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Patterns of Cyberbullying Victimization in US Adolescents: A Latent Class Analysis

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Abstract

This study used latent class analysis (LCA) with binary observed indicators to identify latent classes of victimization, based on the extent to which adolescents in the U.S. experienced traditional victimization and cyber-victimization. Data were collected by the National Center for Education Statistics and the Bureau of Justice Statistics using 2013 School Crime Supplement of the National Crime Victimization Survey. The sample included 4,939 individuals ages 12-18. LCA yielded a four-class solution: a) “Non-victims” (N=4,274), b) “Traditional victims” (N=486), c) “Cyber-victims” (N=107), and d) “Traditional victims and cyber-victims” (N=72). These findings inform practitioners of the most prevalent types of victimization in the population of adolescents and facilitate the identification of individuals who are at risk of being victimized.

Keywords

cyberbullying; adolescent education

Introduction

Bullying continues to be a critical issue to students, educators, parents, school psychologists, counselors, school administrators, and school districts. With the development of new technology and access to social media a new form of bullying, cyberbullying, emerged. (Kowalski, Limber, & Agatston, 2008). Cyberbullying involves the use of information and communication technologies such as e-mail, cell phone and pager text messages, instant messaging, websites, etc. to support deliberate, repeated hostile behavior by an individual or group (Olweus, 1993). The term cyber-aggression was more recently introduced to describe all harmful behaviors (e.g. gossiping, saying mean things to intentionally harm someone, spreading rumors) that occur via any information or communication technologies such as social networks, chat programs, or text messaging (Pornari & Wood, 2010). Cyber-aggression includes cyberbullying as well as other behaviors that occur in the virtual environment such as hacking a social network account and sending harassing messages to the person's contacts (Grigg, 2010).

Multiple studies found that cyberbullying and face-to-face bullying are frequently associated in that victims of cyberbullying are also bullied in traditional environments (e.g., Bayar & Ucanok, 2012; Bliic, Flander, & Rafajac, 2014; Cappadocia, Graig, & Pepier, 2013; Chang, Lee, Chuiui, His, Huang, & Pan, 2013). Bliic et al. (2014) summarized the relationship between cyberbullying and traditional bullying as part of "cycles of violence transferred from school to the virtual environment and vice versa" (p. 27).

To facilitate the prevention and early identification of bullying and cyberbullying victimization, professionals dealing with youth must be informed of the most prevalent types of victimization. The purpose of the current study was to differentiate latent classes of victimization based on the extent to which U.S. adolescents experienced traditional bullying and cyberbullying. In the current study, bullying victimization is defined as repeated exposure to negative actions by an individual or group with superior physical or psychological strength (Olweus, 1994). Different forms of bullying victimization were taken into account: a) direct, through verbal or physical attacks (e.g. making fun, name-calling, spreading rumors, threatening with harm, pushing, shoving, destroying property on purpose, physical injuries), and b) indirect, through exclusion from communities or activities (Robers, S., Kemp, J., Rathbun, A., & Morgan, R. E., 2014). The authors also made the distinction between traditional (face-to-face) bullying and cyberbullying victimization. The degree of bullying victimization was determined by the prevalence and severity of the harmful behaviors, as suggested by Bosworth, Espelage, and Simon (1999).

Review of Literature

In the U.S., approximately 28% of students, ages 12-18, reported being bullied at school or during the school year, and 9% reported being cyberbullied anywhere, including school (National Center for Educational Statistics & Bureau of Justice Statistics, 2013). Further, approximately half of cyberbullying victims reported knowing the bully from school (Juvonen & Gross, 2008). Recently, in the United States, there have been many wide-spread media reports of death and suicide involving various cyberbullying behaviors; these events dramatically affected individuals, schools, families, and communities. Similarly, bullying was linked to extreme cases of school violence, such as school shootings (Anderson, Kaufman, Simon, Barrios, Paulozzi, & Ryan, 2001; Vossekuil, Fein, Reddy, Borum, & Modzeleski 2002; Leary, Kowalski, Smith, & Phylips 2003). In fact, the stated principle motive of school shooters was obtaining revenge for being teased or ridiculed (Verlinden, Hersen, & Thomas, 2000).

Bullying and Cyberbullying Linked

Literature on bullying and cyberbullying in the school setting shows that most individuals who are victimized in the cyber-environment are also victimized face-to-face (Burton, Florell, & Wygant, 2013; Chang et al., 2013; Rey, Elipe, & Ortega-Ruiz, 2012). Multiple studies found that students who were victims of face-to-face bullying were more likely to be victimized online, and face-to-face bullying often preceded cyberbullying (Erentaité, Bergman, and Žukauskiené, 2012; Cappadocia, et al., 2013; van den Eijnden, Vermulst, van Rooij, Scholte, & van de Mheen, 2014).

Several studies showed that victims of bullying and cyberbullying often respond with cyber-aggression and cyberbullying (Hinduja & Patchin, 2009; Sanders, 2009; Köenig, Gollwitzer, & Steffgen, 2010). This reaction stems from feelings of anger and frustration and the desire for revenge (Patchin & Hinduja, 2011). Similarly, peer rejection, as a source of strain, was positively associated with face-to-face aggressive behavior (Newcomb, Bukowski, & Pattee, 1993; Werner & Crick, 2004). Further, adolescents who feel rejected experience enduring patterns of victimization (Pettit, Lansford, Malone, Dodge, & Bates, 2010; Veenstra, Lindenberg, Munniksma, & Dijkstra, 2010; Ostrov, 2008; Salmivalli & Isaacs, 2005). Both cyberbullying and peer rejection were related to relational and verbal cyber-aggression (Wright & Li, 2013).

The effects of bullying in multiple contexts aggravate social problems for victims and increase problems for educators who must deal with face-to-face bullying at school as well as bullying that occurs in other environments (Fredstrom, Adams, & Gilman, 2011). Thus, as Fredstrom et al. (2011) suggested, psychosocial and adjustment difficulties are best examined through viewing victims of bullying in multiple contexts, not as victims of a single form of bullying.

Consequences of Bullying and Cyberbullying

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

The psychosocial effects of bullying are substantial and are derived from cyberbullying as well as face-to-face bullying. Bullying, in both traditional and cyber-environments, was associated with higher levels of psychosocial difficulties (Fredstrom et al., 2011). Both the act of cyberbullying as well as being a victim of cyberbullying are positive predictors of psychological distress and mental health problems such as anxiety, depression, and stress (Wigderson & Lynch, 2013; ÇetÍna, Eroglu, Peker, Akbaba, and Pepsoy, 2012;). Widgerson and Lynch (2013) concluded that the negative effects of cyberbullying are of tremendous importance in that cyber-victimization has the potential to negatively affect numerous factors involved in adolescent well-being. In fact, involvement in cyberbullying as either a cyber-victim or a cyber-bully, was a significant predictor of depression and suicidal ideation (Bonanno & Hymel, 2013).

Exposure to relational and verbal face-to-face bullying was associated with subsequent cyberbullying in adolescents (Erantaite, Bergman, & Zukauskiene, 2012). Perren, Dooley, Shaw, and Cross (2010) also linked the two types of bullying and suggested that both forms were “part of the same cluster of socially inappropriate behaviors” (p. 8). As Bliic et al. (2014) concluded, “bullying does not originate from one source, but results from and interaction between more factors” (p. 28).

Fredstrom, Adams, and Gilman (2011) found that bullying in both face-to-face and cyber-environments was associated with higher levels of psychosocial difficulties. This relationship held true for cyberbullying, even when controlling for face-to-face bullying (Fredstrom et al., 2011).

Spears, Slee, Ownens, and Johnson (2009) also examined aspects of covert and cyberbullying, and showed that victims often experience negative emotions and behaviors such as (1) strong negative feelings, (2) fear, (3) impact on self and (4) disruption of life. A commonality among these themes was a fear of safety, avoiding others, avoidance of school, and even changing school. Similarly, Nishina, Juvonen, and Witkow (2005) found that students who were the targets of peer aggression expressed higher rates of anxiety and loneliness, which often resulted in overall disengagement from school and avoidant behavior.

Typologies of Victimization in the School Setting

Typologies or classifications are frequently used in educational settings (Rutter, Maugham, Mortimore, & Ouston, 1979). The rationale for developing typologies is that membership in a defined group implies additional information about a person. Typologies allow statements or predictions about relationships with peers, school performance, likelihood of responding to a certain type of intervention, or future behavior (Quay, 1986) and help educators identify groups of students who may be in need of targeted interventions, often before problems become too ingrained.

Several researchers aimed to develop typologies of school bullying and cyberbullying victimization and to identify the psycho-social characteristics of the victims. For instance, Nylund, Muthén, Nishina, Bellmore, and Graham (2007) used latent class analysis to identify victimization patterns among middle school students and distinguished three victim classes: a) "victimized," b) "sometimes victimized," and c) "non-victimized." These groups differed in the degree of victimization rather than the type of victimization (physical versus relational, face-to-face versus online, etc.). A variable measuring depressive symptoms was included in the latent class model as a distal outcome. Results showed that, with the exception of sixth grade, average depression scores were lowest for the non-victimized groups and increased for classes with higher degrees of victimization.

A similar study, conducted by Want, Iannotti, Luk, and Nansel (2010) investigated the co-occurrence of five types of bullying victimization among adolescents and identified a three-class model. One class experienced all types of victimization, another class experienced mostly verbal/relational types of victimization, whereas the third class had minimal victimization experience. Individuals included in classes with higher levels of victimization reported more depression, medicine use, injuries, sleeping problems and nervousness.

Bradshaw, Waasdorp, and O'Brennan (2013) examined ten different forms of bullying victimization among middle school and high school students. With middle school students, the authors identified four victimization types: a) Verbal and Physical, b) Verbal and Relational, c) High Verbal, Physical, and Relational, and d) Low Victimization/Normative. With the exception of the Verbal and Physical type, the same types were identified with high school students. Cyber-victimization, and sexual comments/gestures were the only types of victimization that did not have a lower prevalence in high school.

A more recent study (Mindrila, Davis, & Moore, 2018) developed a typology of victimization based on the extent to which students experienced both face-to-face (traditional) victimization and/or cyber-victimization and, consequently, manifested fear and avoidant behaviors. The sample consisted of 497 adolescents (ages 12-18) who took the 2011 School Crime Supplement (SCS) of the National Crime Victimization Survey and had at least one cyber-victimization experience. Latent profile analysis (LPA) with a 3-step estimation procedure was employed, using school behavior management as a covariate and weapon carrying as a distal outcome. LPA yielded three latent profiles: a) Average (N=441), b) Traditional & Cyber-victims (N=33), and c) Traditional victims (N=23). As behavior management effectiveness increased, the likelihood of being assigned to groups with higher levels of victimization decreased. Further, the Average group was 57.6% less likely to carry a weapon than the Traditional & Cyber-victims group. The probability of carrying weapons did not differ significantly between the two groups with severe levels of victimization. The current study continues this line of research by using data from the 2013 administration of the SCS. The purpose of the current study is to identify the latent classes of victimization that underlie the survey data and to improve the accuracy of the results by including all survey respondents in the analysis (including non-victims) and using individual survey items as input rather than composite variables.

Data Sources

Data for the current study were collected by the National Center for Education Statistics (NCES) and the Bureau of Justice Statistics using 2013 SCS of the National Crime Victimization Survey (NCVS). NCES households were selected using a stratified, multistage cluster sampling design. The SCS was administered to all eligible respondents ages 12 through 18 within NCVS households. In 2013, a total of 5,008 adolescents completed the SCS (Lessne, & Cidade, 2015). From this sample, individuals without any missing responses on selected variables were included in the current study. The resulting sample included 4,939 individuals. In 2013, individual item response rates for the 2013 SCS were high—the unweighted item response rates for all respondents on all the 2013 SCS items exceeded 85 percent. On the majority of items, the response rate was 95 percent or higher (Lessne, & Cidade, 2015); therefore, no explicit imputation procedure was used to correct for item nonresponse. The SCS sample weights, which are a combination of household-level and person-level adjustment factors (Burns & Wang, 2011), were used in this study to avoid bias in standard errors and point estimates (Brick & Kalton, 1996).

Method

Latent Class Analysis

Latent class analysis (LCA) is a special case of mixture modeling, which explains the relationships between observed indicators and latent categorical variables by classifying individuals into categories (Muthen & Muthen, 2010). The software used to conduct statistical analysis was M*plus* 7.4. A set of fourteen binary observed indicators was used as input for latent class analysis (LCA). These observed indicators were used to specify a categorical variable (*C*). To identify the optimal latent class model, models with two (Model 2), three (Model 3), four (Model 4), and five (Model 5) latent classes were estimated. Each model was examined based on the interpretability of the latent classes, the precision of the classification process, as well as the degree to which each model fitted the data; therefore, the information used to select the optimal solution consisted of the class centroids, hit rates (the percentage of correct classifications), entropy, and goodness of fit indices.

For each group, the centroid information was examined to determine whether the identified latent classes represented distinct patterns of victimization. Classes were labeled based on their patterns of high and low probability values while making sure that the definitions had substantive meaning (Muthén & Muthén, 2004).

Another criterion to evaluate and select an optimal model was the degree of classification certainty. For each case, posterior probabilities reflect the probability of belonging to each latent class specified in the model tested (Vermunt & Magidson, 2002). Cases may, therefore, be associated with more than one class. They are assigned to the class with the highest membership probability, but may have fractional class memberships across groups. In a perfect classification system, cases would have a probability of 1 of belonging to one class and 0 membership probability for the rest of the classes. Individual posterior probabilities are used to estimate the overall classification precision for each latent class. Results are presented in a *k* x *k* table (where *k* is the number of classes specified in the model), which reports the average posterior probabilities for the individuals in each class. The diagonal of the classification table represents the average posterior probabilities for the classes where cases were assigned to, whereas the other coefficients are the average probabilities of belonging to other classes in the model. When classes are easily distinguished, the largest posterior probabilities are on the diagonal of the classification table. They are interpreted as indices of classification certainty and reflect the percentage of correctly classified cases, whereas the off-diagonal elements in the classification table represent the percentage of misclassifications (DiStefano, 2012).

Another measure of classification precision is entropy, which summarizes the information presented in the classification table with one index. Entropy shows how well the model predicts class memberships (DiStefano, 2012), or how distinct classes are from one another (Ramaswamy, Desarbo, Reibstein, 1993). Entropy values range from 0 to 1, where higher values indicate better class membership prediction (Vermunt & Magdison, 2002).

The fit indices used to determine how well the model fits the data were the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC). They are relative fit indices that permit comparisons between solutions with different numbers of latent categories and/or different model specifications (DiStefano, 2012). Lower AIC/BIC values indicate a better model fit and higher model parsimony (achieving an acceptable model fit with the minimum number of classes) (Muthén, 2004; Vermunt & Magidson, 2002). For these indices, the more parameters are estimated, the higher the value of AIC/BIC (DiStefano, 2010).

Furthermore, the Lo-Mendel-Rubin (LMR) likelihood ratio test was used to provide information on model fit. LMR is a global test that can be used to compare models with the same specifications but different number of classes (DiStefano, 2012). When estimating a model with *k* groups, LMR compares the two models and tests the hypothesis that *k*-1 classes are sufficient to explain the patterns in the data. If the probability value of the test statistic is less than 0.05, then the model with *k* classes is superior. When only this criterion is taken into account for model selection, models with additional classes are tested until the *p* value of the test statistic is greater than 0.05, at which point the previous model is accepted (Lo, Mendell, Rubin, 2001).

Results

Model 4 had the highest entropy (0.92) and the lowest BIC value (Table 1). Additionally, the four classes included in this model were the most informative and had clearly distinguishable characteristics; therefore, Model 4 was selected as the optimal latent class model. Average latent class and classification probabilities showed accurate assignment of cases to groups with classification probabilities ranging between 70% and 99% (Table 2), and average latent class probabilities ranging between 87% and 98% (Table 3).

Table 1.
Goodness of Fit Indices

Index	Model 2 (2 classes)	Model 3 (3 classes)	Model 4 (4 classes)	**Model 5** (5 classes)
Akaike (AIC):	16698.567	16335.625	16193.244	**16128.342**
Bayesian (BIC):	16887.210	16621.842	**16577.034**	16609.706
Sample-Size Adjusted BIC:	16795.058	16482.025	16389.553	**16374.560**
Loglikelihood:				
H0 Value:	-8320.284	-8123.813	-8037.622	-7990.171
H0 Scaling Correction Factor for MLR:	1.0510	1.1129	**1.1404**	1.1290
Lo-Mendell-Rubin Adjusted LRT Test:				
Statistic:	4515.458	389.886	171.041	94.164
p-value:	0.0000	0.3822	0.4337	0.9134
Entropy	0.916	0.909	**0.920**	0.836

Table 2.

Classification Probabilities for the Most Likely Latent Class Membership (Column) by Latent Class (Row)

	Class 1	Class 2	Class 3	Class 4
Class 1	**0.818**	0.042	0.140	0.000
Class 2	0.043	**0.701**	0.157	0.099
Class 3	0.006	0.016	**0.810**	0.168
Class 4	0.000	0.000	0.004	**0.996**

Table 3.

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

	Class 1	Class 2	Class 3	Class 4
Class 1	**0.878**	0.079	0.043	0.000
Class 2	0.031	**0.872**	0.080	0.017
Class 3	0.022	0.043	**0.904**	0.031
Class 4	0.000	0.003	0.021	**0.976**

The four latent classes included in Model 4 differed in the extent to which individuals were victims of different forms of traditional bullying and cyberbullying (Figure 1). The most numerous group (*N*=4,274) was labeled "Non-victims" (NV), because individuals in this group experienced little or no bullying victimization. The second largest group (*N*=486) was labeled "Traditional victims" (TV); the majority of individuals in this group experienced traditional forms of bullying such as being made fun of, called names, or insulted (75%) or being the subject of rumors (65%). The third group included 107 individuals and was labeled "Cyber-victims" (CV); a large proportion of this latent class was the subject of rumors (67%) and also experienced high levels of other forms of cyberbullying such as being insulted through text messaging (49%), through instant messaging or chat (44%), or through hurtful Internet posts (44%). The fourth group (N=72) was the smallest in size but experienced increased levels of both traditional bullying and cyberbullying and was, therefore, labeled "Traditional Victims and Cyber-victims" (TVCV). Most individuals in this group were the subject of rumors (100%), have been made fun of, called names, or insulted (96%), were excluded from activities on purpose (67%), were pushed, shoved, tripped, or spit on (57%), and threatened with harm (57%). Individuals in this latent class also experienced high levels of cyberbullying by being threatened or insulted through text messaging (75%), hurtful posts on the Internet (53%), or instant messaging (48%). For each latent class, the probability estimates of the observed indicators along with the corresponding *t* statistics (estimate/*SE*) and two-tailed *p* values are reported in Appendix A.

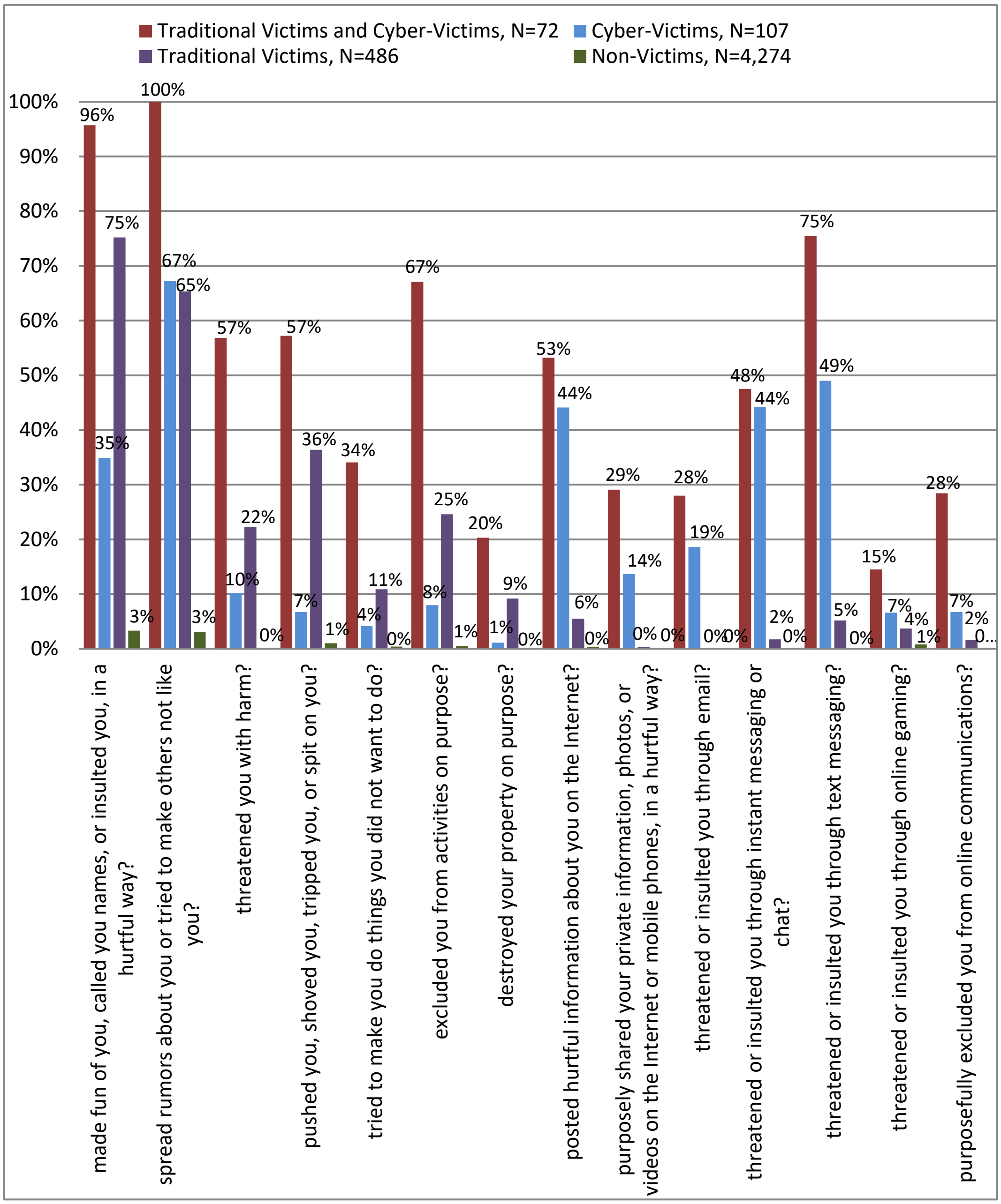

Figure 1. Latent class results in probability scale

For each observed indicator, odds ratios were calculated to compare probabilities of victimization across latent classes. These estimates along with the corresponding *t* statistics and p values are reported in Appendix B. Statistically significant odds ratio values showed that members of the TVCV latent class were significantly more likely than individuals in the CV latent class to be victimized through hurtful posts on the Internet. Similarly, the TVCV latent class recorded significantly higher probabilities of traditional victimization and victimization via hurtful Interned posts than individuals in the TV and NV latent classes.

Compared to NV, individuals in the TV latent class were significantly more likely to be the victims of traditional forms of victimization as well as hurtful Internet posts. Individuals in the CV latent class were significantly more likely to be the victims of hurtful Internet posts and rumors, but significantly less likely to be made fun of, called names, or insulted than individuals in the TV latent class. Individuals in the CV latent class were significantly more likely than NV to be the target of hurtful Internet posts and rumors, or to be called names, made fun of or insulted.

Conclusion

The goal of the current study was to develop a typology of victimization based on the extent to which respondents of the 2013 SCS were victims of traditional bullying and cyberbullying. Results showed that most adolescents (N=4, 274) experienced low levels of bullying victimization or no victimization at all. Nevertheless, the rest of the respondents experienced various forms of traditional bullying and/or cyberbullying. While a small group of respondents experienced severe levels of both traditional bullying and cyberbullying (N=72), a fairly large group of individuals experienced moderate levels of traditional bullying (N=486) and cyberbullying (N=107). The TV and TVCV latent classes were also identified with the 2011 SCS data (Mindrila et al., 2018). These two groups were similar in size and experienced similar types and levels of victimization. What differed with the 2013 model was the identification of the NV and CV groups. This can be explained by inclusion of non-victims in the analysis, which also allowed a better differentiation of the victims who experienced mostly cyberbullying.

Theoretical Contributions and Practical Implications

Behavior typologies ease communication among researchers (Aldenderfer & Blashfield, 1984) and facilitate the application of research to practice (Achenbach, 1982). They allow researchers and practitioners to communicate using a common terminology in reference to behavior by specifying the components of behavioral aggregates (Aldenderfer & Blashfield, 1984).

In the school setting, typologies are used to (a) evaluate stuednts' behavioral patterns; (b) group students for further assistance, treatment, interventions, or targeted instruction (Rutter et al., 1979); (c) differentiate students' behaviors based on etiology (Cantwell, 1996); and (d) identify the students who are at risk (Kagan, 1997), or may be in need of special services (Reynolds & Kamphaus, 2004). When an individual is assigned to a distinct group, practitioners can make inferences about the characteristics, degree of adaptability, and responsiveness to intervention of that particular individual. School psychologists or counselors may provide information on the defining characteristics of each identified type, as well as an inventory of research-based intervention strategies for each category.

Findings from this study contribute to the literature by identifying the patterns of bullying and cyberbullying victimization that are most prevalent among U.S. adolescents, thus facilitating the identification of individuals who are at risk of being victimized. Given the psycho-social consequences of bullying victimization in the school setting (Mindrila, Moore, & Davis, 2015; Mindrila et al., 2018), these findings are of great concern. Teachers, school counselors, school psychologists, etc. can provide targeted intervention to the victims, to improve their functionality in the school environment, and prevent problem behaviors from reaching clinical levels. Such students may be at-risk for maladaptive behaviors such as carrying weapons to school (Mindrila et al., 2018) and may benefit from counseling services. Further, school representatives may intervene to resolve conflicts among students and to prevent further victimization. They may implement programs that assist schools in clarifying behavior rules, teaching appropriate social behavior, providing positive reinforcement for desirable behavior, consistently providing appropriate consequences for rule violation, and monitor data on student behavior (Metzler, Biglan, Rusby, & Sprague, 2001).

Limitations

The current study used data from the 2013 administration of the SCS and aimed to improve the victimization latent class model; therefore, the estimated model did not have the same structure as the latent class model estimated using the 2011 SCS data (Mindrila, et al., 2018). The next step in this investigation is to reanalyze the 2011 SCS data using the same model specifications and compare the 2011 and 2013 results for consistency. Further, additional research using data from other SCS collection years is also needed to determine the extent to which latent class results are consistent across time. It is also of interest to include variables measuring psychosocial consequences of victimization in the model as distal outcomes, as well as measures of behavior management at the school level as a covariate. Further, the relationships between bullying and cyberbullying victimization and other risk factors (e.g. social interaction difficulties, lack of participation in school related activities, lack of friends or caring adults at school, etc.) should be investigated to facilitate the prevention and early identification bullying victimization and its consequences.

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Appendix A

TVCV Latent Class Results in Probability Scale, N=72

During this school year, another student has…	Estimate	SE	Estimate/SE	Two-tailed p-value
spread rumors about you or tried to make others dislike you?	1.000	0.000		
made fun of you, called you names, or insulted you, in a hurtful way?	0.957	0.035	**27.645**	**0.000**
excluded you from activities on purpose?	0.671	0.097	**6.903**	**0.000**
posted hurtful information about you on the Internet?	0.532	0.085	**6.284**	**0.000**
threatened or insulted you through text messaging?	0.754	0.125	**6.011**	**0.000**
pushed you, shoved you, tripped you, or spit on you?	0.572	0.109	**5.231**	**0.000**
threatened you with harm?	0.568	0.109	**5.202**	**0.000**
threatened or insulted you through instant messaging or chat?	0.475	0.093	**5.122**	**0.000**
purposefully excluded you from online communications?	0.284	0.070	**4.037**	**0.000**
tried to make you do things you did not want to do?	0.341	0.085	**4.019**	**0.000**
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	0.291	0.082	**3.525**	**0.000**
threatened or insulted you through email?	0.280	0.085	**3.304**	**0.001**
destroyed your property on purpose?	0.203	0.065	**3.120**	**0.002**
threatened or insulted you through online gaming?	0.145	0.055	**2.640**	**0.008**

CV Latent Class Results in Probability Scale, N=107

During this school year, another student has…	Estimate	SE	Estimate/SE	Two-tailed p-value
spread rumors about you or tried to make others not like you?	0.672	0.081	**8.262**	**0.000**
posted hurtful information about you on the Internet?	0.441	0.070	**6.258**	**0.000**
threatened or insulted you through text messaging?	0.490	0.090	**5.426**	**0.000**
threatened or insulted you through instant messaging or chat?	0.442	0.094	**4.714**	**0.000**
made fun of you, called you names, or insulted you, in a hurtful way?	0.349	0.103	**3.398**	**0.001**
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	0.137	0.043	**3.169**	**0.002**
threatened or insulted you through email?	0.186	0.060	**3.083**	**0.002**
threatened you with harm?	0.102	0.045	**2.268**	**0.023**
pushed you, shoved you, tripped you, or spit on you?	0.067	0.037	1.801	0.072
tried to make you do things you did not want to do?	0.042	0.023	1.780	0.075
purposefully excluded you from online communications?	0.067	0.038	1.770	0.077
threatened or insulted you through online gaming?	0.066	0.039	1.713	0.087
excluded you from activities on purpose?	0.080	0.076	1.054	0.292
destroyed your property on purpose?	0.011	0.016	0.701	0.483

TV Latent Class Results in Probability Scale, N=486

During this school year, another student has…	Estimate	SE	Est./SE	Two-tailed p-value
made fun of you, called you names, or insulted you, in a hurtful way?	0.752	0.033	**22.711**	**0.000**
spread rumors about you or tried to make others not like you?	0.653	0.034	**19.417**	**0.000**
pushed you, shoved you, tripped you, or spit on you?	0.364	0.031	**11.877**	**0.000**
excluded you from activities on purpose?	0.246	0.024	**10.061**	**0.000**
threatened you with harm?	0.223	0.027	**8.139**	**0.000**
tried to make you do things you did not want to do?	0.109	0.016	**6.958**	**0.000**
destroyed your property on purpose?	0.092	0.016	**5.633**	**0.000**
posted hurtful information about you on the Internet?	0.055	0.016	**3.497**	**0.000**
threatened or insulted you through text messaging?	0.052	0.017	**3.097**	**0.002**
threatened or insulted you through online gaming?	0.037	0.014	**2.642**	**0.008**
threatened or insulted you through instant messaging or chat?	0.017	0.011	1.556	0.120
purposefully excluded you from online communications?	0.016	0.011	1.380	0.168
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	0.003	0.005	0.527	0.598
threatened or insulted you through email?	0.000	0.000	0.000	1.000

NV Latent Class Results in Probability Scale, N=4,274

During this school year, another student has…	Estimate	SE	Est./SE	Two-tailed p-value
spread rumors about you or tried to make others not like you?	0.031	0.004	**8.802**	**0.000**
made fun of you, called you names, or insulted you, in a hurtful way?	0.033	0.004	**8.404**	**0.000**

NV Latent Class Results in Probability Scale, N=4,274

During this school year, another student has…	Estimate	SE	Est./SE	Two-tailed p-value
pushed you, shoved you, tripped you, or spit on you?	0.010	0.002	**5.082**	**0.000**
threatened or insulted you through online gaming?	0.008	0.002	**4.864**	**0.000**
excluded you from activities on purpose?	0.005	0.001	**3.503**	**0.000**
tried to make you do things you did not want to do?	0.004	0.001	**3.489**	**0.000**
posted hurtful information about you on the Internet?	0.003	0.001	**2.682**	**0.007**
destroyed your property on purpose?	0.002	0.001	**2.501**	**0.012**
threatened you with harm?	0.002	0.001	**2.475**	**0.013**
purposefully excluded you from online communications?	0.002	0.001	1.884	0.060
threatened or insulted you through text messaging?	0.001	0.001	1.642	0.101
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	0.001	0.001	1.510	0.131
threatened or insulted you through email?	0.000	0.000	0.194	0.847
threatened or insulted you through instant messaging or chat?	0.000	0.000	0.000	1.000

Appendix B

Odds Ratio Results for TVCV Latent Class Compared to CV Latent Class

During this school year, another student has…	Estimate	S.E.	Est./S.E.	Two-Tailed *p*-value
spread rumors about you or tried to make others not like you?	*****	0.000		
posted hurtful information about you on the Internet?	1.445	0.619	**2.335**	**0.020**
threatened or insulted you through instant messaging or chat?	1.144	0.633	1.807	0.071
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	2.585	1.494	1.731	0.083
threatened you with harm?	11.545	7.248	1.593	0.111
threatened or insulted you through email?	1.698	1.077	1.577	0.115
pushed you, shoved you, tripped you, or spit on you?	18.648	12.219	1.526	0.127
tried to make you do things you did not want to do?	11.934	8.134	1.467	0.142
purposefully excluded you from online communications?	5.485	4.068	1.348	0.178
threatened or insulted you through online gaming?	2.387	1.868	1.278	0.201
threatened or insulted you through text messaging?	3.190	2.647	1.205	0.228
made fun of you, called you names, or insulted you, in a hurtful way?	41.944	36.105	1.162	0.245
excluded you from activities on purpose?	23.337	27.385	0.852	0.394
destroyed your property on purpose?	22.566	32.762	0.689	0.491

Odds Ratio Results for TVCV Latent Class Compared to TV Latent Class

During this school year, another student has…	Estimate	S.E.	Est./S.E.	Two-Tailed *p*-value
spread rumors about you or tried to make others not like you?	*****	0.000		
threatened or insulted you through email?	*****	0.000		
posted hurtful information about you on the Internet?	19.443	7.781	**2.499**	**0.012**
tried to make you do things you did not want to do?	4.242	1.762	**2.408**	**0.016**
excluded you from activities on purpose?	6.252	2.751	**2.272**	**0.023**
pushed you, shoved you, tripped you, or spit on you?	2.326	1.109	**2.097**	**0.036**
destroyed your property on purpose?	2.500	1.195	**2.093**	**0.036**
threatened you with harm?	4.602	2.305	**1.996**	**0.046**
threatened or insulted you through instant messaging or chat?	51.866	32.035	1.619	0.105
threatened or insulted you through text messaging?	56.373	36.356	1.551	0.121
threatened or insulted you through online gaming?	4.404	2.955	1.490	0.136
purposefully excluded you from online communications?	25.014	20.130	1.243	0.214
made fun of you, called you names, or insulted you, in a hurtful way?	7.417	6.464	1.147	0.251
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	148.979	285.633	0.522	0.602

Odds Ratio Results for TVCV Latent Class Compared to NV Latent Class

During this school year, another student has…	Estimate	S.E.	Est./S.E.	Two-Tailed *p*-value
spread rumors about you or tried to make others not like you?	*****	0.000		
threatened or insulted you through instant messaging or chat?	*******	0.000		
tried to make you do things you did not want to do?	128.714	60.027	**2.144**	**0.032**
threatened or insulted you through online gaming?	21.005	9.795	**2.144**	**0.032**
pushed you, shoved you, tripped you, or spit on you?	137.246	67.759	**2.025**	**0.043**
posted hurtful information about you on the Internet?	427.583	211.668	**2.020**	**0.043**
excluded you from activities on purpose?	415.250	213.436	1.946	0.052
destroyed your property on purpose?	143.002	81.444	1.756	0.079
purposefully excluded you from online communications?	241.569	142.516	1.695	0.090
threatened you with harm?	564.523	338.872	1.666	0.096
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	522.455	389.143	1.343	0.179
made fun of you, called you names, or insulted you, in a hurtful way?	653.616	568.154	1.150	0.250
threatened or insulted you through text messaging?	2229.964	2024.265	1.102	0.271
threatened or insulted you through email?	12052.208	62892.887	0.192	0.848

Odds Ratio Results for CV Latent Class Compared to TV Latent Class

During this school year, another student has…	Estimate	S.E.	Est./S.E.	Two-Tailed *p*-value
threatened or insulted you through email?	*****	0.000		
posted hurtful information about you on the Internet?	13.453	5.421	**2.482**	**0.013**
spread rumors about you or tried to make others not like you?	1.091	0.458	**2.383**	**0.017**
made fun of you, called you names, or insulted you, in a hurtful way?	0.177	0.088	**2.001**	**0.045**
threatened or insulted you through text messaging?	17.670	9.218	1.917	0.055
threatened you with harm?	0.399	0.216	1.849	0.064
tried to make you do things you did not want to do?	0.355	0.224	1.589	0.112
pushed you, shoved you, tripped you, or spit on you?	0.125	0.079	1.586	0.113
threatened or insulted you through instant messaging or chat?	45.346	35.785	1.267	0.205
threatened or insulted you through online gaming?	1.845	1.588	1.162	0.245
excluded you from activities on purpose?	0.268	0.288	0.931	0.352
purposefully excluded you from online communications?	4.561	5.212	0.875	0.382
destroyed your property on purpose?	0.111	0.165	0.670	0.503
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	57.626	115.891	0.497	0.619

Odds Ratio Results for CV Latent Class Compared to NV Latent Class

During this school year, another student has…	Estimate	S.E.	Est./S.E.	Two-Tailed *p*-value
threatened or insulted you through instant messaging or chat?	*****	0.000		
spread rumors about you or tried to make others not like you?	64.397	24.566	**2.621**	**0.009**
made fun of you, called you names, or insulted you, in a hurtful way?	15.583	7.356	**2.118**	**0.034**
posted hurtful information about you on the Internet?	295.855	139.665	**2.118**	**0.034**
pushed you, shoved you, tripped you, or spit on you?	7.360	4.632	1.589	0.112
threatened you with harm?	48.899	31.547	1.550	0.121
threatened or insulted you through text messaging?	698.988	456.427	1.531	0.126
tried to make you do things you did not want to do?	10.785	7.090	1.521	0.128
threatened or insulted you through online gaming?	8.800	6.048	1.455	0.146
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	202.088	160.979	1.255	0.209
purposefully excluded you from online communications?	44.043	38.590	1.141	0.254
excluded you from activities on purpose?	17.793	19.032	0.935	0.350
destroyed your property on purpose?	6.337	9.507	0.667	0.505
threatened or insulted you through email?	7096.211	36395.090	0.195	0.845

Odds Ratio Results for TV Latent Class Compared to NV Latent Class

During this school year, another student has…	Estimate	S.E.	Est./S.E.	Two-Tailed *p*-value
spread rumors about you or tried to make others not like you?	59.017	10.325	**5.716**	**0.000**
made fun of you, called you names, or insulted you, in a hurtful way?	88.121	17.431	**5.055**	**0.000**
pushed you, shoved you, tripped you, or spit on you?	59.000	13.560	**4.351**	**0.000**
excluded you from activities on purpose?	66.424	20.897	**3.179**	**0.001**
tried to make you do things you did not want to do?	30.340	10.365	**2.927**	**0.003**
threatened you with harm?	122.682	52.267	**2.347**	**0.019**
destroyed your property on purpose?	57.190	25.723	**2.223**	**0.026**
threatened or insulted you through online gaming?	4.770	2.259	**2.111**	**0.035**
posted hurtful information about you on the Internet?	21.992	10.557	**2.083**	**0.037**
threatened or insulted you through text messaging?	39.558	27.590	1.434	0.152
purposefully excluded you from online communications?	9.657	9.481	1.019	0.308
purposely shared your private information, photos, or videos on the Internet or mobile phones, in a hurtful way?	3.507	6.992	0.502	0.616
threatened or insulted you through email?	0.010	0.000		
threatened or insulted you through instant messaging or chat?	57001.035	0.000		