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Adjustment outcomes of victims of cyberbullying: The role of personal and contextual factors

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ABSTRACT

With many of today's youth utilizing technology to bully their peers, there is a need to better understand both predictors and consequences of cybervictimization. However, few researchers have employed a multi-level approach to jointly identify potential individual (e.g., gender) and school-level (e.g., urbanicity) predictors of cybervictimization, or examined a range of psychosocial and adjustment outcomes. The current study used survey data from 28,583 students from 58 high schools to explore the risk factors associated with cybervictimization. We also examined the association between cybervictimization and adjustment outcomes (e.g., psychological, academic), as well as a possible moderators (e.g., student connectedness) that may buffer youth from these negative outcomes. Self-report measures assessed experiences with cybervictimization, adjustment problems, and student connectedness using previously validated measures. A series of two-level hierarchical linear modeling analyses revealed that females, underclassman, and those who are traditionally victimized or were perpetrators of cyberbullying were at significantly increased risk of cybervictimization. Cybervictimization was also associated with an increased risk of psychological (internalizing problems, sleep problems, stress problems) and academic (truancy, poor grades) adjustment problems. However, student connectedness buffered the internalizing problems experienced by victims of cyberbullying. These findings extend prior research on cybervictimization predictors, outcomes, and buffers, and in turn inform the potential use of school-based efforts aimed at preventing cyberbullying.

1. Introduction

With the recent advances in technology, computers and cell phones have become new venues for social interaction among youth and adults alike. Yet emailing, text messaging, and posting on social media sites are other forums through which youth can engage in bullying behaviors. This behavior, known as cyberbullying, Internet aggression, or electronic aggression, is defined as an aggressive act that is deliberately and repetitively carried out in an electronic context (e.g., instant messaging, emails, Facebook, text messaging) against a person who cannot easily defend him or herself (Kowalski, Limber, & Agatston, 2012). A meta-analysis of 131 studies on cyberbullying found that, in general, the lifetime prevalence of being the target of a cyberbully ranges between 10% and 40% (Kowalski, Giumetti, Schroeder, & Lattanner, 2014). Although rates of cyberbullying are lower than traditional (e.g., verbal, physical) forms of bullying, cyberbullying remains a pervasive issue for today's youth (Kowalski et al., 2014). Furthermore, there is some evidence that experiencing cybervictimization may be perceived as more hurtful and predict adjustment problems, over and above

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that of traditional forms of victimization (Bonanno & Hymel, 2010; Dempsey, Sulkowski, Nichols, & Storch, 2009).

A growing body of literature has attempted to identify potential predictors and outcomes of cyberbullying. Moreover, researchers have identified possible personal and contextual factors that may contribute to cyberbullying and cybervictimization, as well as exacerbate mental health outcomes among victimized youth (see Kowalski et al., 2014). Although previous research has demonstrated that cybervictimization is associated with a range of psychological adjustment problems (e.g., anxiety, depression, loneliness), few studies have explored the broader range of negative outcomes, such as academic adjustment problems. Additionally, few studies have examined the role that contextual factors play in the risk for cybervictimization and negative mental health outcomes among adolescents (Kowalski et al., 2014). The current paper aimed to address these gaps in the literature by exploring the association between cybervictimization and multiple adjustment problems as well as the extent to which contextual factors contribute to and potentially exacerbate or buffer risk of cybervictimization and adjustment problems. Identifying individual and contextual risk factors for cybervictimization is important for bullying prevention efforts, as it can elucidate the high-risk groups and contexts that warrant particular attention when developing prevention and intervention programs for bullying.

1.1. Theoretical frameworks

Unlike the broader aggression literature, research on cyberbullying has generally lacked a solid theoretical foundation (Slonje, Smith, & Frisén, 2012). However, there has been some interest in the application of the general aggression model to cyberbullying, as it may inform our understanding of the personal and contextual factors involved in aggression (Anderson & Bushman, 2002; DeWall, Anderson, & Bushman, 2011). Specifically, the general aggression model is an integration of several domain-specific theories of aggression that together give a more parsimonious view of both cyberbullying perpetration and victimization (Kowalski et al., 2014; Vannucci, Nocentini, Mazzoni, & Menesini, 2012). This socio-cognitive, developmental model uses the interactions between situational and personal factors to explain aggressive behavior and victimization. Specifically, the model allows for aggression to be explained in light of the dynamic interplay between multiple levels of factors that influence the individual, including the person, the situation, and aspects of the social encounter through which the bullying occurs (Anderson & Carnagey, 2004). For example, aggressive behavior may be explained in part by the interplay between a student's individual level of impulsivity and the extent to which those responsive are triggered by aspects of an unpredictable school environment. The theoretical basis of the general aggression model provides the structure to inform our exploration of individual and contextual factors that impact cybervictims and the related adjustment problems.

The social-ecological model also highlights the relevance of contextual factors, like the school and peer context, that should be considered in addition to individual-level risk factors (Bronfenbrenner & Morris, 1998). Related research on social disorganization theory (Sampson & Groves, 1989) suggests that structural characteristics of communities, such as ethnic heterogeneity, disrupt social organization, which leads to increases in crime and violence. This theory has been applied to school communities, such that school-level indicators of disorder may be predictors of bullying-related attitudes and behaviors (Bradshaw, Sawyer, & O'Brennan, 2009). Both the social-ecological model and the general aggression model provide frameworks to examined the potential influence of contextual and organization factors that may increase the risk for involvement in aggression and bullying.

1.2. Adjustment outcomes related to cyberbullying

1.2.1. Psychological adjustment

Cyberbullying has been linked to numerous negative mental health outcomes, including anxiety, depression, substance abuse, stress, and sleep problems (Beran & Li, 2005; Mitchell, Ybarra, & Finkelhor, 2007; Perren, Dooley, Shaw, & Cross, 2010). A recent meta-analysis of 131 studies indicated that depression, anxiety, loneliness, emotional problems, and stress are all outcomes related to being cybervictimized. Among those negative outcomes, stress (r = 0.34) and suicidal ideation (r = 0.27) had the strongest associations with cybervictimization (Kowalski et al., 2014). Both traditional and cybervictimization have been linked with high stress (Fredstrom, Adams, & Gilman, 2011). In fact, research suggests that approximately 32% of youth cybervictims have experienced at least one symptom of stress as a result of cybervictimization, whereas another study found that 41% of college student cybervictims reported frequently feeling stressed as a result of being a victim of cyberbullying (Finkelhor, Mitchell, & Wolak, 2000; Schenk & Fremouw, 2012). Even after controlling for traditional victimization, cybervictimization continues to be linked with negative mental health outcomes, including depression and anxiety (Fredstrom et al., 2011; Olenik-Shemesh, Heiman, & Eden, 2012). For example, Perren et al. (2010) found that cybervictimization was a significant predictor of depressive symptoms over and above that of being traditionally bullied.

Sleep problems is another health outcome that has been linked to cybervictimization. Adolescent cybervictims and cyberbully-victims (but not cyberbullies only) were at a significantly higher risk of developing sleeping problems than their non-victimized peers (Sourander et al., 2010). This finding is consistent with other research that found that bullied youth were at an increased risk of having sleep problems (Fekkes, Pijpers, Fredriks, Vogels, & Verloove-Vanhorick, 2006). Although researchers have established a clear link between cybervictimization and psychological adjustment problems, less is known about how personal and contextual factors may attenuate or exacerbate these outcomes.

1.2.2. Academic adjustment

A meta-analytic review of 33 studies that examined peer victimization and academic achievement found a small but significant negative association, such that peer victimization is related to concurrent academic struggles (Nakamoto & Schwartz, 2011). Despite this consensus among studies of traditional peer victimization, there is less consensus about the association between cybervictimization and academic difficulties. Victims of Internet harassment (a concept closely related to cyberbullying) reported higher rates of skipping school and higher rates of truancy than their non-harassed peers (Ybarra, Diener-West, & Leaf, 2007). Similarly, a study of middle and high school students found that, compared to their non-involved peers, victims of cyberbullying are at a significant increased risk of leaving school early and receiving poor grades (Kowalski & Limber, 2013). Despite these findings relating to poor academic performance, the meta-analysis of cyberbullying research found that the association between academic achievement and cybervictimization was not significant (Kowalski et al., 2014), thereby suggesting a need for further investigation into how cybervictimization may be associated with academic performance. The current study also aimed to inform our understanding of some of the mixed findings by examining whether high school victims of cyberbullying are more likely to be absent from school or receive low grades.

1.3. Individual level risk factors for cyberbullying victimization

1.3.1. Gender

Given that boys are more likely than girls to be victims of traditional forms of bullying (Nansel et al., 2001), researchers have investigated if this association holds among victims of cyberbullying. In fact, several studies have found that females were more likely to be cybervictims (Cappadocia, Craig, & Pepler, 2013; Sourander et al., 2010; Ybarra et al., 2007), yet, other studies have found no gender differences when predicting cybervictimization (e.g., Cappadocia et al., 2013; Williams & Guerra, 2007; Ybarra & Mitchell, 2004). The mixed findings suggest that additional research is needed to more thoroughly examine the association between gender and cybervictimization.

1.3.2. Student ethnicity

Within the traditional bullying literature, some researchers have found no significant differences in bullying prevalence between Caucasian and African American students (Seals & Young, 2003). Other studies of traditional forms of bullying (e.g., physical, verbal, social) comparing White, African American, and Hispanic youth have found that African American children are less likely to be victimized than their White or Hispanic peers (Sawyer, Bradshaw, & O'Brennan, 2008; Spriggs, Iannotti, Nansel, & Haynie, 2007). Yet few studies have examined ethnicity as it pertains specifically to cyberbullying, as the majority of studies on cyberbullying have been conducted with predominantly Caucasian samples. The available research exploring the association between ethnicity and cybervictimization have not found significant differences in cybervictimization by race/ethnicity (Wang, Iannotti, & Nansel, 2009) Given the limited research on this topic, further investigation is needed to better understand the role of race/ethnicity in cybervictimization.

1.4. Student grade level

Similar to the trends in the traditional bullying literature, cyberbullying appears to peak during the middle school years (Kowalski et al., 2012; Williams & Guerra, 2007). The transition to high school (grade 9) has also been identified as a risk factor for cybervictimization, as a one-year longitudinal study of cybervictimization among high school students found that students in ninth grade at Time 1 were about 50% more likely than students in tenth and eleventh grade at Time 1 to be involved in cybervictimization at Time 2 (Cappadocia et al., 2013). With regard to adjustment problems, studies evaluating how age may moderate the relationship between victimization and mental health problems have yielded mixed results. Specifically, middle school aged cybervictims reported more emotional symptoms (e.g., depression, anxiety, stress) and peer problems than high school aged cybervictims (Dooley, Shaw, & Cross, 2012). This finding is inconsistent with studies of traditional bullying. For example, when compared to elementary and middle school victims of bullying, high school victims were more likely to report internalizing symptoms (O'Brennan, Bradshaw, & Sawyer, 2009). Because of the negative mental health outcomes that are linked to cybervictimization as well as traditional victimization, knowing the age groups that are at greatest risk of victimization and experiencing negative outcomes may help schools identify whom to target through bullying intervention and prevention initiatives.

1.4.1. Traditional bullying

There has been considerable debate in the literature as to how cyberbullying is different from traditional forms of bullying (social, verbal, physical). There is overlap between being a victim of traditional and cyberbullying, as one-third of cybervictims report concurrent traditional victimization (Waasdorp & Bradshaw, 2015; Ybarra et al., 2007). Conversely, students who were traditionally victimized were almost four times more likely than their non-victimized peers to report cybervictimization and/or cyber-perpetration (Cappadocia et al., 2013). Despite this overlap, there is a subset of youth (~10–15% of victimized youth) who experience cyberbullying or victimization in the absence of traditional forms of victimization (Olweus, 2012; Raskauskas, 2010). Mental health outcomes of cybervictimization have also paralleled findings in traditional victimization; however, because those who experience cyberbullying are often involved in other types of bullying (verbal, physical, relational), it is difficult to understand the unique contribution of cyberbullying on maladjustment. Despite the overlap, cybervictimization has been found to influence adolescent well-being above and beyond traditional victimization (Wigderson & Lynch, 2013). Research in Australia and Switzerland has found that cybervictimized youth experienced more depression symptomology and academic problems (e.g., low grades) than non-victimized youth and cyberbullies, even after controlling for involvement in traditional bullying (Perren et al., 2010). Given the overlap between traditional victimization and cybervictimization, it is possible that traditional victimization places youth at increased risk for being cybervictimized, and in turn, they are at an increased risk for adjustment problems (Waasdorp & Bradshaw, 2015).

1.5. Contextual factors for cyberbullying victimization

As described above, a number of theoretical models highlight the significant of contextual factors in relation to involvement in bullying. For example, while several studies have examined population density, or urbanicity, in relation to aggression and violence, there is a paucity of literature on bullying that has compared the experiences of urban and non-urban youth (Bradshaw et al., 2009; Demaray & Malecki, 2003; Varjas, Henrich, & Meyers, 2009). Some research suggests that urban victims of bullying are more likely than non-urban victims to be racially bullied (Goldweber, Waasdorp, & Bradshaw, 2013), whereas other research suggests that children in suburban schools are disproportionately affected by bullying (Bradshaw et al., 2009). These studies have looked primarily at traditional forms of bullying as well as at elementary and middle school youth; therefore, additional research is warranted to examine the role of urbanity for cybervictims and among high school students.

The percentage of minority students in a school may also be associated with risk for cybervictimization and psychological consequences. Research on the effect of ethnic diversity in schools found that middle school students who are victims of bullying and members of a majority ethnic group might be at additional risk of the negative psychological consequences of peer victimization (Bellmore, Witkow, Graham, & Juvonen, 2004; Graham & Juvonen, 2002). Less is known about the association between school-based ethnic heterogeneity and high school aged victims of cyberbullying.

School size is another contextual factor that may be related to cybervictimization. Of the seven studies included in a systematic review of contextual factors related to school bullying three found a significant positive association between bullying behaviors and school size (Azeredo, Rinaldi, de Moraes, Levy, & Menezes, 2015). Other studies have not found effects of school size on bullying (Klein & Cornell, 2010; Whitney & Smith, 1993). Additionally, rather than assessing school size as a risk factor, studies on school climate and bullying using multilevel modeling have typically controlled for school size in analyses (e.g., Gregory et al., 2010). Our review of the literature did not reveal any studies that looked exclusively at cyberbullying victimization and school size, indicating a need to examine this relationship in the current study.

1.6. Student connectedness

Student connectedness is defined as the perception of belonging to peers, specifically the perception that students help, like, trust, and respect one another (Bradshaw, Waasdorp, Debnam, & Lindstrom Johnson, 2014). Students' perceived connectedness to their peers has been linked with less perpetration of bullying, including cyberbullying (Williams & Guerra, 2007). For example, youth who described their school environment as having a trusting, fair, and pleasant atmosphere reported less bullying. Additionally, youth who perceived their friends as trustworthy, caring, and helpful had significantly lower participation in bullying, including cyberbullying (Williams & Guerra, 2007). Although several studies have examined how student connectedness may act as buffers of the association between victimization and adjustment problems, they did not look specifically at cybervictimization, or at the buffering effect among high school students (Davidson & Demaray, 2007; Schmidt & Bagwell, 2007). Related research suggests that social support from close friends moderates the effects of relational and overt forms of victimization on adjustment (Prinstein, Boergers, & Vernberg, 2001). Less is known about the moderating effects of student connectedness and support on the adjustment problems of victims of cyberbullying.

1.7. Current study

The current study sought to explore how student connectedness could play a buffering role for the cybervictims who experience these adjustment outcomes. We used data from a school-based climate survey, the Maryland Safe and Supportive Schools Initiative (MDS3), to examine student- and school-level risk factors for cybervictimization. Given the nested nature of data, we employed two-level hierarchical linear modeling techniques (Raudenbush & Bryk, 2002) to address the following three research aims. Specifically, our first research aim intended to identify the individual- and school-level factors that place students at an increased risk of being cybervictimized. As evidenced through previous studies (see Kowalski et al., 2014), we predicted that being a victim of traditional forms of bullying or a perpetrator of cyberbullying would place a student at an increased risk of being cybervictimized. Consistent with prior research, we also hypothesized that being female, Caucasian/White, and an underclass (9th and 10th grade) student would also be risk student-level factors for cybervictimization. As suggested by social disorganization theory (Sampson & Groves, 1989), we hypothesized that an urban school setting, a larger school size, and a heterogeneous racial/ethnic school would place students at an increased for cybervictimization.

Our second research aim intended to identify the adjustment problems associated with cybervictimization. We were particularly interested in how cybervictimization may increase risk for psychological adjustment (internalizing problems, sleep problems, stress problems) and academic adjustment (poor grades, truancy). In particular, we were interested in determining whether cybervictims experienced more negative outcomes than their non-cybervictimized peers, while accounting for their demographic characteristics (gender, grade level, race/ethnicity) and other engagement in bullying (as a cyber perpetrator, as a traditional victim) and school-level factors. Consistent with prior research (e.g., Perren et al., 2010; Ybarra & Mitchell, 2004), we predicted that cybervictims would be at increased risk of psychological adjustment and academic adjustment problems.

Our third aim investigated the potential influence of student connectedness, hypothesizing that it would serve as a buffer against the risk of adjustment problems for victims of cyberbullying. Specifically, consistent with prior research (Williams & Guerra, 2007), we hypothesized that student connectedness would moderate the negative outcomes associated with cybervictimization.

Table 1
Individual and school-level demographic characteristics of the sample.

Characteristics of participating schools (n = 58 schools)	Mean	(SD)	Percentage
Enrollment	1268.5	(466.8)	
Minority students (%)	45.9	(25.1)	
Urbanicity			
City			6.9
Suburb			58.6
Town			6.9
Rural			27.6

Characteristics of participating students (n = 28,583)	Percentage[a]
Gender	
Males	48.8
Females	48.3
Ethnicity	
White	48.7
Black/African American	30.7
Hispanic/Latino	4.5
Asian/Pacific Islander	4.3
Native American/American Indian	1.5
Native Hawaiian/Other Pacific Islander	0.6
Other	6.7
Grade	
9th	26.8
10th	24.3
11th	23.3
12th	22.4

Note. School-level demographic data were obtained from the Maryland State Department of Education.
[a] Does not total to 100 due to missingness.

2. Method

2.1. Participants

Data came from 58 Maryland high schools participating in the statewide MDS3 project, which examined school climate and school safety. Data were collected in the spring of 2012 through a collaboration between the Johns Hopkins Center for the Prevention of Youth Violence, the Maryland State Department of Education, and Sheppard Pratt Health System. A web-based survey was voluntarily completed by 28,583 high school students. The sample was approximately equal in gender representation. Approximately half of the sample was White/Caucasian, whereas one-third was Black/African American. See Table 1 for additional demographic details of the sample.

2.2. Procedure

Public high schools in Maryland enrolled in the MDS3 Project on a voluntary basis after being approached to participate by the Maryland State Department of Education. Following district and school-level approval of the project, the online survey was administered using a waiver of active parental consent. Approximately 25 (M = 24.83) language arts classrooms per school were randomly selected to participate in the data collection. School staff administered the survey by following a written protocol. The MDS3 research team obtained approval for analysis of the de-identified data through the Johns Hopkins University and University of Virginia Institutional Review Boards.

2.3. Measures

2.3.1. MDS3 School Climate Survey

The MDS3 School Climate Survey (Bradshaw et al., 2014) is a self-report measure that includes several scales that have been previously published and validated for research purposes (e.g., the Youth Risk Behavioral Surveillance System; CDC, 2011). Reliability information is provided below using data from the current sample. In addition, prior psychometric analyses have confirmed the factor structure and measurement invariance, and examined differential item functioning using Item Response Theory (Lindstrom Johnson, Reichenberg, Shukla, Waasdorp, & Bradshaw, 2017; Shukla et al., in press). The current study analyzed the following scales from the MDS3 School Climate Survey.

2.3.2. Demographic characteristics

The students answered a series of questions relating to their basic demographic characteristics. These included measures such as school, grade level (1 = 11th/12th grade, 0 = 9th/10th grade), gender (1 = male, 0 = female) and race/ethnicity. Race was dichotomized as White/Caucasian (0) and Non-White/Caucasian (1) in the current analyses. Details regarding demographic characteristics are summarized in Table 1. Several of the demographic characteristics were dichotomized to facilitate comparison of at risk youth and for efficiency in interpreting the findings (MacCallum, Zhang, Preacher, & Rucker, 2002).

2.3.3. Involvement in traditional bullying perpetration and victimization

Prior to answering questions regarding bullying, participants were provided a definition of bullying which read, "A person is bullied when he or she is exposed, repeatedly and over time, to negative actions on the part of one or more other persons. Bullying often occurs in situations where there is a power or status difference. Bullying includes actions like threatening, teasing, name-calling, ignoring, rumor spreading, sending hurtful emails and text messages, and leaving someone out on purpose" (Olweus, 1993). After reading this definition, the students answered questions about their involvement in bullying as an aggressor or as a victim within the past 30 days (see the Olweus Bully/Victim Questionnaire validation study [Solberg & Olweus, 2003]; Bradshaw, Sawyer, & O'Brennan, 2007). They were asked, "In what way(s) were you bullied during the past 30 days?" and instructed to check all that applied. Options included: calling you bad names, threatening to hit or hurt you, teasing, picking on, or making fun of you, pushing or shoving you, hitting, slapping, or kicking you, stealing your things, spreading rumors or lies about you, ignoring you or leaving you out on purpose. These items, all examples of traditional forms of bullying, were scored 0 if the student did not endorse the item or 1 if the student did endorse the item. The items were then summed for each student, and based on the distribution of responses, the item was dichotomized (0 = *no traditional victimization*, 1 = *one or more experiences of traditional victimization*. Importantly, "e-mailing, e-messaging, texting, or posting something bad about you on the internet (Facebook)" was also a response option on this list; it was not included in the analysis as it is an example of cybervictimization. Previous research has validated this approach to assessing bullying (Solberg & Olweus, 2003; Sawyer et al., 2008). The measurement of cybervictimization and cyber perpetration is further explained below.

2.3.4. Involvement in cyberbullying

Before responding to questions about cyberbullying, the participating youth were prompted to read the following definition of cyberbullying: "Cyberbullying involves posting or sending electronic messages (text, pictures, video) that result in a person feeling hurt, humiliated, or like a victim." After reading the definition, the youth responded to the question, "In the past three months, have you been 'cyberbullied'?" to assess cyberbullying victimization. Cyberbullying perpetration was assessed via the question, "In the past three months, how many times have you 'cyberbullied' someone else (intentionally or unintentionally)?" Response options for these questions included *never*, *once or twice*, or *more than twice* (Willard, 2007). Given the distribution of the responses, the items were dichotomized for cybervictimization (*not cybervictimized* = 0, *cybervictimized at least once* = 1) and for cyber perpetration (*not a perpetrator of cyberbullying* = 0, *cyberbullied another student at least once* = 1). The traditional and cyberbullying variables were dichotomized due to the desire to analyze group differences between those that had been victimized or bullied against those students who did not endorse involvement in bullying.

2.3.5. Psychological adjustment

Scales were derived for four types of psychological adjustment: internalizing problems, sleep problems, and stress problems. These measures were all based on previously validated scales (for additional information on the MDS3 Survey, see Bradshaw et al., 2014). Specifically, participants completed a five-item measure of internalizing symptoms (e.g., I feel sad, I feel nervous or anxious; $\alpha = 0.85$) derived from the previously validated Self Report of the Behavioral Assessment System for Children, Second Edition (BASC-2; Reynolds & Kamphaus, 2004). They also completed a two-item measure of sleep problems (CDC, 2011; Harris et al., 2009) (e.g., Have trouble falling asleep, Feel you did not get enough sleep or rest; Spearman's rho = 0.62) and a two-item measure of stress problems (Brown, Nobiling, Teufel, & Birch, 2011; Harris et al., 2009) (e.g., felt that difficulties were piling up so high that you could not overcome them; feel stressed; Spearman's rho = 0.81). All responses for internalizing problems, stress problems, and sleep problems were measured on a 4-point Likert scale from 1 (*Almost Always*) to 4 (*Never*). Items were reverse scored and averaged such that higher scores indicated more impairment.

2.3.6. Academic adjustment

Youth self-reported their academic performance by responding to a question, which read, "On your last report card, what grades did you receive?" The response options were Mostly As, Mostly Bs, Mostly Cs, Mostly Ds, or Mostly Fs. Given the distribution of responses, the item was dichotomized with responses Mostly As and Bs (0 = 71.8%) versus Mostly Cs or worse (1 = 28.2%) (Bradshaw et al., 2009). Truancy was assessed through a question adapted from YRBS (CDC, 2011). The question read, "During the past 30 days, how many days of school have you missed because you skipped or 'cut'?" Response options were 0 days, 1 day, 2 or 3 days, 4 or 5 days, 6 or more days. Based on the distribution of responses, the truancy score was dichotomized as 0–1 day (0 = 82.5%) versus 2 or more days (1 = 17.5%).

2.3.7. Student connectedness

Five items from the previously validated California Healthy Kids Survey (Hanson & Kim, 2007) assessed students' connection to other students (e.g., I feel like I belong; Students trust one another, $\alpha = 0.86$). All responses were measured on a 4-point Likert scale

(1 = *Strongly Disagree*; 4 = *Strongly Agree*), and averaged such that higher scores indicated high levels of connectedness (also see Bradshaw et al. (2014) and Shukla et al. (in press) for additional psychometric information).

2.3.8. School-level variables

School-level demographic variable information was obtained from the Maryland State Department of Education. Information included school enrollment (total number of students), the percentage racial and ethnic minorities in the student body (minority %), and the urbanicity of the school setting. Urbanicity was coded such that urban areas were the reference group, as compared to suburban, town, and rural. The schools' urbanicity was determined by trained on-site observers as part of a larger study of school physical environment and confirmed by a school district representative (Bradshaw, Milam, Furr-Holden, & Lindstrom Johnson, 2015). The school-level student enrollment was divided by 100 in order to facilitate easier interpretation of the coefficients (i.e., a one unit change is not one student, but rather 100 students). These variables were included in the model as school-level variables (due to the nested nature of the data) to account for salient indicators consistent with social disorganization theory (Bradshaw et al., 2009; Sampson & Groves, 1989). In addition to the school-level demographic information, school climate indices were derived as an average of the scores of students within a school. Specifically, scores for student connectedness (described in detail above) were aggregated up to the school level for each of the 58 schools (Bradshaw et al., 2009). See Table 1 for additional details of the school demographics.

2.4. Overview of the analyses

A two-level multilevel modeling analysis was selected for the current study because the data and hypotheses are multilevel (Raudenbush & Bryk, 2002). Moreover, the students in the study were nested within schools and our hypotheses include the exploration of factors at both individual- and school-level factors in relation to cyberbullying victimization and adjustment problems. Given that students changed classes during the day, and we lacked any covariates at the classroom level to meaningfully model influences at this level, we elected to use a two level model, rather than incorporating classroom level clustering. The two-level modeling technique accounted for this non-independence of students within schools through adjustment of the standard errors (Luke, 2004). Prior to conducting the multilevel analyses, we used SPSS 21 to check for multicollinearity among the student- and school-level variables (Aiken & West, 1991) in order to ensure that the control and predictor variables were not highly intercorrelated. Inspection of the correlations and variance inflation factors (VIF) suggested that multicollinearity was not a significant concern for any of the victimization/perpetration variables (e.g., traditional victimization and cybervictimization). Violations of multicollinearity existed for the support variable at the school level (i.e., student connectedness). Due to these violations, the student connectedness variable and their respective student-level aggregate variables were all added to the models independently in order to test the third aim. Given the number of tests conducted for exploring the interactions, we also applied a Bonferroni correction, which set a more conservative *p*-value of 0.003.

Level-1 continuous variables were group mean centered. For our models, group mean centering was more appropriate than grand mean centering when “the primary substantive interest involves a Level 1 (i.e. person level) predictor” as it yields a more accurate estimate of the slope variance (Enders & Tofighi, 2007, p. 128). Moreover, group mean centering at Level-1 deviates Level-1 student scores from the respective Level-2 mean school score, allowing for a more relative effect interpretation of the outcome (Brincks et al., 2017; Peugh, 2014). All Level-2 variables were grand mean centered. Similarly, grand mean centering at Level-2 deviates the Level-2 school mean score from the mean score of all schools in the sample, allowing for a more absolute effect interpretation. The dichotomous outcomes were treated as binomial in the HLM analyses and odds ratios (ORs) were computed, whereas the continuous variables were treated as continuous in the analyses (Garson, 2013; Raudenbush & Bryk, 2002). A mixed-effects logistic regression in the Stata analyses was used to estimate dichotomous outcomes, in which odds ratios (ORs) were computed. Similarly, a mixed-effects linear regression was used to estimate continuous outcomes (StataCorp, 2015).

In order to determine if the interactions supported the buffering hypothesis, significant interactions were further probed through graphing of the models as well as through examination of the simple slopes. Consistent with the analytical method recommended by Aiken and West (1991) and Preacher, Curran, and Bauer (2006), simple slope analyses were conducted to test the significant relationship between cybervictimization and the outcome of interest as a function of different levels of student connectedness. The simple slopes were plotted and the graphic display was used to examine the nature and directionality of the significant interactions.

2.5. Missing data

Our preliminary analysis of the data found no missing data at the school level. Of the 13 student level variables used in the analyses, missingness ranged from 0 to 12%. As a result, missing data patterns in the data were further explored. As first described by Rubin (1976), missing patterns in the data fall under three types of missing mechanisms: Missing Completely at Random (MCAR), Missing at Random (MAR), and Not Missing at Random (NMAR). MCAR is a process in which the probability of a value missing is independent of observed and unobserved variables in the data. MAR is a process in which the probability of a value missing is independent of unobserved variables, but dependent on observed variables in the data. Lastly, NMAR is a process in which the probability of a value missing is dependent on unobserved variables in the data. While MCAR missing data mechanism is directly testable, both MAR and NMAR missing data mechanisms require further analysis.

Little's (1988) univariate test of MCAR revealed the data did not meet the assumptions of the MCAR missing data mechanism, χ^2 (45) = 75.65, *p*-value = .003. As a result, multiple imputation techniques were used to address the issue of missing data. Using the imputation methods available in the Stata software program, an assumed multivariate normal distribution of the observed data was used to estimate values for missing data (StataCorp, 2015). Specifically, a fully conditional specification technique was employed using the multivariate imputation using chained equations (MICE) command available in Stata 14 (StataCorp, 2015). This approach allows for a combination of categorical and continuous variables to be imputed appropriately, by not imposing certain distributional assumptions. See Raghunathan, Lepkowski, Van Hoewyk, and Solenberger (2001), Enders (2016), Enders, Keller, and Levy (2017), and van Buuren, Brand, Groothuis-Oudshoorn, and Rubin (2006) for additional discussion of this topic. This technique also addresses the hierarchical nature of the data. As described by Enders, Mistler, and Keller (2016), a single-level imputation model for multilevel data ignores between-group variation, ultimately biasing results. By imputing data for each school separately, we allow for the distributions of imputed values to be unique for each school, accounting for between-school variability in the imputation model.

More specifically, following Enders (2010) proposition, this distribution was drawn from both the variables to be used in the analyses, as well as significantly correlated auxiliary variables. As suggested by Rubin (1987), a total of $m = 5$ replicate data sets were produced. Finally, each of the $m = 5$ data sets were pooled to allow for a more unbiased estimation of parameter estimates and standard errors than listwise deletion alone, which is the default in the HLM software. The multiple imputation process employed resulted in a single set of coefficient and standard error estimates from a full analytic sample of $n = 28{,}583$ students for each model.

3. Results

3.1. Intraclass correlation coefficients

Before building our multi-level models, we computed the intraclass correlation coefficients (ICCs). The fully unconditional HLM model (without covariates) provided information about the amount of variance in our outcomes of interest (cybervictimization; psychological and academic outcomes) that was accounted for by schools. The ICCs derived from the fully unconditional models delineated the certain percentage of the variability in cybervictimization and other adjustment outcomes of interest that can be accounted for by school, thereby distinguishing if students tend to experience cybervictimization and other adjustment outcomes more similarly within schools or across schools. The ICCs were calculated as follows: cybervictimization = 0.017; internalizing = 0.007; sleep = 0.008; stress = 0.013; letter grades = 0.074; truancy = 0.022. These relatively low ICCs indicated that 1.7% of the variance in students' cybervictimization and 0.7 to 7.4% of the variance in the adjustment outcomes of interest is potentially associated with characteristics of the school attended.

3.2. Aim 1: multilevel analyses for risk factors of cybervictimization

To address our hypotheses, we used a student-level cybervictimization variable as the primary dichotomous outcome, which was coded 1 = cybervictimized or 0 = not cybervictimized. The following student-level demographic variables were entered at Level 1: gender, grade level, and race/ethnicity. To control for other types of bullying and victimization, experiences with traditional victimization in the last 30 days as well as experiences within the last three months as a perpetrator of cyberbullying were also added to the model at Level 1. The following school-level characteristics were all grand mean centered at Level 2: urbanicity of the school, percentage of minority students, and school size.

The coefficients reported in Table 2 indicated that gender and grade level were significant student-level predictors of

Table 2
Multilevel analysis results for Level 1 (student) and Level 2 (school) predictors of being cybervictimized.

Variables	Coefficient	SE	t	Odds ratio
Intercept	−2.011	0.136	−14.83*	0.134**
Level 2. School				
Minority %	−0.002	0.001	−1.24	0.998
Enrollment/100[†]	0.001	0.007	0.11	1.001
Urbanicity	0.001	0.037	0.02	1.001
Level 1. Student				
Upperclassman	0.173	0.052	3.33	1.188**
Male	−0.345	0.045	−7.71	0.708**
Non-Caucasian	−0.046	0.055	−0.83	0.955
Traditional victim	1.208	0.047	25.72	3.346**
Cyber perpetrator	1.657	0.052	32.16	5.242**

Coefficient derived from the population-average model with robust standard errors. Variables were dichotomized as follows. Cybervictimization (1 = cybervictimized, 0 = not cybervictimized). Gender (1 = male, 0 = female). Grade level (1 = 11th/12th grades, 0 = 9th/10th grades). Race/ethnicity (0 = White/Caucasian, 1 = Non-White/Caucasian). Traditionally victimized (0 = not traditionally victimized, 1 = traditionally victimized). Cyber perpetration (0 = no perpetration of cyberbullying, 1 = cyberbullied another student). The school level variables were all grand mean centered.

* $p < .05$.

** $p < .001$.

† Indicates the school enrollment variable was divided by 100 to facilitate interpretation of the coefficient. SE = Standard Error.

Table 3
Individual and school level indicators of academic adjustment.

Predictor variables	Academic adjustment			
	Truancy		Poor grades	
	Coefficient	Odds ratio	Coefficient	Odds ratio
Reference intercept	−1.666	0.189**	−1.592	0.204**
Level 2. School				
Minority %	0.002	1.002	0.006	1.006*
Enrollment/100†	0.012	1.012	−0.009	0.991
Urbanicity	0.152	1.164**	0.016	1.016
Level 1. Student				
Upperclassman	0.559	1.749**	−0.213	0.808**
Male	−0.018	0.983	0.627	1.872**
Non-Caucasian	−0.004	0.996	0.495	1.640**
Traditional victim	0.114	1.121**	−0.049	0.952
Cyber victim	0.410	1.507**	0.177	1.194*
Cyber perpetrator	0.803	2.231**	0.350	1.418**

† Indicates the school enrollment variable was divided by 100 to facilitate interpretation of the coefficient.
* $p < .05$.
** $p < .001$.

cybervictimization, such that males were at a decreased risk of being cybervictimized (OR = 0.708). Upperclassman status (11th and 12th grade) was associated with an increased risk in cybervictimization (OR = 1.19). Experiencing traditional victimization and being a perpetrator of cyberbullying were also associated with increased risk of cybervictimization ($OR_{traditional} = 3.35$; $OR_{cyberperpetrator} = 5.24$). This indicates that youth who reported being a victim of traditional bullying were 3.35 times more likely to be a victim of cyberbullying as well. Likewise, youth who reported being perpetrators of cyberbullying were 5.24 times more likely to be concurrent victims of cyberbullying. School size, urbanicity, and the percentage of racial/ethnic minority students in a school were not significantly associated with cybervictimization.

3.3. Aim 2: multilevel analysis for adjustment problems

To examine how being a victim of cyberbullying may increase the risk of development of a range of adjustment problems, we created separate models for our student-level continuous outcomes of interest (internalizing problems, $SD = 0.73$; stress problems, $SD = 0.96$; sleep problems, $SD = 0.86$). Additionally, we computed ORs for the dichotomous outcomes of truancy ($M = 0.30$, $SD = 0.46$) and poor grades ($M = 0.31$, $SD = 0.46$). These modeling decisions were made due to the type of data distribution of the outcome variables and are consistent with Stata modeling and estimation practices (Garson, 2013; StataCorp, 2015).

Cybervictims' risk of developing a range of psychological, academic, and social adjustment problems were assessed while controlling for their age, gender, and race, as well as controlling for their experience as a perpetrator of cyberbullying and as a victim of traditional forms of bullying. School-level characteristics were also added to the model to control for the nested nature of the data (students within schools). White, female, underclass (9th and 10th grade) students who were uninvolved in cyberbullying as a victim or a perpetrator and did not report traditional forms of victimization served as the reference group. The association between cybervictimization status and the various problems are delineated below and summarized in Tables 3 and 4.

3.3.1. Psychological adjustment

Parameter estimates indicated that compared to their respective reference categories, victims of cyberbullying reported significantly higher levels of internalizing problems ($\gamma = 0.325$, $p < .001$), sleep problems ($\gamma = 0.205$, $p < .001$), and stress problems ($\gamma = 0.312$, $p < .001$). See Table 4 for additional details.

3.3.2. Academic adjustment

Results indicated that cybervictimization was also significantly associated with truancy, such that cybervictims are at 50.7% increased risk of skipping two or more days of classes in a 30-day period (OR = 1.507, $p < .001$). Cybervictimization was also a significant student-level predictor, such that cybervictims' odds of receiving poor grades (Cs or worse) increased by 19.4% (OR = 1.194, $p < .05$). See Table 3 for additional details.

3.4. Aim 3: multilevel analyses involving student connectedness

Student connectedness ($SD = 0.67$) was significantly inversely associated with all negative outcomes. Specifically, students who reported higher levels of student connectedness reported lower levels of internalizing problems ($\gamma = -0.189$, $p < .001$), stress problems ($\gamma = -0.233$, $p < .001$), and sleep problems ($\gamma = -0.189$, $p < .001$). Students who reported higher levels of student connectedness also reported lower levels of academic problems; specifically they reported lower odds of truancy (OR = 0.736,

Table 4
Individual and school level indicators of psychological adjustment.

Psychological adjustment						
Predictor variables	Internalizing problems		Sleep problems		Stress problems	
	Coefficient	*t*	Coefficient	*t*	Beta	*t*
Reference intercept	1.784	50.15**	2.522	40.35**	2.322	28.71**
Level 2. School						
Minority %	−0.000	−0.33	−0.000	−1.28	−0.000	−0.38
Enrollment/100†	0.002	1.32	0.006	2.55*	0.008	2.89*
Urbanicity	−0.029	−3.48**	−0.025	−1.77	−0.038	−2.05*
Level 1. Student						
Upperclassman	0.031	3.50**	0.061	5.80**	0.144	9.65**
Male	−0.100	−9.52**	−0.174	−15.45**	−0.306	−20.08**
Non-Caucasian	−0.031	−2.55*	−0.099	−7.13**	−0.123	−7.81**
Traditional victim	0.541	38.82**	0.286	18.77**	0.504	35.44**
Cyber victim	0.325	19.82**	0.205	11.45**	0.312	13.92**
Cyber perpetrator	0.161	9.82**	0.153	8.37**	0.151	7.99**

† Indicates the school enrollment variable was divided by 100 to facilitate interpretation of the coefficient.
* $p < .05$.
** $p < .001$.

$p < .001$) and lower odds of poor grades (OR = 0.748, $p < .001$). See Tables 5–7 for additional details.

With regard to the school-level aggregate predictor of student connectedness, like in the student-level effects, we found that at the school level it was associated with reduced odds of truancy (OR = 0.558, $p < .001$) and reduced odds of poor grades (OR = 0.155, $p < .001$). That is, an aggregate school-level score of student connectedness was associated with lower rates of truancy and better grades. This school-level variable was also a significant predictor of each of the other psychological adjustment problems (internalizing, sleep, and stress problems). Contrary to our hypotheses, this result suggested that students in schools with greater student connectedness were more likely to report internalizing problems ($\gamma = 0.115$, $p < .001$), sleep problems ($\gamma = 0.128$, $p < .001$), and stress problems ($\gamma = 0.211$, $p < .001$).

3.4.1. *Student connectedness interaction models*

A within-level interaction of cybervictimization and student connectedness was added to the model to explore the potential moderating role of student connectedness on negative outcomes for victims of cyberbullying. Results indicated significant interactions for just one of the five models tested. Specifically, there was a significant interaction between cybervictimization and student connectedness for internalizing problems ($\gamma = -0.086$, $p < .001$). Follow-up simple slope analyses revealed that cybervictims who

Table 5
Multilevel analysis results for Level 1 (student) and Level 2 (school) predictors of stress problems and internalizing problems.

Predictor variables	Stress problems				Internalizing problems			
	Model 1		Model 2		Model 1		Model 2	
	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio
Reference intercept	1.843	6.89**	1.843	6.88**	1.692	13.87**	1.695	13.88**
Level 2. School								
Minority	0.000	0.82	0.000	0.83	0.000	0.24	0.000	0.27
Enrollment/100†	0.007	2.87*	0.007	2.87*	0.002	1.29	0.002	1.28
Urbanicity	−0.037	−2.39*	−0.037	−2.39*	−0.029	−3.64**	−0.029	−3.64**
Student connectedness	0.211	3.81**	0.209	3.76**	0.115	5.05**	0.108	4.80**
Level 1. Student								
Upperclassman	0.133	8.88**	0.133	8.87**	0.021	2.50*	0.021	2.46*
Male	−0.268	−19.50**	−0.268	−19.57**	−0.069	−6.99**	−0.071	−7.15**
Non-Caucasian	−0.145	−9.11**	−0.145	−9.11**	−0.045	−3.94**	−0.045	−3.93**
Traditional victim	0.437	32.12**	0.437	31.93**	0.487	34.13**	0.485	33.66**
Cyber victim	0.271	12.33**	0.264	12.09**	0.291	18.13**	0.268	16.38**
Cyber perpetrator	0.12	6.68**	0.122	6.65**	0.136	8.38**	0.135	8.31**
Student connectedness	−0.233	−18.21**	−0.229	−17.55**	−0.189	−14.90**	−0.177	−15.56**
CV+ X student connectedness	–	–	−0.026	−1.21	–	–	−0.086	−3.72**

† Indicates the school enrollment variable was divided by 100 to facilitate interpretation of the coefficient.
* $p < .05$.
** $p < .001$.
+ CV = cyber victim.

Table 6
Multilevel analysis results for Level 1 (student) and Level 2 (school) predictors of sleep problems.

Predictor variables	Sleep problems			
	Model 1		Model 2	
	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio
Reference intercept	2.360	10.22**	2.361	10.22**
Level 2. School				
Minority	−0.000	−0.53	−0.000	−0.52
Enrollment/100†	0.001	2.38*	0.005	2.37*
Urbanicity	−0.024	−1.92	−0.024	−1.92
Student connectedness	0.128	2.71*	0.127	2.68*
Level 1. Student				
Upperclassman	0.051	4.67**	0.052	4.68**
Male	−0.143	−13.23**	−0.143	−13.28**
Non-Caucasian	−0.113	−8.42**	−0.113	−8.43**
Traditional victim	0.233	15.22**	0.233	15.23**
Cyber victim	0.171	9.73**	0.169	9.45**
Cyber perpetrator	0.128	6.83**	0.128	6.81**
Student connectedness	−0.189	−15.74**	−0.188	−15.20**
CV+ X student connectedness	–	–	−0.010	−0.45

† Indicates the school enrollment variable was divided by 100 to facilitate interpretation of the coefficient.
* $p < .05$.
** $p < .001$.
+ CV = cyber victim.

Table 7
Multilevel analysis results for Level 1 (Student) and Level 2 (School) predictors of truancy and poor grades.

Predictor variables	Truancy				Poor grades			
	Model 1		Model 2		Model 1		Model 2	
	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio
Reference intercept	0.640	1.896	0.640	1.896	3.979	53.487**	3.977	53.363**
Level 2. School								
Minority	−0.001	0.999	−0.001	0.999	0.000	1.000	0.000	1.000
Enrollment/100†	0.015	1.015*	0.015	1.015*	−0.001	0.999	−0.001	0.999
Urbanicity	0.152	1.164**	0.152	1.164**	0.011	1.011	0.011	1.011
Student connectedness	−0.583	0.558*	−0.583	0.558*	−1.867	0.155**	−1.855	0.157**
Level 1. Student								
Upperclassman	0.543	1.721**	0.543	1.721**	−0.247	0.781**	−0.247	0.781**
Male	0.027	1.027	0.027	1.027	0.677	1.968**	0.678	1.970**
Non-Caucasian	−0.030	0.971	−0.030	0.971	0.477	1.611**	0.477	1.611**
Traditional victim	0.30	1.030	0.30	1.030	−0.128	0.880	−0.126	0.882*
Cyber victim	0.353	1.424**	0.354	1.425**	0.115	1.122*	0.136	1.146*
Cyber perpetrator	0.761	2.140**	0.761	2.140**	0.295	1.343**	0.295	1.344**
Student connectedness	−0.307	0.736**	−0.307	0.736**	−0.290	0.748**	−0.302	0.740**
CV+ X student connectedness	–	–	0.002	1.002	–	–	0.072	1.074

† Indicates the school enrollment variable was divided by 100 to facilitate interpretation of the coefficient.
* $p < .05$.
** $p < .001$.
+ CV = cyber victim.

reported higher levels of student connectedness had significantly lower levels of internalizing problems (simple slope = −0.25, $p < .001$) than cybervictimized youth who reported lower levels of student connectedness. Fig. 1 provides a graphical representation of this interaction.

4. Discussion

The present study aimed to identify individual- and school-level risk factors for cybervictimization, identify adjustment problems associated with cybervictimization, as well as identify potential contextual buffers that may attenuate those problematic outcomes. This study extends prior research on risk factors, outcomes, and contextual buffers related to cybervictimization. Data from a large, diverse, high school-age sample provided sufficient power to explore a wide range of potential risk factors and problematic outcomes.

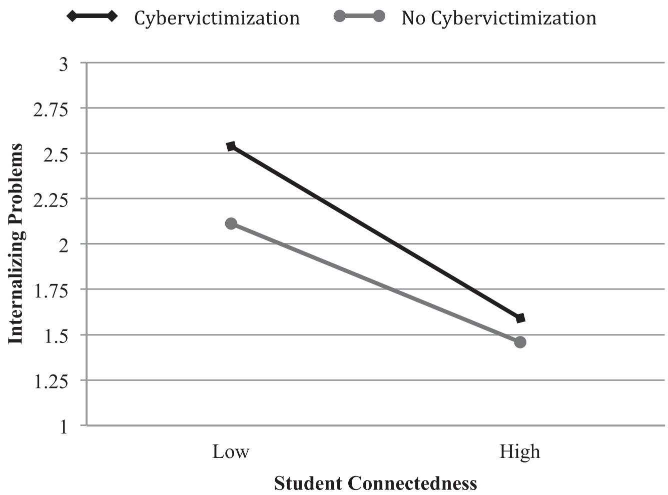

Fig. 1. The interaction of cybervictimization and student connectedness for internalizing problems.

The ICCs, reflecting the amount of clustering of students within schools, observed in this study were relatively small and consistent with previous research that found that between 0.6 and 2% of the variance in victimization among elementary and middle school students was associated with the clustering of students within schools (Bradshaw et al., 2009). Specifically, the cybervictimization ICC for this study was 0.017. These low ICCs suggest that there was little between group variance, however, the variance that did exist illustrated that students' response should not be assumed to be independent; therefore, analyses should adjust for the clustering of participants (Luke, 2004: Raudenbush & Bryk, 2002).

4.1. Aim 1: multilevel analyses for risk factors of cybervictimization

Consistent with previous findings (Kowalski et al., 2014), the multilevel analyses indicated that being a victim of traditional bullying and being a perpetrator of cyberbullying were also significant risk factors for cybervictimization (also see Waasdorp & Bradshaw, 2015). Additionally, consistent with previous research, being female was an individual risk factor for cybervictimization (e.g., Cappadocia et al., 2013; Sawyer et al., 2008; Sourander et al., 2010; Spriggs et al., 2007; Ybarra et al., 2007). We also found that upperclass students (11th and 12th grade) had a greater odds of cybervictimization. Although there has been some inconsistency in the findings for age and cybervictimization (Cappadocia et al., 2013), it is quite possible that as youth age, they gain great private access to mobile technologies and thus have more opportunity to be cybervictimized (Kowalski et al., 2012). Additional research is warranted to further examine grade level as a risk factor for cybervictimization. However, we found no significant association between race/ethnicity and risk for cybervictimization. Together, these findings highlight the importance of further exploring individual risk factors for cybervictimization.

Contrary to expectations and social disorganization theory, none of the school-level predictors (urbanicity, size of school, and the racial/ethnic heterogeneity of the school) was significantly associated with cybervictimization. Given that studies attempting to understand the complex relationship between racial differences and bullying prevalence have yield mixed results, additional research, perhaps of the qualitative nature, needs to be conducted to better capture the nuances of the bullying experience for minority students (Goldweber et al., 2013).

4.2. Aim 2: multilevel analysis for adjustment problems

We found that, compared to non-victimized youth, those who were cybervictimized had more problematic outcomes across all of the outcomes included in the study. As expected, cybervictims had an increased odds of experiencing internalizing problems, sleep problems, and stress problems. This finding further substantiates prior evidence that cybervictims report high levels of depressive symptoms, even after controlling for their involvement in traditional forms of bullying (Perren et al., 2010). As hypothesized, cybervictims were at an increased risk of skipping school. Although we had not predicted that cybervictims would be at an increased risk of receiving poor grades, our results indicated that cybervictims were 12% more likely to receive poor grades (i.e., C or worse). Parents, teachers, and other school personnel may benefit from inquiring about students' experience with cybervictimization when discussing issues related to poor academic performance.

4.3. Aim 3: multilevel analyses involving contextual buffers

Our findings were consistent with the general aggression model, which purports that situational factors, such as high levels of student connectedness, may play a protective role for victims of cyberbullying. Specifically, student connectedness was negatively associated with all five of the outcomes of interest, suggesting that students' connection to peers was associated with mental and behavioral health. These findings support the use of the general aggression model and social-ecological models to understand and interpret cyberbullying, specifically how student connectedness serves as an important contextual factor for victims of cyberbullying. The simple slopes derived from the interaction between student connectedness and cybervictimization were significant for internalizing problems. Student connectedness significantly attenuated the risk for internalizing problems among cybervictims. For example, the results indicate that a student who is cybervictimized may have a lower risk of depressive and anxious symptoms if the student experiences high levels of student connectedness. That is, students' feelings of belongingness among school peers may play a role in attenuating their risk of internalizing problems. These findings partially supported our hypothesis, as student connectedness only attenuated adjustment for one of the five outcomes of interest, internalizing problems. Perhaps the attenuation was limited to internalizing problems because connectedness reduces a sense of isolation among victimized youth, thereby they were less likely to endorse symptoms of depression or anxiety. More research is needed to further understand the relationship between student connectedness and the attenuated internalizing problems for victims of cyberbullying. Although previous studies have reported that perceived support from peers was associated with a decreased likelihood of cybervictimization (Williams & Guerra, 2007), the current study is one of the first to look at how student connectedness may attenuate negative mental and behavioral health outcomes. Future research could consider the potential buffering role of other contextual factors, such as school safety or parental involvement.

4.4. Limitations

Although the current sample was large and diverse, it is unclear the extent to which these findings will generalize to other samples, such as elementary or middle schoolers; research within elementary and middle school-aged youth could further inform our understanding of cybervictimization among younger youth. Nevertheless, our significant finding is consistent with previous research that suggests that being in the transitional year to high school (i.e., grade 9) is a risk factor for cybervictimization (Cappadocia et al., 2013). The current study is also cross-sectional; therefore, no causal relationships can be inferred. For example, it is possible that being depressed, receiving poor grades, or endorsing retaliatory beliefs may place a student at risk of being cybervictimized. Longitudinal research is needed to better understand the directionality of the relationships described in the current study. Additionally, traditional forms of bullying were measured over the past 30 days, whereas cyber forms of bullying were measured over the past three months. This discrepancy in time frame may alter how the results are interpreted, as it is possible that more students would have endorsed a history of traditional bullying if the time frame had been extended to the past three months. Future research would benefit from measuring both forms of bullying within the same time frame.

Issues of multicollinearity also precluded us from including other contextual factors in the multi-level models. A proxy for school-level socio-economic status (i.e., percentage of students receiving free or reduced meals) was not included in the model, due to its high correlation with other variables of interest (e.g., urbanicity). Given that higher socio-economic status was found to increase the risk of cyber perpetration and cybervictimization (Wang et al., 2009), future research should further explore this potential contextual factor. Consistent with the general aggression and social-ecological models, we explored some potential contextual risk and protective factors. However, closer consideration of these factors as well as situational factors may provide further insight into the extent to which these frameworks are relevant to cyberbullying specifically, as compared to other forms of aggressive behavior and peer victimization. Additionally, future studies would benefit from directly examining other aspects of the general aggression model, such as internal states or appraisals.

Although the frequency of missing data in this study was relatively low for survey research, we used multiple imputation techniques to address this potential concern. This analytic technique provided a more unbiased estimate of model coefficients and standard errors than list-wise deletion.

4.5. Conclusions and implications

Taken together, the results of the present study suggest that cybervictimization is associated with a host of negative outcomes, even after controlling for demographic factors, contextual factors, and other bullying involvement. The study extends previous research by assessing cybervictimization among a large and diverse sample of youth. Following the Kowalski et al. (2014) meta-analysis of cyberbullying research and integration of the general aggression model, future research directions were delineated that included the rigorous testing of additional person and situation factors that may contribute to cybervictimization and related distal outcomes. The current study aimed to fill some important gaps in the literature by assessing the relationship between a wide range of individual- and school-level factors and the risk of cybervictimization and related negative outcomes.

The results of the current study also suggest that there are important factors and outcomes to consider when monitoring the cyberbullying climate among youth. In particular, these findings may inform the design of bullying prevention programs, as the results offer specific insight into the experiences and risk factors of cybervictims. Although the vast majority of bullying prevention programs are designed for elementary and middle school students, very few have been planned, implemented, and shown to be effective at the high school level (Ttofi & Farrington, 2011); moreover, even fewer studies have examined the impact of prevention programs on cyberbullying specifically. The findings of the current study highlight the significance of school connectedness as a possible target for cyberbullying prevention programming, as these findings suggest it may buffer the effects of cybervictimization on internalizing problems. Taken together, these findings suggest that the general aggression and social-ecological frameworks may inform further investigation into the various personal and contextual factors that could influence the trajectory of cybervictims' adjustment problems.

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