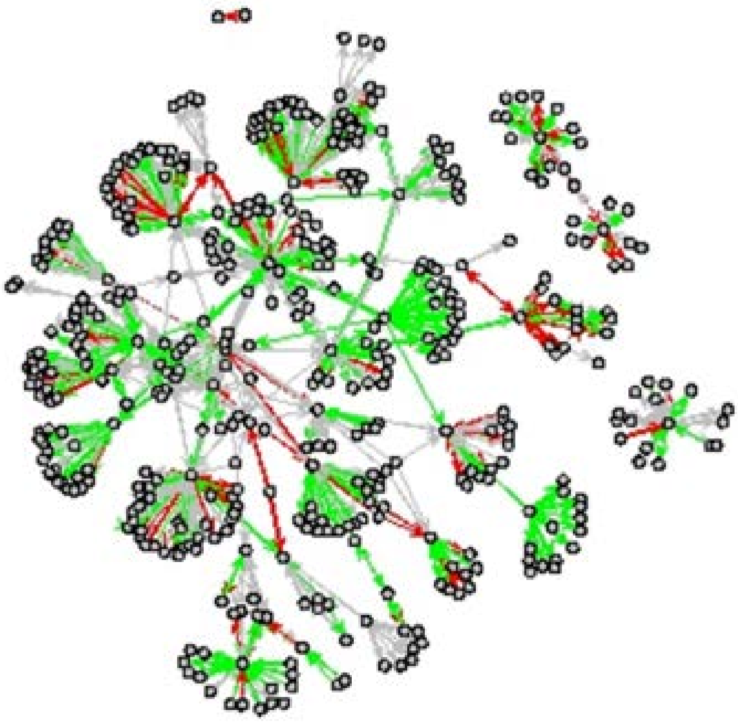


Figure 2. Negative Sentiment in Networks



	Mutual	Asymetric	Ratio	OR
Positive	242	200	1.21	Ref
Negative	155	225	0.69	0.57
Neutral	461	537	0.86	0.71

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