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Differential Longitudinal Outcomes of In-Person and Cyber Victimization in Early Adolescence

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Abstract

Objective: Few studies have tested a commonly held assumption that cyber victimization is more harmful than in-person victimization. This study examined differential longitudinal relations between in-person and cyber victimization and outcomes, including problem behaviors and distress symptoms. Possible moderation by gender and grade was also explored.

Method: Participants were 1,542 sixth, seventh, and eighth grade students (77% African American or Black; 21% Latino/a) who completed surveys in the fall, winter, spring, and summer.

Results: The two forms of victimization combined to predict increases in physical and relational aggression, cyberbullying, and delinquency, but victimization did not predict increases in distress or substance use. There were generally no differences in the strength of relations between in-person and cyber victimization for longitudinal outcomes, although there were some cross-sectional differences. Cyber victimization predicted increases in delinquency for boys but not for girls, but there were no other differences in effects across gender or grade.

Conclusions: Overall, there was little support for the argument that cyber victimization produces greater harm than in-person victimization. Future research examining outcomes of cyber victimization should focus on longitudinal relations, given the different patterns of outcomes in this study's cross-sectional and longitudinal findings.

Keywords

victimization; cyberbullying; adolescence; aggression; delinquency

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Increases in adolescents' use of electronic communication technologies have led to extensive growth in research on cyber victimization. Many definitions of cyber victimization have been offered; most researchers agree that it involves being the target of aggressive behavior perpetrated through electronic communication technologies, but differ in how "aggressive behavior" (bullying, harassment, being mean) and "electronic communication technologies" are specified (e.g., Hertz & David-Ferdon, 2008; Kowalski & Limber, 2007). Although cyber victimization occurs less frequently than in-person victimization (e.g., Modecki,

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Minchin, Harbaugh, Guerra, & Runions, 2014; Wang, Iannotti, & Nansel, 2009), theoretical articles have identified several factors that suggest that cyber victimization has the potential to produce greater harm (e.g., Campbell, 2005; Mehari, Farrell, & Le, 2014; Tokunaga, 2010). This assumption has not, however, been rigorously tested. Major limitations of current research on cyber victimization include the use of cross-sectional rather than longitudinal designs, and the failure to assess the unique impacts of cyber victimization and in-person victimization on outcomes. The purpose of this study was to use a longitudinal design to explore differential outcomes of cyber victimization and in-person victimization.

Multiple theories explain how victimization leads to poor adjustment. Peer victimization directly targets adolescents' self-worth, physical safety, and social relationships. Further, victimization may represent peer rejection, which damages self-esteem and impacts adolescents' abilities to meet their needs for belonging (Lopez & DuBois, 2005). Interpretive processes may also lead to beliefs that the world is unsafe and unpredictable, creating anxiety, as well as selfblame attributions, creating distress and depressive symptoms (e.g., Graham, 2005). General strain theory suggests that the stress caused by peer victimization may lead some adolescents to engage in unhealthy coping behaviors, such as angry-reactive coping (aggressive behavior), self-medication or avoidant coping (substance use), and externalized coping to gain a sense of agency or control (delinquent behavior; e.g., Higgins, Piquero, & Piquero, 2011).

A common theme across theoretical discussions is that cyber victimization may be more psychologically harmful than in-person victimization (Mehari et al., 2014). Researchers have pointed to unique aspects of cyber victimization that support this assumption. These include the potential for a wider audience; the ubiquity of electronic devices, which makes it hard to escape victimization; its permanence on the Internet, which increases the likelihood of re-victimization; and the ability for perpetrators to be anonymous, which may create generalized fear and distrust (e.g., Campbell, 2005; Hinduja & Patchin, 2007; Tokunaga, 2010). Cyber victimization may also be more invasive and cause greater privacy violations because youth can experience victimization on cell phones or computers even in the privacy of their bedrooms (Hinduja & Patchin, 2007; Slonje & Smith, 2008), and because the aggression itself can constitute a greater violation of privacy (e.g., private or embarrassing photos). It is possible that youth feel more powerless to stop cyber victimization and believe that eybervictimization is more difficult to escape given the pervasiveness of access to communication technologies (e.g., Campbell, 2005; Huang & Chou, 2010; Tokunaga, 2010). These qualitative differences support a theoretical model in which cyber victimization is considered to be a construct distinct from in-person victimization (e.g., Farrell, Thompson, Mehari, Sullivan, & Goncy, 2018) and suggest that cyber victimization may cause more harm to belongingness, prompt more self-blame attributions, increase a sense of generalized threat, and exert more strain, leading to more unhealthy coping behaviors. However, minimal empirical research has rigorously examined this hypothesis.

Relations Between Cyber Victimization and Outcomes

Numerous studies have demonstrated a strong concurrent relation between in-person and cyber victimization. For example, a meta-analysis by Kowalski, Giumetti, Schroeder, and

Lattanner (2014) of predominantly cross-sectional studies found that in-person victimization was the strongest correlate of cyber victimization, compared with other well-established predictors (e.g., risky online behavior, parental control of technology, Internet usage). The limited research exploring longitudinal relations between cyber and in-person victimization has produced inconsistent findings. A longitudinal study of Australian adolescents found no longitudinal relation between cyber and in-person victimization (Gradinger, Strohmeier, Schiller, Stefanek, & Spiel, 2012). However, both measures had low stability overtime. In contrast, a longitudinal study of early to mid-adolescents in New Zealand found that in-person victimization predicted subsequent cyber victimization but that cyber victimization only marginally predicted subsequent in-person victimization (José, Kljakovic, Scheib, & Notter, 2011).

Similarly, research examining the relation between cyber victimization and adjustment has been mostly cross-sectional. A large body of literature has identified a concurrent relation between cyber victimization and a host of negative outcomes (e.g., Huang & Chou, 2010; Kowalski & Limber, 2007). Kowalski and colleagues' (2014) meta-analysis found that cyber victimization is consistently associated with internalizing problems such as feelings of distress, suicide ideation, depressive symptoms, and symptoms of anxiety, and with externalizing problems, such as substance use and conduct problems. It remains unclear whether these effects differ from those found for in-person victimization. In one study, a sample of Swedish adolescents were asked whether cybervictimization was more harmful than in-person bullying; overall, they rated bullying victimization through text or email as causing less harm, but bullying victimization through pictures or videos as causing more harm (Slonje & Smith, 2008).

Determining the unique role of cyber victimization requires simultaneously examining cyber and in-person victimization (e.g., Perren, Dooley, Shaw, & Cross; 2010). However, with few exceptions (e.g., Landoll, La Greca, & Lai, 2015; Salmivalli, Sainio, & Hodges, 2013), most cyber victimization research has not controlled for in-person victimization. There is some evidence that cyber victimization and in-person victimization each uniquely predict outcomes. In a cross-cultural study of adolescents in Australia and Switzerland, both cyber victimization and in-person victimization significantly predicted concurrent depressive symptoms when controlling for the other form (Perren et al., 2010). In contrast, cyber victimization did not uniquely predict depressive symptoms when controlling for in-person victimization, but both forms of victimization uniquely predicted social anxiety in a moderately diverse sample of early to middle adolescents in the U.S. (Dempsey, Sulkowski, Nichols, & Storch, 2009). In a predominantly White American, middle-income sample of late elementary students, both in-person overt victimization and cyber victimization were uniquely associated with concurrent loneliness and social acceptability (Jackson & Cohen, 2012). In a predominantly Latino American sample of high school students, cyber victimization uniquely predicted subsequent depressive symptoms whereas relational victimization uniquely predicted subsequent social anxiety (Landoll et al., 2015). These findings suggest that there may be differential patterns of relations between cyber and in-person victimization and outcomes. However, it remains unclear whether cyber victimization is *more* harmful than in-person victimization.

Of note, most research on cyber victimization has been conducted among Caucasian American adolescents in middle-income families. This is a serious problem given that descriptive research has suggested that adolescents in low-income families and African American adolescents are more likely to connect with friends via social media and messaging apps than are adolescents in high-income families or Caucasian American adolescents (Lenhart et al., 2015). This higher usage may increase their risk of cyber victimization, so there is an urgent need to understand how cyber victimization predicts subsequent adjustment among African American youth and youth in low-income contexts.

Gender Differences in Cyber Victimization

Research on gender differences in experiences of cyber victimization has produced mixed findings. Although the majority of studies have found no gender differences (e.g., Beran & Li, 2007; Jackson & Cohen, 2012; Werner, Bumpus, & Rock, 2010; Wolak, Mitchell, & Finkelhor, 2007), some research suggests that girls are more likely than boys to report cyber victimization (e.g., Kowalski & Limber, 2007; Wang et al., 2009). This may be due to differences in measurement, with gender differences found when the word “bullied” was used (e.g., Kowalski & Limber, 2007; Wang et al., 2009) but not when the word “bullied” was avoided (e.g., Beran & Li, 2007; Jackson & Cohen, 2012; Wolak et al., 2007; Werner et al., 2010). It may be more socially acceptable (and gender congruent) for girls to report being bullied than for boys. In addition to differences in rates, it is possible that gender moderates the effects of cyber victimization. For example, Kowalski and colleagues’ (2014) meta-analysis found a stronger relation between cyber victimization and depressive symptoms in samples that included a higher proportion of girls, suggesting that girls may be more strongly impacted by cyber victimization than boys, at least for depression. One study in the Netherlands found that cyber victimization predicted subsequent global mental health problems for adolescent girls but not for boys (Bannink, Broeren, van de Looji-Jansen, de Waart, & Raat, 2014). This underscores the need to consider the moderating role of gender in studies evaluating outcomes of cyber victimization.

The Present Study

The purpose of this study was to explore whether cyber victimization was more strongly predictive of problem behaviors (physical aggression, relational aggression, cyber aggression, delinquent behavior, substance use) and subjective distress compared to in-person victimization. We tested these relations within a large sample of middle school students who completed measures four times over the course of a year. Analysis of longitudinal data collected on a quarterly basis allowed us to examine more immediate changes in patterns of relations. Given that most other longitudinal studies of cyber victimization have obtained data in the fall and spring of the school year or 12 months apart (e.g., Salmivalli et al., 2013), they may not have been able to capture more immediate relations between victimization and adjustment. We also tested whether the pattern of relations between victimization and longitudinal outcomes was constant across gender and grade. Of note, our sample was predominantly African American and low income.

Hypotheses

We hypothesized that (1) cyber victimization and in-person victimization would be closely related to each other concurrently, and that in-person victimization in the beginning of the school year would predict subsequent changes in cyber victimization. We also hypothesized that (2) cyber victimization would be more frequent in seventh and eighth grade than in sixth grade, based on research suggesting that cyber victimization increases after children enter middle school (e.g., Kowalski & Limber, 2007). This pattern may also be reflected over the course of the school year, such that adolescents may increase their use of cyber aggression when they become more technologically adept through observational learning.

Related to the pattern of relations between victimization and subsequent adjustment, we hypothesized that (3) both cyber victimization and in-person victimization would predict subsequent externalizing behaviors (cyber aggression, physical aggression, relational aggression, and delinquent behavior), substance use, and distress. We hypothesized that (4) cyber victimization would be more strongly predictive of delinquent behavior, substance use, and distress compared with in-person victimization, but that both would uniquely contribute to the prediction of adjustment. We also hypothesized that (5) cyber victimization would be more closely associated with subsequent cyber aggression, and that in-person victimization would be more closely associated with subsequent physical and relational aggression, based on the high concurrent correlations between victimization and aggression within forms (e.g., Casper & Card, 2017; Kowalski et al., 2014). We hypothesized that (6) gender would moderate the relations between cyber victimization and adjustment, such that the relations between cyber victimization and indicators of adjustment would be stronger among girls than among boys. We also conducted exploratory analyses examining the consistency of pattern of relations between victimization and outcomes across grades.

Method

Participants

We conducted secondary analyses of data collected as part of a large project evaluating a school-based violence prevention program (the Olweus Bully Prevention Program) using a multiple baseline design (Farrell, Sullivan, Sutherland, Corona, & Masho, 2018). The larger project collected data from random samples of students from three urban middle schools in the southeastern United States. Most participants were from low-income families, and 76% to 100% were eligible for the free lunch program according to school records. The current study is based on data collected between 2015 and 2018. Our final sample of 1,542 students had a mean age of 12.71 (*SD* = 0.98) years (averaged across waves); slightly over half (51%) were female. Sixty-nine percent identified as only African American or Black, with an additional 8% endorsing multiple racial categories including African American or Black; about 7% identified as White; and 14% did not endorse any racial category (the majority of those students identified as Hispanic or Latino). In total, 21% identified as Hispanic or Latino. About 28% reported living with both parents; 23% with a single mother and no other adult; and 23% with a parent and stepparent. Of note, 85% reported they had access to a cell phone, and 92% reported access to the Internet.

Procedures

Students were provided information about the project and received a $5 gift card for returning consent forms regardless of whether parents gave consent. All participants provided both written parental consent and informed assent. Students received $10 gift cards at each wave for completing any part of the survey. Data were collected in the fall, winter, spring, and summer during each year of the project. Students completed the measures on a computer-assisted survey in small groups during the school year and at their homes or in public settings in the summer. The project used a planned-missing design that randomly assigned each student to complete two of the four waves each year they participated. Such designs reduce costs, carryover effects, participant burden, fatigue, and attrition (Graham, Taylor, & Cumsille, 2001). In order to maximize our use of the available data we examined within-person changes across the four waves of data within a specific grade using data from a single grade for those participants who only participated during one school year, and from one randomly selected grade for those who participated during more than one grade. This provided data on 1,542 students, including 557 sixth grade, 464 seventh grade, and 521 eighth grade students.

Measures

The Problem Behavior Frequency Scale-Adolescent Report Version 2.0 (PBFS-AR; Farrell et al., 2018) assessed multiple types of victimization and aggression in addition to delinquent behavior and substance use. For all PBFS-AR scales, participants reported on their experiences during the past 30 days on a 6-point frequency scale ranging from 1 = *Never* to 6 = *20 or more times*. The PBFS-AR has established construct validity based on correlations with teacher report of adolescents' behavior and school discipline referrals (Farrell et al., 2016, Farrell et al., 2018). For example, student with office referrals for physical aggression self-reported higher rates of physical aggression (large effect size) and higher rates of other forms of aggression, delinquency, and substance use (small to medium effect sizes; Farrell et al., 2018). The physical aggression, delinquent behavior, and substance use subscales were positively associated with the Conduct Disorder scale based on their teacher's report on the Behavior Assessment System for Children (BASC; Reynolds & Kamphaus, 1992) and not associated with their teacher's report of anxiety on the BASC-2 (Farrell et al., 2016). High test-retest reliability for each scale has been reported for adolescents who score above the mean, with decreasing reliability for adolescents with lower scores (Farrell et al., 2018).

The in-person victimization scale consisted of 10 items that assessed physical (e.g., "Someone threw something at you to hurt you), verbal (e.g., "Someone said something disrespectful to you about your family"), and relational forms (e.g., "Spread a false rumor about someone"). Previous research indicated that a one-factor model (i.e., a single in-person victimization scale that did not differentiate between physical, verbal, and relational victimization) fit the data better than models that differentiated among physical, verbal and relational forms of victimization (Farrell et al., 2018). Internal consistency (i.e., Cronbach's alpha) in the present study ranged from .90 to .91 across waves.

The cyber victimization scale of the PBFS-AR consisted of 11 items assessing physical threats (e.g., "Someone used text messaging to threaten to hurt you physically"), verbal victimization (e.g., "Someone called you mean names online or using a cell phone"), and relational victimization (e.g., "Someone sent or posted embarrassing pictures of you") experienced electronically. The measure was based on a review of the quantitative and qualitative literature. Previous research found that a factor structure that differentiated between cyber and in-person victimization fit the data better than combining both types of victimization into a single factor (Farrell et al., 2018). Internal consistency for the cyber victimization scale in the present study ranged from .85 to .91 across waves.

The PBFS-AR aggression scales included 5 items to assess physical aggression (e.g., "Hit or slapped someone"); 6 items to assess relational aggression (e.g., "Spread a false rumor about someone"); and 11 items to assess cyber aggression (e.g., "posted rude comments about someone you know online"). Factor analyses indicated that physical, relational, and cyber aggression were distinct constructs (Farrell et al., 2018; Mehari & Farrell, 2016). Internal consistency ranged from .75 to .77 (physical aggression), .65 to 77 (relational aggression), and .85 to .88 (cyber aggression) across waves. It should be noted that although the victimization and aggression items were parallel, the factor structures were different (i.e., a two-factor victimization construct compared to a three-factor aggression construct; see Farrell et al., 2018).

The delinquent behavior scale assessed the frequency of nonviolent illegal behaviors such as theft and vandalism (e.g., "Written things or sprayed paint on [tagged] walls or sidewalks or cars where you were not supposed to"; α = .68 to .78 across waves). The substance use scale included 9 items that assessed use of alcohol (beer, wine/wine coolers, liquor, and having been drunk), inhalants, marijuana, cigars, and cigarettes (e.g., "Smoked cigars [like Black *Sc* Milds]"; α = .78 to .88 across waves).

Symptoms of psychological distress were assessed by the Checklist of Children's Distress Symptoms (CCDS; Richters *&* Martinez, 1990), a scale based on the diagnostic criteria for posttraumatic stress disorder. Participants responded to 28 items assessing hyperarousal, sense of safety, rumination, avoidance, and re-experiencing on a 5-point frequency scale from 1 = *Never* to 5 = *Most of the time*. Example items include "How often do you worry about being safe?;" "How often do you keep remembering something upsetting, or have thoughts that kept going through your mind about something upsetting - even when you don't want to think about it or remember it?" Children's composite symptom scores on the CCDS have been significantly related to exposure to trauma and violence (e.g., Mathews, Dempsey, & Overstreet, 2009). Internal consistency in the current study was strong (α = .95 across waves).

Data Analysis Plan

We log-transformed scores on the PBFS-AR to reduce their overall skewness and kurtosis and used linear transformations to provide scores with means and standard deviations equivalent to the original measures. We used MPlus Version 8 (Muthén & Muthén, 2017) for all analyses. All models addressed missing data using full information maximum likelihood estimation and computed standard errors using a robust estimator (i.e., MLR) to account for nonnormality. We used sandwich estimators (i.e., MPlus type=complex and stratification options) to address non-independence resulting from nesting in grade, cohort, and school (Muthén & Satorra, 1995). All models included correlations among the variables within each wave and controlled for intervention status, ethnicity, gender, and grade. We used guidelines by Hu and Bentler (1999) to evaluate model fit based on their root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI). We also compared models using the scaled chi-square difference test (Satorra & Bentler, 2010). A power analysis based on 1,000 Monte Carlo simulations using parameter estimates obtained in our model estimated the power at over .80 to detect standardized regression coefficients of .10 or greater in absolute value and differences in correlations of. 11 or larger.

To test Hypothesis 1, we ran cross-lagged path models to investigate longitudinal reciprocal relations between cyber and in-person victimization. To test Hypothesis 2, we expanded this model to examine longitudinal relations between both forms of victimization and each of the six outcomes (see Figure 1). For both hypotheses, we evaluated the combined effects of the two forms of victimization by calculating the change in R^2 for models that included both of their effects to baseline models that did not, and Wald tests to determine the significance of their combined effect. We evaluated the unique effects of each form of victimization using significance tests on standardized regression coefficients that controlled for the other form of victimization and previous levels of adjustment, and compared the magnitude of these coefficients across forms using the constraint command provided by Mplus (Hypothesis 4 and 5). We also examined correlations between the residual variances within each wave to identify unique concurrent relations.

We ran additional models to examine the consistency of effects over time and across gender and grade. We examined the stability of relations across waves (i.e., autoregressive and cross-variable relations) by comparing models in which cross-wave coefficients were constrained across waves (i.e., each path coefficient linking the Wave t variable to the Wave $t+1$ variable was constrained to the same value for t =1,2, and 3) with models in which they were allowed to vary across waves. We used Wald tests within unconstrained multiple group models to examine whether the relations between both forms of victimization and each outcome differed by gender and grade (Hypothesis 6).

Results

The frequency for each item on the victimization scales is reported in Table 1. Overall, in-person victimization (M = 1.24) occurred more frequently than cyber victimization (M = 1.09; t[1530] =22.89, p < .001). The most frequently endorsed cyber victimization experiences were being called mean names electronically (16% of youth) or a person pretending to be someone else to trick the participant (13% of youth). Table 2 reports d-coefficients representing mean differences across gender and grade. There were no gender differences in experiencing victimization. There were small- to medium-sized differences across grades that differed across waves. At three of the waves, sixth grade students reported higher frequencies of in-person victimization than did seventh grade (ds = .22 to .31) and eighth grade students (ds = .18 to .46). Compared with eighth grade students, they also reported higher frequencies of cyber victimization, but only at the start of the school year (d = .22).

Means and standard deviations at each wave and correlations among the variables at Wave 1 are reported in Table 2. As hypothesized, in-person and cyber victimization were highly correlated (r = .60), and each had moderate positive correlations with relational aggression (r = .43 and .40, respectively), and delinquent behavior (r = .32 and .35, respectively). Several correlations with outcomes significantly differed for the two forms of victimization. Compared with in-person victimization, cyber victimization was more strongly correlated with cyber aggression (rs = .47 versus .35,p < .001) and with substance use (rs = .30 versus .19,p = .01). In contrast, in-person victimization was more strongly correlated with physical aggression (rs = .42 versus .27, p < .001), and with distress symptoms (rs = .57 versus .35, p < .001).

Relations Between Cyber Victimization and In-Person Victimization

Our analyses of models examining bidirectional relations between cyber victimization and in-person victimization over time found support for a model in which all path coefficients were constrained overtime (see Table 3, Model 3; RMSEA = .008, CFI = .999, TLI = .996). As we hypothesized (Hypothesis 1), in-person victimization predicted subsequent increases in cyber victimization (β = 0.14, p = .008, ΔR^2 = .06 to . 13 across waves; see Table 4), controlling for demographics and prior levels of cyber victimization. In contrast, cyber victimization did not predict changes in in-person victimization (β = 0.07, p = .166, ΔR^2 = .06 to .10 across waves). Although these effects were significant for in-person, but not for cyber victimization, the standardized regression coefficients were not significantly different from each other *(p* = .38). There were no gender (Wald χ^2 [6] = 4.65, p = .59) or grade differences (Wald χ^2 [12] = 20.07, p = .07) in the reciprocal relations between in-person and cyber victimization.

Relations Between Victimization and Cyber Aggression

We expanded the victimization-only model to include cyber aggression as an outcome (see Figure 1). The model constraining path coefficients overtime (see Cyber Aggression Model 3 in Table 3) fit the data well (RMSEA = .024, CFI = .98, TLI = .95). The two forms of victimization predicted changes in cyber aggression (Wald χ^2 [2] = 19.46, p< 0.001; ΔR^2 = .03 to .08 across waves). Within this model, cyber victimization uniquely predicted significant increases in cyber aggression across time (β = 0.16, p = .007), but in-person victimization did not (β = 0.07,p = . 102; see Table 4), partially supporting Hypothesis 3. However, contrary to Hypothesis 5, the two coefficients were not significantly different from each other *(p* = .23). Compared with in-person victimization, cyber victimization was more strongly concurrently related to cyber aggression at every wave *(ps* < .01; rs ranged from .25 to .48 for in-person victimization and .40 to .63 for cyber victimization). There were no gender (Wald χ^2 [6] = 5*.69, p* = .46) or grade differences (Wald χ^2 [12] = 14.89, p = .25) in patterns of relations.

Relations Between Victimization and Physical Aggression

Comparison of models examining relations between in-person and cyber victimization and subsequent physical aggression again found support for constraining coefficients across waves (see Model 3 in Table 2; RMSEA = .024, CFI = .98, TLI = .95). The two forms of victimization as a set significantly predicted changes in physical aggression (Wald χ^2 [2] = 11.78, $p = 0.003$; AR^2 = .01 to .02 across waves). However, neither cyber victimization nor in-person victimization was a unique predictor of subsequent physical aggression (βs = 0.05 to 07, *ps* > .06; see Table 4). These findings likely reflect their shared variance, and did not support Hypothesis 3, that there would be unique relations, or Hypothesis 5, that the relation would be stronger for in-person victimization. In-person and cyber victimization were both significantly related to concurrent physical aggression (*rs* = .32 to .52 for in-person victimization and .14 to .33 for cyber victimization within each wave). Compared with cyber victimization, in-person victimization was more strongly concurrently related to physical aggression at every wave (*ps* < .05). There were no gender (Wald χ^2 [6] = 12.21,$p = 0.06$) or grade (Wald χ^2 [12] = 6.00, $p = 0.92$) differences in the relations between victimization and subsequent physical aggression.

Relations Between Victimization and Relational Aggression

The model constraining the relations between in-person and cyber victimization and relational aggression over time fit the data well (see Relational Aggression Model 3 in Table 3; RMSEA = .012, CFI = .995, TLI = .99). Victimization as a set significantly predicted changes in relational aggression (Wald χ^2 [2] = 20.99,$p < 0.001$; ΔR^2 = .02 to .04 across waves). In-person victimization uniquely predicted significant increases in relational aggression across time (p = 0.13, $p = .002$), but cyber victimization did not (β = 0.07, $p = .24$; see Table 4). This partially supported Hypothesis 3, that both forms of victimization would uniquely predict relational aggression. The relations between in-person and cyber victimization and subsequent relational aggression did not significantly differ from each other (Δβ = 0.05, $p = .57$), which did not support Hypothesis 5. In-person and cyber victimization were significantly related to relational aggression (*rs* ranged from .33 to .57 for in-person victimization and .30 to .47 for cyber victimization within each wave), and those relations were not significantly different from each other (*ps* > .05). There were no gender (Wald χ^2 [6] =9.31 ,$p = 0.157$) or grade (Wald χ^2 [12] = 7.85, $p = 0.797$) differences in the patterns of relations.

Relations Between Victimization and Delinquent Behavior

The model examining the relations between victimization and subsequent delinquency fit the data well when autoregressive coefficients were allowed to vary (see Delinquent Behavior Models in Table 3; RMSEA = .022, CFI = .98, TLI = .94). Victimization as a set significantly predicted changes in delinquent behavior (Wald χ^2 [2] = 6.42, $p = .04$; ΔR^2 = −.002 to .022 across waves). Neither cyber nor in-person victimization was uniquely related to changes in delinquent behavior (βs = 0.04 to 0.07, $p >$. 194; see Table 4), counter to Hypothesis 3 and 4. In-person and cyber victimization were significantly related to concurrent delinquency (*rs* ranged from .24 to .46 for in-person victimization and .20 to .36 for cyber victimization within each wave). Compared with cyber victimization, in-person victimization was more strongly concurrently related to delinquent behavior at Wave 4 ($p = .039$), but not at any other wave ($ps > .05$).

There were gender differences in the longitudinal pattern of relations (Wald χ^2 [6] = 18.88, $p = 0.004$; $\Delta R^2 = .01$ to .16 and .003 to .03, for boys and girls respectively), but no grade differences (Wald χ^2 [12] = 18.91, $p = 0.09$). We examined gender differences within a multiple group model that allowed cross-wave parameters to vary over time (see Delinquent Behavior Model 4 in Table 3). This unconstrained model fit the data significantly better than models that constrained the cross-variable coefficients ($\chi 2\Delta$ [8] = 45.39, p < .001) or the cross-variable and autoregressive coefficients ($\chi 2\Delta$ [12] = 21.37, p < .05). Cyber victimization predicted significant changes in delinquent behavior for boys but not for girls. This did not support Hypothesis 6, that the relation would be stronger for girls. Cyber victimization predicted an increase in boys' delinquent behavior at Wave 2 ($\beta = 0.41$, $P < .002$), and a decrease at Wave 3 ($\beta = -0.3$, $p = .02$). In-person victimization did not predict changes in delinquent behavior for boys or girls at any of the waves.

Relations Between Victimization and Substance Use

The model examining the relations between victimization and subsequent substance use fit the data well when regression coefficients were allowed to vary across waves (see Substance Use Models in Table 3; RMSEA = .024, CFI = .98, TLI = .93). Victimization as a set did not significantly predict changes in substance use (Wald χ^2 [6] = 11.78, $p = .07$; $\Delta R^2 = .011$ to .026 across waves), inconsistent with Hypothesis 3. However, in-person and cyber victimization were significantly related to concurrent substance use (*rs* ranged from .20 to .28 for in-person victimization and .28 to .31 for cyber victimization across waves). Compared with in-person victimization, cyber victimization was more strongly concurrently related to substance use at Wave 1 ($p = .034$), but not at any other waves ($ps > .05$). There were no gender (Wald χ^2 [6] = 8.74, $p = 0.19$) or grade (Wald χ^2 [12] = 5 .00, $p = 0.96$) differences in the pattern of relations.

Relations Between Victimization and Distress Symptoms

The model examining the relations between in-person and cyber victimization and relational aggression over time fit the data well when relations were constrained over time (see Distress Symptoms Model 3 in Table 3; RMSEA = .029, CFI = .98, TLI = .94). Victimization as a set did not significantly predict changes in distress symptoms (Wald χ^2 [2] = 2.96, $p = .23$, $\Delta R^2 = .004$ to .005 across waves). However, in-person and cyber victimization were significantly related to concurrent distress symptoms (*rs* ranged from .37 to .56 for in-person victimization and .25 to .35 for cyber victimization). These correlations were stronger for in-person victimization than for cyber victimization at Waves 1 through 3 ($ps < .05$) but not at Wave 4 ($p = .16$). Multiple group models did not reveal any gender (Wald χ^2 [6] = 5.41, $p = 0.49$) or grade differences (Wald χ^2 [12] = 15.36, $p = 0.22$) in the pattern of longitudinal relations.

Discussion

The purpose of this study was to (1) examine the relation between in-person and cyber victimization overtime in early adolescence; (2) empirically test a common assumption that cyber victimization results in more harm than does in-person victimization; and (3) examine whether gender and grade moderate the relations between victimization and adjustment. We found support for our hypothesis that in-person victimization would predict increases in cyber victimization. As previously noted, prior longitudinal studies have been mixed, with some studies finding no longitudinal relations (e.g., Gradinger et al., 2012) and others finding that in-person victimization was a better predictor of cyber victimization than the reverse (José et al, 2011). We found support for in-person victimization predicting cyber victimization, but we also found that there were no differences in the magnitude of the effects of each form of victimization on the other over time. In other words, although the cross-variable effect for predicting the other form of victimization was significantly different from zero for in-person victimization but not for cyber victimization, the two effects were not different from each other.

We hypothesized that as adolescents become more technologically savvy and engaged over the course of middle school, they would be more likely to experience victimization through technologies, and their in-person victimization experiences would be carried over into online settings. That is, as their peers increase their use of technologies for social communication, those who were already being victimized in person would begin to be more frequently victimized online. For example, if classmates were already spreading rumors about an adolescent in person, they would begin to propagate those rumors via texting and social media. However, the relation between in-person victimization and subsequent changes in cyber victimization did not change across the sixth, seventh, and eighth grades or within grade. In addition, there was some evidence that mean levels of cyber victimization were higher in sixth grade than in eighth grade, especially in the fall, refuting the idea that adolescents are learning this behavior over the course of middle school. Given the results of this study, it is possible that the relation between in-person and cyber victimization actually stabilizes even earlier, with children becoming well acquainted with electronic communication technologies at younger and younger ages. Future research should examine cyber victimization and related risk factors in younger children, such as in middle and late elementary school. Of note, in-person victimization remained slightly more frequent than cyber victimization, which is consistent with previous research (e.g., Modecki et al., 2014).

The second aim of the study was to test our hypothesis that cyber victimization was more harmful than in-person victimization by directly comparing their relations with externalizing behaviors and distress. Together, cyber victimization and in-person victimization predicted increases in physical aggression, relational, and cyber aggression, and in delinquent behavior. There were, however, no differences in the strength of their individual relations to those outcomes. That is, in-person and cyber victimization appear to be equally important in influencing adolescents' subsequent behavior problems, specifically aggression and delinquent behavior. This suggests that cyber victimization does not exert more of a strain on adolescents than in-person victimization, despite significant qualitative differences in how it is experienced.

Cyber victimization did not predict subsequent changes in cyber aggression more strongly than did in-person victimization, and in-person victimization did not predict changes in in-person physical or relational aggression more strongly than did cyber victimization. This suggests that retaliatory aggression will not necessarily take the same form as the received victimization. This finding stands in stark contrast to our hypothesis and to a large body of cross-sectional research that suggests that in-person victimization is more strongly related to in-person aggression, and that cyber victimization is more strongly related to cyber aggression. For example, Kowalski et al.'s (2014) meta-analysis estimated that the concurrent relation (adjusted rs) between cyber victimization and cyberbullying was .51 (cyber victimization), which was statistically significantly stronger than the relation between in-person victimization and cyberbullying (.21). It is possible that the co-occurrence between cyber victimization and cyber aggression is high, but that cyber victimization does not predict increases in cyber aggression more than in-person victimization does. The concurrent findings of this study support that idea (within waves, cyber aggression was correlated with cyber victimization at $r = .47$ and with in-person victimization at $r = .31$, and these relations were significantly different). Similarly, in-person victimization was more strongly concurrently related to relational aggression (but not to physical aggression) than was cyber victimization. However, these differences were not found in their relations over time.

Cyber and in-person victimization, either as a set or individually, did not predict changes in substance use. This is consistent with a recent meta-analysis of longitudinal studies of bullying suggesting that in-person bullying victimization was not predictive of subsequent substance use.However, the small number of studies included in the meta-analysis made it difficult to draw conclusions (Ttofi, Farrington, Lösel, Crago, & Theodorakis, 2016). Our findings are also consistent with a study of adolescents in Spain that found that cyber victimization did not predict subsequent substance use (Gámez-Guadix, Orue, Smith, & Calvete, 2013). Although we did not find significant longitudinal relations between victimization and substance use, we did find that changes in the frequency of victimization experiences across waves were related to cross-wave changes in substance use. This suggests that similar factors that influence victimization may also influence in substance use. For example, adolescents who are using substances during middle school may be engaging in other risky or unconventional behavior that places them at risk for cyber victimization. It is also possible that here is a cause-effect relation between cyber victimization and substance use, but the effect occurs rather quickly such that the three months interval between waves may have been too long to capture these more immediate changes.

Similar to the findings for substance use, neither form of victimization predicted increases in subjective distress. However, within-wave correlations among residuals between each form of victimization and distress were positive and moderate to strong, and were significantly stronger for in-person victimization than for cyber victimization at three of the four waves. Although many researchers have provided theoretical arguments to contend that cyber victimization causes more harm than in-person victimization (e.g., Tokunaga, 2000), our findings suggest otherwise. If in-person victimization experiences are happening at school, adolescents may experience more symptoms of traumatic distress, partly because the victimization may be physical, and partly because they feel unsafe at school. Under those conditions, hypervigilance, difficulty concentrating, and re-experiencing symptoms may be more likely to be triggered at school. There is a variety of possibilities as to why victimization was associated with distress concurrently but not longitudinally. It is possible that because victimization tends to be stable, it has already exerted its influence on distress. This would make it difficult to detect subsequent changes because equilibrium has already been achieved. Another possibility is that the longitudinal relation is reversed, such that children who are distressed from previous traumatic events are more likely to be victimized because of their traumatic stress symptoms (e.g., withdrawal, irritability/reactivity, disconnectedness; Terranova, Boxer, & Morris, 2009).

Gender did not play an important role in predicting victimization experiences or in moderating the impact of victimization. We did not find gender differences in the prevalence of in-person or cyber victimization. As discussed previously, prior research has been mixed about whether cyber victimization experiences vary by gender. It is possible that our use of a measure that focused on behavior rather than referring to “bullying” might have reduced the influence of gender socialization or concepts of masculinity. Although no definitive conclusions can be drawn from this study alone, these results provide emerging evidence that both cyber and in-person victimization are equally harmful for boys and for girls. An interesting pattern emerged in the longitudinal relation between delinquent behavior and cyber victimization for boys. Specifically, cyber victimization in the fall was positively related to changes in delinquent behavior in the winter, but cyber victimization in the winter was inversely related to changes in delinquent behavior in the spring. It may be that social status order is being established in the fall, and that cyber victimization is a form of peer rejection that results in increased delinquent behavior with other rejected peers over the course of the first semester. In turn, continued rejection in the winter may result in withdrawal, passivity, or damaged relationships even within a deviant peer group, which would decrease the likelihood of continued delinquent behavior. Alternatively, it may be that the initial increase in delinquent behavior associated with higher levels of cyber victimization is short-lived and quickly reverts.

Limitations

Our study was limited by the specific outcomes we assessed. We did not examine anxiety or depression, healthy psychological functioning (e.g., well-being, self-esteem), or academic functioning. Although we did not find that cyber victimization and in-person victimization differed in their relations to subsequent problem behaviors, they may have differential relations to other outcomes. Another limitation was that all of our measures were self-report, which may have inflated the relations between factors. Our measures also did not assess bullying perpetration or victimization, which by definition include a power imbalance between perpetrator and victim and repetition overtime (e.g, Gladden, Vivolo-Kantor, Hamburger, & Lumpkin, 2014). Although cyberbullying experiences may have constituted a subset of adolescents’ reports on the PBFS, the strength of the correlations between forms of victimization and aggression in this study suggest that much of the victimization may have taken place in the context of mutually aggressive interactions. It is possible that cyberbullying victimization would have had a differential and potentially stronger impact on outcomes compared to cyber victimization outside of the context of a bullying relationship.

Participants in the current study were predominantly African American and Latino American, and attended underresourced schools in high-violence neighborhoods. There may be cultural and environmental differences in the experiences of and responses to in-person and cyber victimization that were not captured by this study. Although ethnicity likely does not moderate the impact of in-person victimization (Mehari & Farrell, 2014; Graham et al., 2009), future research should examine ethnicity, urbanicity, and socioeconomic status as potential moderators of cyber victimization. In addition, this study may not generalize to the future. There are secular trends in use of electronic communication technologies; the results of this study present a picture in time, but may quickly become obsolete.

Implications for Research

This study was one of the first to directly compare the relations between cyber victimization and in-person victimization and subsequent adjustment. This study had the benefit of collecting data every three months, which allowed for a close examination of change over short periods of time in early adolescence, a period of incredibly rapid change in physical, social, and cognitive domains. Although our cross-sectional findings were consistent with existing research, our longitudinal findings reflected a rather different pattern. Overall, these findings point to the importance of examining both in-person and cyber victimization longitudinally, rather than drawing conclusions based solely on cross-sectional research. Longitudinal research, perhaps over even shorter intervals, will be necessary to clarify the relations between the two forms of victimization and outcomes, perhaps especially distress and substance use.

Future research should also consider the context and content of cyber victimization experiences. For example, cyber victimization in the context of a bullying relationship may have a stronger negative impact. Although the ability to define a power imbalance in the context of interactions using electronic communication technologies has been debated (e.g., Wolak et al., 2007), researchers should attempt to assess for a power imbalance and repetition over time to see if those contextual factors magnify the impact of cyber victimization. It is also possible that variations in the perpetrator (e.g., an adult, an anonymous perpetrator, a popular vs. rejected peer) might impact the harm caused by cyber victimization. Finally, the content of cyber victimization might play a role as well—it is likely that some content is much more harmful (e.g., sending nude photos of a young female adolescent to classmates, sharing private information about someone’s sexual orientation or behaviors) is more harmful than others (e.g., a single unknown perpetrator making one insulting statement on a platform like YouTube).

Cyber victimization researchers should take advantage of the advanced statistical methods that are available to determine patterns of relations with more precision. For example, methodologically, it is important to be precise in reporting results that compare outcomes of the two forms of victimization, only reporting differences as differences if they have been tested and determined to be statistically significant. Approaches such as latent class analyses that include cyber and in-person aggression and victimization could identify groups of children that have specific patterns of experiences. Perhaps even more usefully, latent transition analyses could examine how children move in and out of those groups over time.

These analyses and others like them (e.g., latent growth curve analyses) could shed light on children’s experiences overtime.

Implications for Prevention

The results of this study strongly support the need for early intervention and prevention, both to reduce victimization experiences and to mitigate the impact of victimization on adolescents’ functioning. Parents, teachers, and policymakers should understand that victimization predicts aggression, both online and in person. Having a binary view of violence (that a youth is either a victim or an aggressor) is not accurate to the actual phenomenon, and may result in the vilification of victimized youth. More research is needed to explore whether factors that buffer the relation between in-person victimization and outcomes also buffer the relation between cyber victimization and outcomes. Extreme cases, such as suicides of adolescents who have been cyber victimized, have been highlighted in the media, but this study and others show that those are not typical responses to cyber victimization. It is important to identify what makes some youth vulnerable and some youth resilient to victimization, and then to intervene with high-risk youth by building resilience. Education on and practice in how to cope with stressors such as victimization across multiple settings should be included in such programs.

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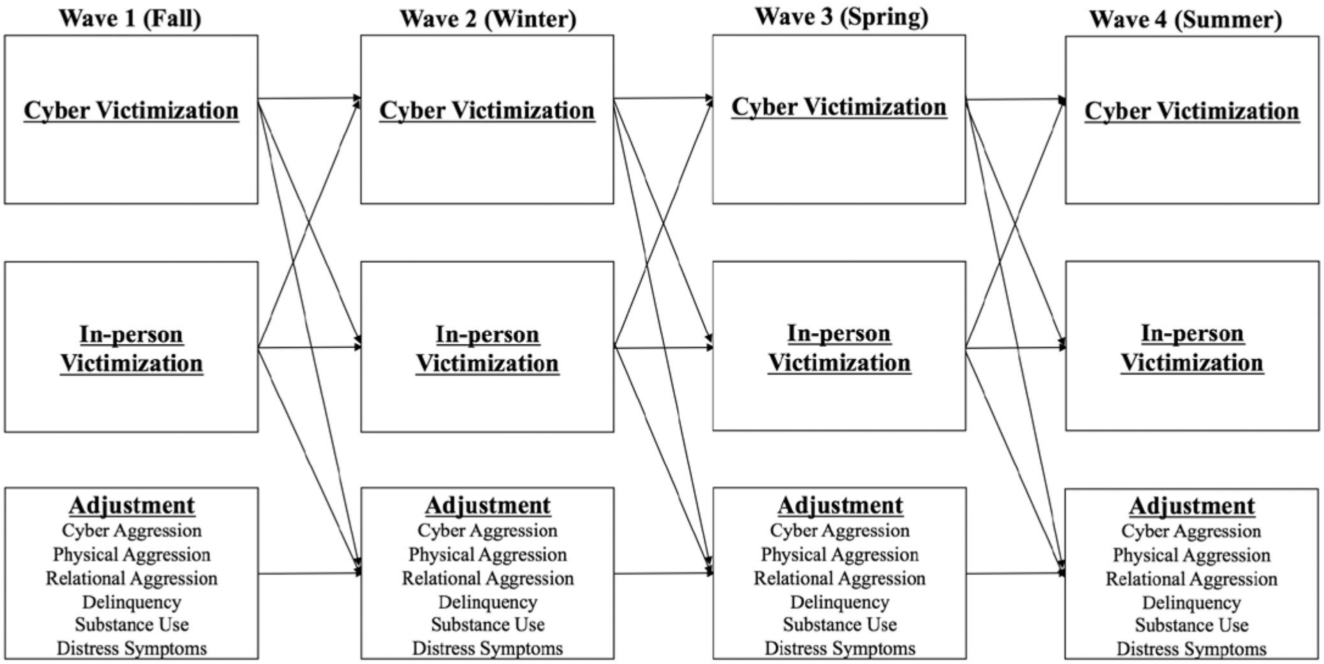

Figure 1.

Path model examining relations between adolescents' report of their frequency of cyber victimization, in-person victimization, externalizing behaviors, and distress across four waves within the school year. Demographic covariates and covariances between measures within each wave were included in the model but not shown in the figure. Problem behaviors were included in separate models.

Table 1.

Percentages of Participants Endorsing Victimization over the Past 30 Days per Each Frequency Category

Item	Never	1–2 times	3–5 times	≥6 times
In-person victimization				
Someone threatened to hit or physically harm you	74.6	19.6	3.4	2.4
Someone pushed or shoved you	59.1	31.0	6.0	3.9
Someone threatened or injured you with a weapon (gun, knife, club, etc.)	94.1	5.0	0.6	0.3
Someone threw something at you to hurt you	77.1	19.0	2.6	1.3
Someone hit you hard enough to hurt	77.6	16.8	3.2	2.4
Someone put you down to your face	89.7	8.5	1.2	0.6
Someone said something disrespectful to you about your family	66.5	23.3	6.2	4.0
Someone teased you to make you mad	63.7	24.9	6.6	4.8
Someone yelled at you or called you mean names	67.9	23.0	4.9	4.2
Someone made fun of you to make others laugh	67.6	22.7	5.1	4.6
Someone who was mad at you tried to get back at you by not letting you be in their group	83.2	14.2	1.6	1.0
Someone said they wouldn't like you unless you did what he or she wanted	85.2	13.1	1.1	0.6
Someone left you out on purpose when it was time to do an activity	86.9	10.5	1.6	1.0
Someone spread a false rumor about you	74.9	19.7	3.3	2.1
Someone tried to keep others from liking you by saying mean things about you	79.4	15.2	3.2	2.2
Cyber victimization				
Someone used text-messaging to threaten to hurt you physically	92.2	5.9	1.1	0.8
Someone used cell phone pictures to threaten to hurt you physically	95.5	3.7	0.7	0.1
Someone used cell phone pictures to make fun of you	90.9	7.9	0.5	0.7
Someone used text-messaging to make fun of you	92.2	6.7	0.6	0.5
Someone used a chat room or Internet website to make fun of you	94.6	4.2	0.7	0.3
Someone called you mean names online or using a cell phone	84.1	11.9	2.9	1.1
Someone sent or posted embarrassing pictures of you without your permission	88.9	9.5	0,9	0.7
Someone pretended to be someone else online or using a cell phone to trick you	86.8	11.5	0.9	0.8
Someone left you out of an online group or unfriended you on Facebook	89.5	2.7	1.6	0.7
Someone posted rude comments about you online				
Someone spread rumors about you online or by texting	88.1	9.5	1.6	1.0

*Note. N*s ranged from 1,527 to 1,532 due to missing data on individual items.

Table 2

Means; Standard Deviations, Wave 1 Correlations, and D-coefficients Comparing Gender and Grade Differences for All Study Variables

	1	2	3	4	5	6	7	8
1. In-Person Victimization	-							
2. Cyber Victimization	.60***	-						
3. Cyber Aggression	.31***	.47***	-					
4. Physical Aggression	.42***	.27***	.54***	-				
5. Relational Aggression	.43***	.40***	.61***	.50***	-			
6. Delinquent behavior	.32***	.35***	.58***	.52***	.50***	-		
7. Substance Use	.19***	.30***	.44***	.38***	.28***	.51***	-	
8. Distress Symptoms	.57***	.35***	.18***	.30***	.31***	.21***	.14***	-
Means (SD)								
Wave 1	1.29 (0.44)	1.09 (0.25)	1.11 (0.29)	1.37(0.52)	1.20 (0.36)	1.14 (0.35)	1.07 (0.24)	1.93 (0.79)
Wave 2	1.21 (0.37)	1.08 (0.26)	1.12 (0.29)	1.31(0.50)	1.15 (0.33)	1.11 (0.33)	1.09 (0.29)	1.81 (0.75)
Wave 3	1.22 (0.39)	1.08 (0.26)	1.11 (0.29)	1.37(0.52)	1.15 (031)	1.13 (0.35)	1.08 (0.26)	1.89 (0.80)
Wave 4	1.18 (0.37)	1.09 (0.25)	1.09 (0.26)	1.31 (0.50)	1.12 (0.31)	1.10 (0.29)	1.07 (0.24)	1.86 (0.75)
***d*-coefficients**								
Girls v boys								
Wave 1	0.03	0.00	−0.09	0.02	0.02	−0.12	0.01	0.44***
Wave 2	0.01	0.07	0.03	0.02	0.05	−0.13	0.01	0.47***
Wave 3	0.14	0.11	0.01	0.05	−0.02	−0.10	0.03	0.47***
Wave 4	0.02	0.08	−0.03	0.07	0.04	−0.05	0.10	0.56***
6th versus 7th grade								
Wave 1	0.31***	0.09	0.06	0.03	0.23**	0.02	−0.21*	0.20*
Wave 2	0.12	−0.12	−0.08	−0.01	0.13	0.05	−0.15	0.05
Wave 3	0.22*	0.04	0.08	0.14	0.32***	0.16	−0.09	0.10
Wave 4	0.22*	−0.13	−0.05	0.06	0.18	0.11	−0.11	0.29*
6th versus 8th grade								
Wave 1	0.43***	0.22*	0.00	−0.02	0.36***	0.19*	−0.21*	0.14

	1	2	3	4	5	6	7	8
Wave 2	0.18*	0.01	0.01	−0.11	0.24**	0.13	−0.21*	−0.11
Wave 3	0.12	0.04	−0.13	−0.08	0.15	0.05	−0.17	−0.08
Wave 4	0.46***	0.13	0.22*	0.26*	049***	0.13	−0.04	0.09

Note. N= 1,539. Correlations represent Wave 1 data.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 3

Fit Indices and Comparison of Models Investigating Longitudinal Relations Between Adolescents ' Victimization, Externalizing Behaviors, and Distress Symptoms Across 4 Waves of Data

Model	χ^{2a}	df	$\chi^2\Delta^b$	Comp	Δdf	RMSEA	CFI	TLI
Victimization								
1. Unconstrained across time	12.63	12	-	-	-	.006	1.000	.997
2. Cross-variables constrained across time	13.92	16	1.12	1	4	.000	1.000	1.007
3. Fully constrained across time	21.69	20	8.99	1	8	.008	.999	.996
Cyberaggression								
1. Unconstrained across time	74.00***	33	-	-	-	.029	.980	.922
2. Cross-variables constrained across time	77.89***	37	3.81	1	4	.027	.980	.931
3. Fully constrained across time	87.54***	47	16.65	1	14	.024	.980	.946
Physical Aggression								
1. Unconstrained across time	69.77***	33	-	-	-	.027	.983	.936
2. Cross-variables constrained across time	74.04***	37	3.53	1	4	.026	.983	.943
3. Fully constrained across time	88.09***	47	20.33	1	14	.024	.981	.950
Relational Aggression								
1. Unconstrained across time	42.92	33	-	-	-	.014	.995	.980
2. Cross-variables constrained across time	44.40	37	1.91	1	4	.012	.996	.987
3. Fully constrained across time	57.22	47	14.89	1	14	.012	.995	.986
Delinquent behavior								
1. Unconstrained across time	58.10**	33	-	-	-	.023	.985	.943
2. Cross-variables constrained across time	64.79**	37	6.620	1	4	.022	.984	.944
3. Fully constrained across time	85.25***	47	26.82*	1	14	.023	.977	.939
4. Unconstrained by gender	121.29***	66	-	-	-	.034	.971	.900
Substance Use								
1. Unconstrained across time	60.20**	33	-	-	-	.024	.982	.933
2. Cross-variables constrained across time	76.24***	37	22.44***	1	4	.027	.975	.914
3. Fully constrained across time	-	-	-	-	-	-	-	-

Model	χ^{2a}	df	$\chi^2\Delta^b$	Comp	Δdf	RMSEA	CFI	TLI
Distress Symptoms								
1. Unconstrained across time	88.77***	33	-	-	-	.034	.977	.912
2. Cross-variables constrained across time	90.13***	37	2.53	1	4	.031	.978	.925
3. Fully constrained across time	103.77***	47	19.76	1	14	.029	.976	.937

Note. *Ns* ranged from 1,486 to 1,490 due to missing data on demographics. RMSEA=root mean-square error of approximation. CFI = comparative fit index. Comp = comparison model.

[a] Test of overall model fit.

[b] Difference test comparing fit of each model to the comparison model.

* $p < .001$.

** $p < .01$.

*** $p < .001$.

Table 4

Standardized Regression Coefficients (Standard Errors) for Relations Between Adolescents' Victimization, Externalizing Behaviors, and Distress Symptoms

Wave *t* Measures	Wave *t*+1 Standardized Regression Coefficients							
	In-person Victimization	**Cyber Victimization**	**Cyber Aggression**	**Physical Aggression**	**Relational Aggression**	**Delinquent behavior**	**Substance Use**	**Distress Symptoms**
In-person Victimization	a	.14** (.05)	.07 (.04)	.05 (.04)	.13** (.04)	.04 (.04)	.01 (.05)	.06 (05)
Cyber Victimization	.07 (.05)	a	.16** (.06)	.07 (.04)	.07 (.06)	.07 (.05)	.10 (.06)	.00 (.04)
Stability Coefficient	.59*** (.05)	.42*** (.07)	.34*** (.08)	.57*** (.03)	.40*** (.05)	.60*** (.06)	.63*** (.09)	.64*** (.04)
Treatment Status	.00 (.04)	.00 (.04)	.00 (.04)	−.03 (.04)	.01 (.04)	−.03 (.04)	−.05 (.04)	.00 (.03)
Latino/a	−.05 (.03)	−.07** (.03)	−.06* (.03)	−.05 (.03)	.00 (.03)	.06 (.03)	−.04 (.03)	.03 (.03)
Male	.01 (.03)	−.02 (.04)	−.04 (.04)	.03 (.03)	−.02 (.04)	.03 (.04)	.00 (.04)	−.09** (.03)
7[th] grade	.03 (.04)	.09* (.04)	.06 (.04)	−.01 (.04)	.01 (.04)	.00 (.04)	.02 (.05)	.04 (.04)
8[th] grade	.05 (.04)	.06 (.04)	.02 (.04)	.04 (.04)	−.03 (.04)	−.01 (.04)	.05 (.04)	.09 (.04)
R^2 Baseline	.29 – .33	.21 – .31	.20 – .24	.38 – .42	.23 – .26	.20 – .40	.22 – .37	.42 – .49
R^2 Final	.37 – 40	.27 – .42	.23 – .32	.39 – .43	.26 – .30	.22 – .42	.31 – .41	.42 – .50
ΔR^2	.06 – .10	.06 – .13	.03 – .08	.01 – .02	.02 – .04	.00 – .02	.01 – .03	.00 – .01

Note. Ns ranged from 1,486 to 1,490 due to missing data on individual measures. Variables listed in column headings were regressed on variables listed in row headings. Standardized regression estimates across Wave 1 to Wave 2 are reported. Unstandardized coefficients were constrained across wave, but standardized coefficients may differ somewhat as a function of differences in variances across waves.

[a]Value is reported in row labeled "Stability coefficient."