Cyber-victimization and Its Psychosocial Consequences: Relationships with Behavior Management and Traditional Bullying

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Abstract

The current study investigated the relationship between behavior management, traditional bullying, cyber-victimization, and several psychosocial consequences of cyber-victimization. Findings from previous research were used to specify a complex path model, which allowed the simultaneous estimation of multiple direct and indirect effects. Data were collected in 2011 by the U.S. National Center for Education Statistics and the U.S. Bureau of Justice Statistics using the School Crime Supplement of the National Crime Victimization Survey (N=498). Results showed that being a victim of traditional bullying was a significant predictor of cyber-victimization. Further, increased levels of cyber-victimization predicted higher levels of fear and avoiding behaviors, having fewer friends, carrying a weapon, and, in turn, engagement into physical conflicts. Nevertheless, an effective behavior management at the school level predicted lower levels of cyber-victimization through the reduction of traditional bullying.

Keywords: cyber-victimization, bullying, behavior management, path analysis

With the introduction of new technology and access to social media, a new form of victimization, cyber-victimization, has emerged (Kowalski, Limber & Agatston, 2008). Cyber-victimization involves the use of information and communication technologies, such as e-mail, cell phone and pager text messages, instant messaging, websites, etc., to support deliberate, repeated hostile behavior by an individual or group (Olweus, 1993). Because it occurs in the cyber-space, where adults' access is limited, cyber-victimization is more difficult to identify and address than face-to-face bullying. Many students perceive cyber-bullying as being even more harmful than traditional bullying by leading to increased levels of psychological distress and even suicide (Slovak & Singer, 2011). Youth who experienced traditional bullying or cyber-bullying, as either an offender or a victim, have more suicidal

thoughts and are more likely to attempt suicide than those who have not experienced such forms of peer aggression (Hinduja & Patchin, 2010).

Currently, 37% of teens, ages 12-17, own a smartphone, 74% can access the Internet on a mobile device, and 93% have access to the Internet (Belsey, 2014). Although many states adopted education technology standards to be taught in schools, which include a computer ethics component (International Society for Technology Education, 2014), almost a third of US students, ages 12-18, reported being cyber-bullied at school (National Center for Educational Statistics & Bureau of Justice Statistics, 2013). When such behavior occurs in the school setting, it is within the school's jurisdiction (Englander, 2012). Furthermore, educators must be aware of the dysfunctional or risky behaviors associated with cyber-victimization. As a result, the current study aimed to:

1. Determine whether effective behavior management at the school level predicts less traditional bullying, and, in turn, less cyber-victimization.
2. Determine the extent to which cyber-victimization predicts fear, avoiding behaviors, and having fewer friends at school.
3. Determine the extent to which cyber-victimization predicts weapon carrying and, consequently, participation in physical conflicts.

The relationships above were hypothesized based on the current literature on the topic. While previous studies focused on one or a subset of these relationships, the current study proposed a more comprehensive model, which allowed researchers to simultaneously estimate a multitude of direct and indirect effects, and to identify the strongest relationships.

Theoretical Framework

Bullying continues to be an issue of importance to educators, criminal justice practitioners, school districts, and parents. Cyber-bullying can be far more insidious than traditional bullying, because there is no escape from it (Muscari, 2002). Cyber-bullying can occur inside and outside of the normal school hours, many times anonymously, and can involve many participants because of its global nature. Students who have been both bullies and cyber-victims suffer the most harmful effects of this phenomenon, such as, for example, depreciation of the grade point average, fear, anxiety, depression, and other psychological harm (Juvonen & Gross, 2008; Sourander, et al., 2010). Schoffstall and Cohen (2011) showed that students who engaged in cyber-aggression had higher rates of loneliness and lower rates of social acceptability, peer optimism, number of mutual friendships, popularity, and global self-worth. Further, engagement in cyber-victimization is often associated with problem behavior, depressive symptomatology, poor parent–child relationships, delinquency, and substance use (Wagner, 2008; Ybarra & Mitchell, 2004a; Ybarra & Mitchell, 2004b).

Recently, in the United States, there have been many wide-spread media reports of death and suicide that have involved various cyber-bullying behaviors, affecting communities, school systems, and families. School leaders are dealing with more routine cases daily and often feel they have little legal advice or precedent to guide them in their decision-making, such as the role schools should play in preventing and reacting to cyber-bullying (Nirvi, 2011). When cyber-bullying occurs on the school grounds, the behavior is viewed as being under the school's jurisdiction (Englander, 2010); therefore, school administrators must assess each cyber-bullying case and discipline cyber-bullies (Englander, 2010).

Most states have adopted technology standards, such as the National Education Technology Standards for Students (NETS-S) by the International Society for Technology in Education (ISTE). One of the components of NETS-S contains a standard for ethics that addresses appropriate usage of technology to be taught, along with other standards, such as

technology skills. Nevertheless, cyber-bullying incidents continue to occur. Approximately 28% of students, ages 12-18, reported being bullied at school or during the school year, and 9% reported being cyber-bullied anywhere, including school (National Center for Educational Statistics & Bureau of Justice Statistics, 2013). Further, approximately half of the cyber-victims reported knowing the bully from school (Juvonen & Gross, 2008).

With the exception of gaming and being excluded online, female students reported higher incidences of cyber-victimization than males. White students (28%) were cyber-bullied more than Hispanic (8%) and Black (7%) students; 10th grade students cyber-bullied the most out of grades 6-12; and suburban students cyber-bullied more than urban students (National Center for Educational Statistics & Bureau of Justice Statistics, 2013). According to the U.S. National Center for Educational Statistics (2013), most cyber-bullying occurs once a week (71.9%), and adults were notified 26.1% of the time versus 39.5% for traditional bullying.

Willard (2007) listed several ways in which students can attack and be harmed in the cyber-space: flaming[1], harassment, impersonation, denigration, trickery, outing, cyber-stalking, and exclusion. A study conducted by Juvonen and Grass (2008) reported that most cyber-bullying consisted of name calling and insults and took place through instant messaging. Nevertheless, with the continuous development of new technologies and social networks, school systems are facing new issues, paralleled and fueled by new discipline infractions that must be managed (Wallace, 2013).

Gaggle (2014), a company devoted to protecting students by monitoring their correspondence and reporting issues to administrators, lists current social applications and the potential dangers that each one can impose. Some of the warnings include: a) allowing inappropriate images and text, b) allowing anonymous interaction, c) allowing automatic deletion of text and images, d) encouraging user interactions for dating or sexual purposes, e) allowing participation in chat rooms without phone or Internet connection, f) allowing document sharing when email is limited to in-district communication or turned off, etc. (Gaggle, 2014; Shah, 2011). Although there are companies that can monitor student correspondence and flag problem language to school administrators for investigation when on the school network, this does not affect the usage of social media apps with personal smart phone Internet access during and after regular school hours (Gaggle, 2014).

When social media applications are used inappropriately, either inside or outside the school setting, conflicts can escalate to face-to-face confrontations, causing problems for administrators and creating safety issues for students. Research showed that most cyber-victims are also victims of face-to-face bullying, and multiple studies suggest that the line between traditional victimization and cyber-victimization is not distinct; many victims of cyber-bullying are also bullied in traditional environments (Bayar & Ucanok, 2012; Bilić, Flander, & Rafajac, 2014; Cappadocia, Craig, & Pepler, 2013; Brighi, Guarini, Melotti, Galli, & Genta, 2012; Beran & Li, 2007; Raskauskas & Stoltz, 2007). Cyber-victimization is not a problem that stays in the cyber-world; instead, it is often intertwined with more traditional forms of bullying. Bilić et al. (2014) summarized the relationship between cyber- and traditional bullying as part of "cycles of violence transferred from school to the virtual environment and vice versa" (p. 27); therefore, a way to reduce cyber-victimization could be by effectively addressing and preventing traditional bullying. Although bullying is not a new concept to educators and the public, previous studies are limited in explaining the predictive effect of factors, such as demographic variables, school environmental variables, and school anti-bullying preventive measures (Jeong, Kwak, Moon, & Miguel, 2013). In a study

[1] Flaming is the term used for sending or posting offensive messages called "flames" over the Internet (Christensson, 2006).

examining school safety measures and students' perceptions of school climate, especially school rules and punishment, findings revealed that the variables of security guards, fairness and awareness of school rules, gangs and guns at school, students misbehaving, and teachers' punishment of students were statistically significant predictors of bullying victimization (Jeong et al., 2013).

In summary, the literature provides evidence on the relationships between behavior management, bullying, cyber-victimization, and the psycho-social consequences of cyber-victimization. The current study aims to connect previous findings by integrating these relationships into a complex model, which allows the simultaneous estimation of a multitude of direct and indirect effects using the same data. The hypothesized model postulates that behavior management in the school setting predicts less bullying and, in turn, less cyber-victimization. Further, it is hypothesized that increased levels of cyber-victimization predict more fear, avoiding behaviors, having fewer friends at school, weapon carrying, and, consequently, engagement into physical conflicts.

Method

Data Sources

Data for the current study were collected by the U.S. National Center for Education Statistics (NCES) and the Bureau of Justice Statistics (BJS), using 2011 School Crime Supplement (SCS) of the National Crime Victimization Survey (NCVS). The SCS was conducted in 1989, 1995, and biennially since 1999. Households are selected for the NCVS, using a stratified, multistage cluster sampling design. The SCS is administered to all eligible NCVS respondents, ages 12 through 18, within NCVS households between January and June of the year of data collection. In 2011, approximately 79,800 households participated in the NCVS sample, and those NCVS households included 10,341 members between the ages of 12 and 18. To be eligible for the SCS, these 12- to 18-year-olds must complete the NCVS and meet certain criteria specified in a set of SCS screening questions. These criteria require students to be currently enrolled in a primary or secondary education program leading to a high school diploma or enrolled sometime during the school year of the interview; not enrolled in fifth grade or under; and not exclusively homeschooled during the school year. In 2011, a total of 6,547 NCVS respondents were screened for the 2011 SCS, and 5,857 met the criteria for completing the survey. From this sample, individuals with at least one cyber-victimization experience were selected for the current study. The resulting sample included 498 children (8.5%), with an average age of 15 (standard deviation=1.8). The age and grade level distribution of the selected sample is provided in Table 1.

Responses to the SCS were summarized into a set of variables measuring a) behavior management effectiveness at the child's school (bm), b) the extent to which respondents were victims of traditional bullying (bul); c) the extent to which respondents experienced cyber-victimization (cyv); d) the extent to which respondents experienced fear (fear); e) the extent to which respondents manifested avoiding behaviors (avoid); f) the degree to which respondents agreed to have a peer friends at school (peerf); g) the number of times the respondents have been in physical conflicts (fights); and h) whether they brought different types of weapons to school during the current school year (weapon). A list of variable abbreviations is provided below (Table 2). The bm, bul, cyv, fear, avoid, and weapon variables are composite scores created by adding the responses to several survey items. The survey items represented by each variable, along with the response options and the assigned numerical values are listed in the Appendix. All variables were standardized as z scores (mean=0, standard deviation=1) before being used for further statistical analyses.

Data Analysis

To investigate the distribution of the data, researchers computed univariate indices of skewness and kurtosis for every composite variable. Typically, skewness indices larger than 2 and kurtosis indices larger than 7 show non-normal distribution (Finney & DiStefano, 2010). Additionally, the R.10.1 statistical package was used to conduct Mardia's test of multivariate normality (Mardia, 1970).

Relationships between variables were estimated using path analysis. This procedure uses correlational data to examine and compare the strength of direct and indirect relationships between variables (Lleras, 2005). It is an extension of multiple regression and assumes linear relationships among variables and a multivariate normal distribution (Wright, 1934). Unlike regression models, path models may include any number of dependent and independent variables and allows the simultaneous estimation of several multiple regression equations among a set of observed variables (Schumaker & Lomax, 2010). Further, path models may include mediating variables, which are independent variables in some relationships and dependent variables in others (Muthén & Muthén, 2012). Relationships between variables are estimated through the computation of path coefficients, which are standardized regression coefficients indicating the effect of an independent variable on a dependent variable (Garson, 2014). Path models also allow the computation of indirect effects, which estimate the impact of an independent variable on a dependent variable through one or more mediating variables by multiplying sequential path coefficients (Wuensch, 2012).

The hypothesized path model postulated that effective behavior management at the school level predicted less bullying and, in turn, less cyber-victimization. Further, the proposed model hypothesized that higher levels of cyber-victimization predicted higher levels of fear and avoiding behaviors, having fewer friends, and weapon carrying. The hypothesized model also specified a relationship between weapon carrying and engagement into physical conflicts. Further, the indirect effect of school behavior management on cyber-victimization was computed by multiplying the bm->bul path coefficient by the bul->cyv path coefficient.

To measure the degree of association between dependent variables, the hypothesized model also specified the estimation of covariance coefficients between variables measuring fear, avoiding behaviors, having peer friends, weapon carrying, and engagement in physical conflicts (Figure 1). Covariance estimates show the amount by which two variables change together and are scaled by the product of their standard deviations (Olson, 1987).

After specifying the coefficients to be estimated, the application of the T-rule (Byrne, 1998) showed that the model was over-identified, meaning that sufficient information and enough degrees of freedom (df=15) were left to compute model parameters. Path coefficients and goodness of fit indices were computed using the Mplus 7.1 statistical package with the maximum likelihood (ML) estimation procedure. Coefficients were considered significant when the corresponding t statistics took values above 1.96.

To assess the goodness of fit of the model, the following fit indices were recorded: (1) Chi-square statistic/ degrees of freedom; (2) root mean square error of approximation (RMSEA) and 90% confidence interval; (3) comparative fit index (CFI); and (4) the standardized root mean residual (SRMR). Although the chi-square fit statistic is widely used as an index of how well the model fits a set of data (Jöreskog & Sörbom, 1993), it is sensitive to both sample and model size (Finney & DiStefano, 2006). As a result, chi-square divided by the degrees of freedom was used as an index of fit. Generally, values lower than 3 indicate a good model fit (Finney & DiStefano, 2006). The RMSEA index estimates how well the proposed model approximates reality. Values between .05 and .08 indicate a fair model fit, whereas values smaller than .05 show excellent fit (Jöreskog & Sörbom, 1993). The

comparative fit index (CFI) ranges from 0 to 1, and compares the proposed model to the independence model. Values greater than .90 indicate acceptable fit to the data, whereas values above .95 reflect a very good model fit (Schumaker & Lomax, 2010). SRMR reflects the size of the fitted residuals with small values indicating a better fit. When the variance-covariance residuals are small, the SRMR takes values that are closer to 0, which indicate good model fit. Researchers typically use .08 as a threshold for good fit (Jöreskog & Sörbom, 1993).

Results

Although Mardia's tests of multivariate skewness (Mardia's multivariate skewness=35.94, $p < .001$) and multivariate kurtosis (Mardia's multivariate kurtosis= 49.50, $p < .001$) yielded significant coefficients, the univariate skewness and kurtosis coefficients did not exceed the cutoff values indicative of non-normality, thus justifying the use of ML estimation (Finney & DiStefano, 2006).

The estimated path coefficients had relatively low values but were all statistically significant. The t statistics for path coefficients took absolute values between 2.8 and 10.15 (Table 3). The highest path coefficients were bul->cyv (.414), and cyv->avoid (.277), whereas the weakest relationships were cyv->peerf (-0.125), and weapon->fights (0.179). The bm->bul and cyv->peerf path coefficients took negative values, indicating that high values in one variable were associated with low values in the other variable. All other path coefficients took positive values, indicating positive relationships. Results showed that, when behavior management increased its effectiveness by one unit, traditional bullying decreased by 0.260; a one unit decrease in bullying was associated with a 0.414 decrease in cyber-victimization. Therefore, the indirect effect of school behavior management on cyber-victimization was -0.11.

As indicated in Table 4, the only significant covariance coefficients were between fear and avoidance behaviors and between avoidance behaviors and fights. Non-significant relationships were sequentially eliminated to obtain a final path model (Figure 2). Goodness of fit indices showed that the final path model had a good fit to the data (Table 5). Chi-square/df was higher than 3, but this statistic is sensitive to both sample size and model size (Finney & DiStefano, 2006). Further, the RMSA, CFI, and SRMR indices showed a good model fit.

Discussion

The current study showed that, in schools with a generally effective behavior management, traditional bullying was less likely to occur. This finding was consistent with prior research showing that measures of behavior management effectiveness are significant predictors of bullying victimization (Jeong et al., 2013). Results also showed that traditional bullying was a significant predictor of cyber-victimization. This was the strongest relationship in the path model and confirmed the findings of previous research findings (Bayar & Ucanok, 2012; Bilić et al., 2014; Cappadocia et al., 2013; Brighi et al., 2012; Beran & Li, 2007; Raskauskas & Stoltz, 2007).

The second strongest relationship was between cyber-victimization and avoidance. This relationship is particularly interesting because cyber-victimization occurred in the cyber-space, whereas the *avoid* composite variable measured avoidance of school-related activities and of physical locations within and outside of the school grounds (e.g., school entrance, the shortest route to school, cafeteria, restrooms, parking lot, etc.).

Significant relationships were also found between cyber-victimization and other psychosocial consequences, such as fear and having fewer friends. Although these relationships were not strong, they were statistically significant and confirmed findings of other researchers (Juvonen & Gross, 2008; Sourander et al., 2010; Schoffstall & Cohen, 2011). Further, a strong covariance coefficient was recorded between fear and avoidance, showing that higher levels of avoidant behavior were associated with higher levels of fear.

The hypothesized model also specified relationships between cyber-victimization and weapon carrying, as well as between weapon carrying and engagement into physical conflicts. These relationships were not strong, but were statistically significant and confirmed the hypotheses that cyber-victimization can predict, to a certain extent, aggressive behavior and can put cyber-victims and other individuals at risk.

As indicated above, many of the relationships specified in the hypothesized path model have been investigated by other researchers. Nevertheless, the use of path analysis allowed researchers to simultaneously estimate multiple relationships, to include several mediating variables, and to estimate the indirect effect of school behavior management on cyber-victimization. Although this effect was not strong, results showed that one unit increase in behavior management effectiveness predicted a 0.11 decrease in cyber-victimization. This finding is encouraging, considering that the bm composite variable included only general indicators of behavior management (e.g., fairness and enforcement of school rules, frequency of misbehavior, etc.), which did not directly address cyber-victimization. Targeted interventions addressing victimization may have a higher impact on reducing bullying and cyberbullying. Unlike other factors that cannot be entirely controlled by educators (e.g., access to mobile devices, anonymous online activity, etc.), behavior management can be improved and can be focused on the prevention and sanction of cyber-victimization.

In summary, the findings of most practical relevance are that victims of traditional bullying are also likely to be victims of cyber-bullying and that cyber-victimization predicts increased levels of avoiding behaviors. This information is critical for practitioners, because it facilitates the identification of cyber-victims by indicating behaviors that may be associated with virtual victimization: a) being a victim of traditional bullying, and b) the manifestation of avoiding behaviors.

The current study is based on data from the 2011 administration of the School Crime Supplement. Additional research using data from other collection years is needed to determine the extent to which results are consistent across time. Further, the relationships identified in this study only begin to describe the cyber-victimization phenomenon. More research using person-oriented classification procedures is needed to describe in more detail the characteristics of cyber-victims and to develop a typology of cyber-victimization. Additionally, the relationships between cyber-victimization and other risk factors (e.g., social interaction difficulties, lack of participation in school related activities, etc.) should be investigated to facilitate the prevention and early identification of cyber-victimization.

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