School Victimization in Adolescents: A 3-Step Latent Profile Analysis

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The study aimed to develop a typology of victimization based on the extent to which students experienced face-to-face (traditional) victimization and/or cyber-victimization and, consequently, manifested fear and avoidance. The sample consisted of 497 adolescents (ages 12-18) who took the 2011 School Crime Supplement 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 victimization levels 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.

Keywords: *victimization, cyber-victimization, latent profile analysis, weapon carrying, behavior management*

Victimization continues to be an issue of importance to educators, school psychologists, counselors, criminal justice practitioners, school districts, and parents. With the introduction of new technology and access to social media, a new form of victimization, cyber-victimization, has emerged (Kowalski, Limber, & Agatston, 2008). Cyber-victimization involves the use of information and communication technologies such as e-mail, cell phone and pager text messages, instant messaging, websites, etc. to support deliberate, repeated hostile behavior by an individual or group (Olweus, 1993). More recently, the term cyber-aggression has been used to describe all aggressive behaviors (e.g., gossiping, rumor spreading, saying mean things to someone) that occur via any information or communication technologies such as social networks, chat programs, or text messaging (Pornari & Wood, 2010). Cyber-aggression includes cyber-bullying, 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).

To facilitate the prevention and early identification of cyber-victimization and traditional victimization, professionals dealing with youth must be aware of the most prevalent categories of victims and the psychosocial characteristics of each group. The current study aimed to identify victimization profiles based on the extent to which students experienced cyber-victimization and/or traditional victimization, and psychosocial negative effects such as fear and avoidance of places and activities. The proposed typology takes into account the effect of behavior management on group membership and estimates, for each victimization category, the probability of carrying weapons to school. Groups of individuals with similar characteristics were identified using latent profile analysis (LPA) with a 3-step estimation procedure, which aims to reduce classification error (Asparouhov & Muthen, 2012). Further, the relationship between the victimization categorical latent variable and weapon carrying was estimated while

accounting for the effects of school behavior management on the classification process. Specifically, the authors investigated the following research questions:

1. What are the latent profiles of school victimization that are most prevalent among adolescents?

2. What is the relationship between behavior management and victimization latent profiles?

3. What is the relationship between victimization latent profiles and the probability of carrying weapons to school?

In the current study, victimization was defined as repeated exposure to negative actions by an individual or group with superior physical or psychological strength (Olweus, 1994). Different forms of 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, Kemp, Rathbun, & Morgan, 2014). The authors also made the distinction between face-to-face (traditional) victimization and cyber-victimization. The degree of victimization was determined by the frequency and severity of negative behaviors, as suggested by Bosworth, Espelage, and Simon (1999).

Review of Literature

In 2011, approximately 28% of U.S. students ages 12-18 reported being victimized at school or during the school year, and 9% reported being cyber-victimized anywhere, including school (National Center for Educational Statistics & Bureau of Justice Statistics, 2013). Further, approximately half of the cyber-victims reported knowing the bully from school (Juvonen & Gross, 2008). Multiple studies suggest that the line between cyber-victimization and traditional

victimization is not distinct; many cyber-victims are also victimized in traditional environments (e.g., Bilić, Flander, & Rafajac, 2014; Cappadocia, Craig, & Pepier, 2013; Chang, Lee, Chiu, Hsi, Huang, & Pan, 2013). Cyber-victimization is not a problem that stays in the cyber-world; instead, it is often intertwined with more traditional forms of victimization. Bilić et al. (2014) summarized the relationship between cyber-victimization and traditional victimization as part of "cycles of violence transferred from school to the virtual environment and vice versa" (p. 27).

Recently, in the United States, there have been many widespread media reports of death and suicide that have involved various cyber-victimization behaviors, affecting communities, school systems, and families. Further, traditional victimization 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 principal motive of school shooters was obtaining revenge for being teased or ridiculed (Verlinden, Hersen, & Thomas, 2000).

Cyber-victimization can occur inside and outside of normal school hours, many times anonymously, and can involve many participants because of its global nature. This form of victimization can be far more insidious than traditional victimization because there is no escape from it (Muscari, 2002). Students who have been both cyber-bullies and cyber-victims suffer the most harmful effects of this phenomenon, such as depreciation of grade point average, fear, anxiety, depression, and other psychological harm (Juvonen & Gross, 2008; Sourander, et al., 2010). Schoffstall and Cohen (2011) showed that students who engaged in cyber-aggression had higher rates of loneliness, and lower rates of social acceptability, peer optimism, number of mutual friendships, popularity, and global self-worth. Further, engagement in cyber-victimization is often associated with problem behavior, depressive symptomatology, poor

parent-child relationships, delinquency, and substance use (Wagner, 2008; Ybarra & Mitchell, 2004a; Ybarra & Mitchell, 2004b).

Traditional and Cyber-Victimization Linked

Literature on school victimization describes a pattern of individuals who are victimized in cyber-settings to also be victimized in traditional environments (Burton, Florell, & Wygant, 2013; Chang et al., 2013; Rey, Elipe, & Ortega-Ruiz, 2012). Multiple studies show the connection between cyber-victimization and traditional victimization; students who are exposed to traditional victimization are more likely to be victimized online, and traditional victimization often precedes cyber-victimization (Cappadocia et al., 2013; Erentaité, Bergman, & Žukauskiené, 2012; van den Eijnden, Vermulst, van Rooij, Scholte, & van de Mheen, 2014).

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

The associated effects of victimization in multiple contexts aggravates social problems for victims and increases problems for educators who must deal with victimization at school as well as victimization 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 in multiple contexts, not as victims of a single form of bullying.

Psychosocial Effects

The psychosocial effects of victimization are substantial and are derived from both cyber-victimization and traditional victimization. Victimization, in both traditional and cyber-environments, was associated with higher levels of psychosocial difficulties (Fredstrom et al., 2011). Both the act of cyber-victimization as well as being a victim is a positive predictor of psychological states of disharmony such as anxiety, depression, and stress (ÇetÍna, Eroglu, Peker, Akbaba, & Pepsoy, 2012; Wigderson & Lynch, 2013). Widgerson and Lynch (2013) concluded that the negative effects of cyber-victimization are of tremendous importance in that it has the potential to negatively affect numerous factors involved in adolescent well-being. In addition, adolescents who were involved in cyber-victimization were associated with more internalizing problems that manifested in depressive symptoms and suicidal ideation (Bonanno & Hymel, 2013). In fact, involvement in cyber-victimization as either a cyber-victim or a cyber-bully was shown to be a predictor of both suicidal thoughts and depression (Bonanno & Hymel, 2013).

Avoidance and fear. Avoidance and fear are associated with the anxiety and depression that often result from victimization (American Psychiatric Association, 2013). Randa (2013) found a significant correlation between cyber-victimization and fear. Students who had been cyber-victims experienced increased fear of future victimization, and that fear often produced avoidance behavior in school environments (Brighi, Guarini, Melotti, Galli, & Genta, 2012; Randa & Wilcox, 2010; Spears, Slee, Owens, & Johnson, 2009). Nishina, Juvonen, and Witkow

(2005) found that students who felt they were frequent targets of peer aggression expressed higher rates of anxiety and loneliness; these feelings often resulted in overall disengagement from school and avoidance behavior (Nishina et al., 2005). The authors suggested that the somatic symptoms often associated with peer victimization might be a more socially acceptable way to avoid uncomfortable situations; missing school or going to the nurse's office could be a way to avoid negative stimuli and may become a "maladaptive coping strategy" (Nishana et al., 2005, p. 46). Regardless of other victimization experiences, students who were cyber-victimized had significantly higher incidents of school avoidance and disengagement behavior (Nishina et al., 2005; Randa & Reyns, 2014).

Avoidance patterns may be considered flight in typical fight or flight reactions to aggression. Another likely response to aggression is additional aggression (Kunimatsu & Marsee, 2012). Research suggests that victims are more likely to carry weapons and to engage in fights at school (Carbone-Lopez, Finn-Aage, & Brick, 2010; Esselmont, 2014; Nansel, Overpeck, Haynie, Ruan, & Scheidt, 2003). Dukes, Stein, and Zane (2010) found that increased incidents of traditional, physical victimization predicted increased incidents of weapon carrying. Additionally, the researchers found that all types of victimization resulted in greater frequency of injury (Dukes et al., 2010). Dukes et al. (2010) urged individuals involved with youth to consider both physical and relational types of victimization as carrying great risks; although physical victimization is often more noticeable, all forms of victimization carry additional risks of injury and violence.

The Role of School Climate and Behavior Management

Studies have shown that a positive school climate is associated with fewer incidents of victimization in schools. Allen (2010) examined extant literature on bullying victimization in

relation to school environment, classroom management, and teacher practices and found that harsh discipline methods and disorganized classrooms or school settings can lead to increased likelihood of bullying victimization. Other studies suggest that healthy school climates, including consistent discipline plans and a climate of respect for diversity, are associated with lower levels of student involvement with risky behavior such as victimization and weapon carrying (Gage, Prykanowski, & Larson, 2014; Johnson, Burke, & Gielen, 2011; Klein, Cornell, & Konold, 2012).

As indicated above, research on victimization in the school setting has focused mostly on describing its forms, prevalence, and psycho-social consequences. More recently, researchers have also focused on the development of victimization typologies, which aim to differentiate categories of victims. Such classification systems indicate the specific characteristics of each category of individuals and facilitate the early identification of victims in the school setting.

Typologies of Victimization in the School Setting

Typologies are frequently used in educational settings (Rutter, Maugham, Mortimore, & Ouston, 1979). The rationale for developing typologies is that an individual's membership in a defined group implies additional information about the person. They 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 have aimed to develop typologies of school victimization and to identify the psycho-social characteristics of the identified types. 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). 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 group 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 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, and 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.

Another study conducted by Bradshaw, Waasdorp, and O'Brennan (2013) examined ten different forms of 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.

The current study extends this line of research by including variables measuring psycho-social consequences of victimization such as fear and avoidant behavior in the classification process. Further, the study examines the relationship between individuals' assignment to specific

victimization profiles and observed variables such as behavior management at school and the probability of carrying weapons to school.

Data Sources

Data for the current study were collected by the National Center for Education Statistics (NCES) and the Bureau of Justice Statistics (BJS) using the 2011 School Crime Supplement (SCS) of the National Crime Victimization Survey (NCVS). The SCS was conducted in 1989, 1995, and biennially since 1999. Households are selected for the NCVS using a stratified, multistage cluster sampling design. The SCS is administered between January and June of the year of data collection to all eligible NCVS respondents ages 12 through 18 within NCVS households. In 2011, approximately 79,800 households participated in the NCVS sample, and those NCVS households included 10,341 members between the ages of 12 and 18. To be eligible for the SCS, these 12- to 18-year-olds must complete the NCVS and meet certain criteria specified in a set of SCS screening questions. These criteria require students to be currently enrolled in a primary or secondary education program leading to a high school diploma or enrolled sometime during the school year of the interview; not enrolled in fifth grade; and not exclusively homeschooled during the school year. In 2011, a total of 6,547 NCVS respondents were screened for the 2011 SCS, and 5,857 met the criteria for completing the survey. Individuals with at least one cyber-victimization experience were selected for the current study. The resulting sample included 497 individuals.

Responses to the SCS were summarized by creating sum scores measuring (a) effectiveness of behavior management at the respondent's school (bm), (b) the extent to which respondents experienced traditional victimization (tv), (c) the extent to which respondents experienced cyber-victimization (cyv), (d) the extent to which respondents avoided places and

activities (*avoid*), (e) the extent to which respondents experienced fear of victimization, and (f) whether the respondent brought different types of weapons to school during the current school year (*weapon*). The survey items used to compute composite variables are reported in the Appendix. The variables above were standardized as *z* scores (mean=0, standard deviation=1) before being used for further statistical analyses.

Method

Latent Profile Analysis

Latent profile analysis (LPA) is a variant of latent class cluster analysis (LCCA), along with other classification procedures such as latent class analysis, latent transition analysis, and mixed-mode clustering (DiStefano, 2012). The distinctive characteristic of LPA is that observed variables are continuous rather than categorical.

Latent class clustering procedures aim to group cases based on similarities (Everitt, 1993; Muthén & Muthén, 2010; Vermunt & Magidson, 2002) and are also known under the name of finite mixture modeling (McLachlan & Peel, 2000), mixture-likelihood approach to clustering (Everitt, 1993), or mixture modeling based clustering (Banfield & Raftery, 1993).

As the name implies, LPA is based on a latent variable model. The term "latent" implies that an error-free grouping variable is postulated (Collins & Lanza, 2010). The latent variable is not measured directly, but inferred based on a set of observed variables (latent indicators). In LPA, latent variables are categorical. They consist of a set of latent categories (profiles) and are measured by several observed indicators. Many times, the resulting classifications are used for further analyses, to investigate the relationship between groupings of individuals and other observed variables. Specifically, the categorical latent variable is used to predict observed variables called distal outcomes (Asparouhov & Muthen, 2012).

One of the assumptions that underlie LPA models is that data consist of homogeneous sub-populations that are mutually exclusive and have different probability distributions (Clogg, 1995; Heinen, 1996). Because groups do not overlap, the classes account for 100% of the population (DiStefano, 2012). Another important assumption is that of local independence which states that all relationships between indicators are accounted for by the latent class membership (Clogg, 1995; Muthén, 2004; Vermunt & Magdison, 2002).   Therefore, the correlations between variables within each class are assumed to be zero. In other words, the driving force that relates the observed variables included in one class is represented by their latent class (Muthén, 2004).

In LPA, latent indicators are continuous; therefore, LPA is very similar to non-hierarchical clustering techniques such as the k-means procedure (Everitt, 1993; Vermunt & Magidson, 2002). The main distinction between the two classification methods is that LPA is probabilistic in nature and recognizes a degree of classification uncertainty (DiStefano, 2012). Furthermore, because latent indicators are continuous variables, it is assumed that they have a multivariate normal distribution, which means that their joint distribution is normal within each class (DiStefano, 2012).

Model specification. The hypothesized latent profile model specified the variables *tv, cyv, avoid,* and *fear* as observed indicators of a categorical latent variable (*C*). The impact of the effectiveness of behavior management on the classification process was estimated by specifying the *bm* variable as a covariate on the categorical victimization variable (*C*). To estimate the relationship between *C* and the likelihood of carrying a weapon, the *weapon* variable was included as a distal outcome in the hypothesized model.

Model estimation. Analysis was conducted using the M*plus* 7.3 statistical software. The estimation method employed was robust maximum likelihood (MLR), which uses log-likelihood functions derived from the probability density function underlying the latent class model (Vermunt & Magidson, 2002). The procedure through which cases are assigned to categories of an underlying latent variable is an iterative one and was based on automatic starting values with random starts. When model parameters converge to the same solution from multiple starting points, parameter estimates are more likely to reflect the characteristics of a latent class (Collins & Lanza, 2010). If the solution does not replicate even with many random starts, it is possible that the data do not show signs of having the number of classes specified in the model tested (Muthén & Muthén, 2010). The fact that starting values must be specified for the estimation of model parameters is similar to using seed values for *k*-means analysis. Resulting model parameters consist of means, variances, and covariances for each latent profile. Additionally, results indicate, for each case, the probability of belonging to each one of the groups hypothesized in the statistical model (posterior probabilities), as well as the group with which individuals have the highest degree of association and are, therefore, assigned to (modal assignment); therefore, modal assignment was the procedure employed to determine individuals' latent profile membership.

Analysis was conducted using the 3-step estimation approach proposed by Asparouhov and Muthén (2012). The traditional 1-step approach (estimating the entire model at once) is problematic because the inclusion of a distal outcome may lead to changes group in membership. Furthermore, if the latent profile indicators are used to identify the latent profiles, assessing the strength of the relationship between latent profiles and the distal outcome is compromised. Therefore, many researchers first estimate the latent profile model, and then relate the

classification to the distal outcome. Nevertheless, this approach poses its own problems: unless the classification is very good (based upon model fit statistics), this procedure may give biased estimates and biased standard errors for the relationship with other variables.

Asparouhov and Muthén (2012) proposed a new 3-step method which aims to correct for classification error. In the current study, this approach consisted of the following steps: (a) estimating the LPA model (Figure 1); (b) creating a nominal most likely profile variable N; and (c) using a mixture model for N, C, *weapon*, and *bm*, where N is a C indicator with measurement error rates prefixed at the misclassification rate of N estimated in the Step 1 LPA analysis (Figure 2).
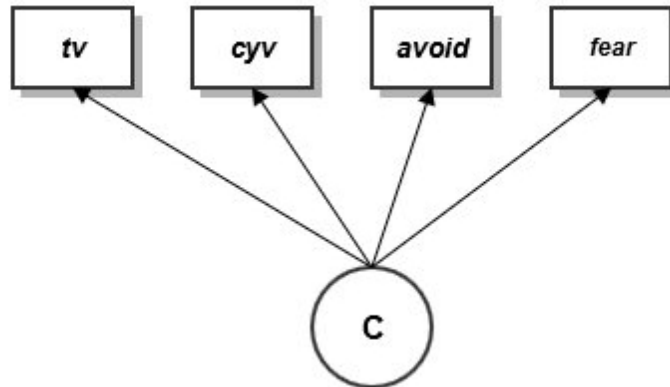
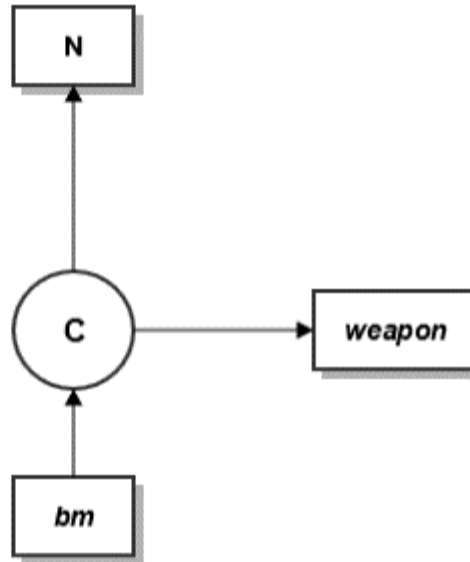*Figure 1*. Hypothesized latent profile model (Step 1).

Figure 2. Latent profile model where a nominal most likely profile variable (N) is a latent profile indicator (Step 3).

Model selection. To identify the optimal latent profile model, models with two (Model 1), three (Model 2), and four (Model 3) latent profiles were estimated. Each model was examined based on the interpretability of the profiles, the precision of the classification process, and the degree to which the proposed models fit the data. The information used to select the optimal solution consisted of latent profile 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 behavior that matched theory or prior research findings. Latent profiles were labeled based on their patterns of high and low subscale scores, while making sure that the definitions had substantive meaning (Muthén, 2004). As with factor analysis, LPA requires the researcher to evaluate the sensibility of the solutions (Crocker & Algina, 1986).

Another criterion to evaluate and select an optimal model was the degree of classification certainty. For each case, posterior probabilities reflected 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 latent profile. They are assigned to the group with the highest membership probability, but may have fractional 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 groups. Individual posterior probabilities are used to estimate the overall classification precision for each latent profile. Results are presented in a k x k table (where k is the number of latent profiles specified in the model), which reports the average posterior probabilities for the individuals in each group. The diagonal of the classification table represents the average posterior probabilities for the latent profiles where cases were assigned, while the other coefficients are the average probabilities of belonging to other latent profiles in the model. When latent profiles 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, while the off-diagonal elements in the classification table represent the percentage of misclassifications (DiStefano, 2012).

The next measure of classification precision is entropy, which summarizes the information presented in the classification table with one index (DiStefano, 2012). Entropy indicates how well the model predicts class memberships (Akaike, 1977), or how distinct latent profiles 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).

Finally, the fit indices used to determine how well the model fitted 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, 2012).

Results

Model 2 had a slightly lower entropy than Model 1 and slightly higher AIC and BIC values than Model 3 (Table 1); however, these differences were small and the latent profiles identified with Model 2 were the most informative and had clearly distinguishable characteristics. Therefore, Model 2 was selected as the optimal latent profile model.

Table 1

Entropy and Goodness of Fit Indices for Model 1, 2, & 3

	Model 1 (two classes)	Model 2 (three classes)	Model 3 (four classes)
Entropy	0.987	0.983	0.962
AIC	5050.680	4790.063	4373.403
BIC	5109.628	4874.275	4482.879

The three identified profiles differed to the extent to which they experienced cyber-victimization and traditional victimization, as well as to the extent to which they experienced fear and manifested avoidant behaviors (Figure 3). The most numerous group (N=441) was

labeled "Average," as average *z* scores measuring traditional victimization, cyber-victimization, fear, and avoidance were close to zero. The second largest group (N=33) was labeled "Traditional & Cyber-Victims." This group experienced both cyber-victimization and traditional victimization to a similar extent (average *z* scores were almost one standard deviation above the mean) and was dominated by avoidance (the average *z* score was almost 2.5 standard deviations above the mean). The third group (N=23) was labeled "Traditional Victims." This group recorded the highest levels of traditional victimization and less cyber-victimization. The dominant characteristic of this group was fear (the average *z* score was almost 4 standard deviations above the mean).

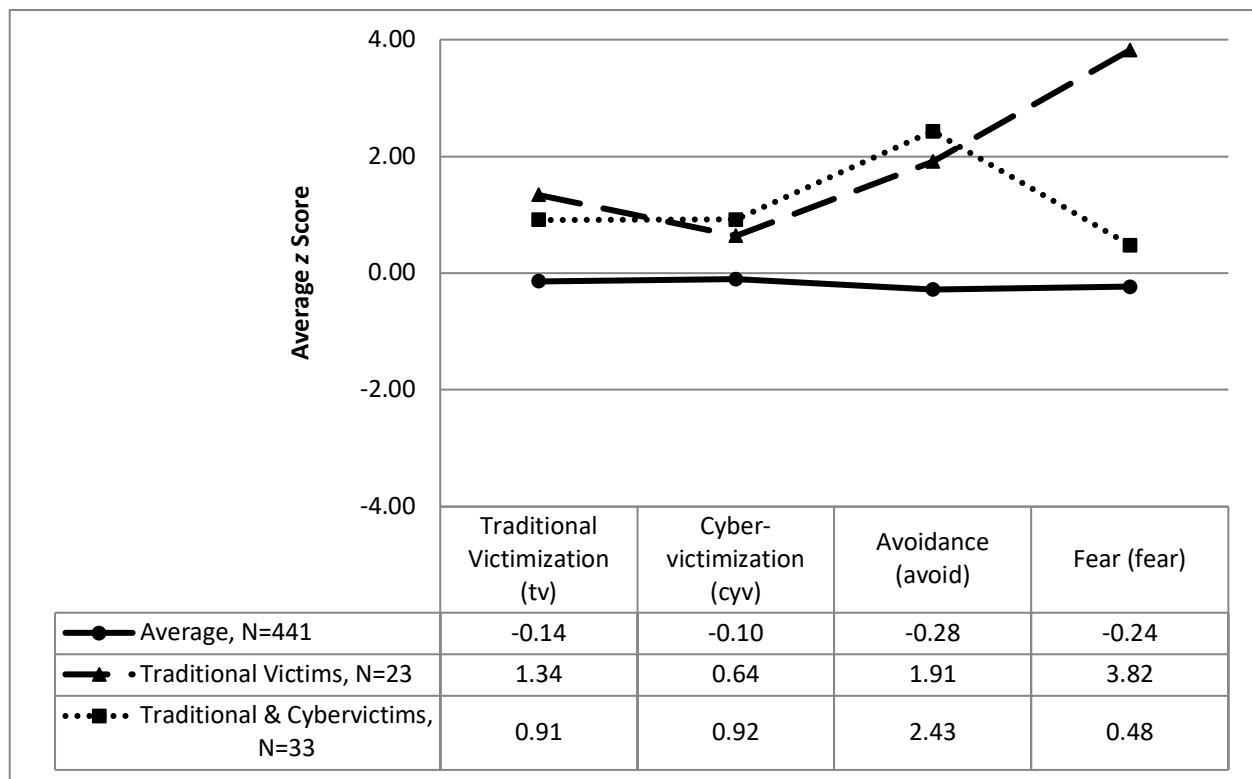|	Traditional Victimization (tv)	Cyber-victimization (cyv)	Avoidance (avoid)	Fear (fear)
Average, N=441	-0.14	-0.10	-0.28	-0.24
Traditional Victims, N=23	1.34	0.64	1.91	3.82
Traditional & Cybervictims, N=33	0.91	0.92	2.43	0.48

Figure 3. Latent profile centroids.

Model fit information indicated that Model 2 had a high degree of classification precision (entropy=0.98). Average latent class and classification probabilities showed accurate assignment

of cases to groups with classification probabilities ranging between 90% and 99%, and average

latent class probabilities ranging between 98% and 99% (Table 2).

Table 2

Average Latent Class Probabilities

	Average	Traditional Victims	Traditional & Cyber-victims
Average Latent Class Probabilities	**0.993**	0.000	0.007
	0.000	**0.999**	0.001
	0.031	0.001	**0.986**
Classification Probabilities	**0.998**	0.000	0.002
	0.000	**0.999**	0.001
	0.098	0.000	**0.902**

Note. Percentages indicating classification certainty were typed in boldface.

The *bm* covariate recorded significant path coefficients for all latent profiles. The *t*

statistic for this parameter had absolute values between 1.993 and 4.560. These parameters

remained statistically significant when different profiles were used as reference. As a general

rule, this path coefficient took negative values for groups with higher degrees of victimization

than the reference group, and positive values for groups with less victimization than the

reference group. For instance, when the Average group was used as reference, the path

coefficient between *bm* and *C* took negative values for all groups. In other words, more effective

behavior management at the school level reduced the likelihood of being assigned to groups with

higher levels of victimization. Specifically, a one unit increase in *bm* decreased the odds of being

assigned to the Traditional & Cyber-Victims and Traditional Victims groups in relation to the

Average group by 53.8% and 30.4% respectively (Table 3).

Table 3

Parameterization of C on bm

Reference Profile		Average	Traditional Victims	Traditional & Cyber-victims
Average	Estimate		-0.362	-0.772
	S.E.		0.157	0.169
	Estimate/S.E.		-2.298	-4.560
	Two Tailed P-Value		0.022	0.000
	Odds ratio		0.696	0.462
Traditional Victims	Estimate	0.362		-0.410
	S.E.	0.157		0.206
	Estimate/S.E.	2.298		-1.993
	Two Tailed P-Value	0.022		0.046
	Odds ratio	1.436		0.663
Traditional & Cyber-victims	Estimate	0.772	0.410	
	S.E.	0.169	0.206	
	Estimate/S.E.	4.560	1.993	
	Two Tailed P-Value	0.000	0.046	
	Odds ratio	2.164	1.506	

To estimate the path coefficient between *C* and *weapon*, the Traditional & Cyber-Victims group was used as reference. In reference to this group, the *C*->weapon path coefficient was statistically significant for the Average group, and not for the Traditional Victims group. Specifically, individuals in the Average group were 57.6% less likely to carry a weapon than the individuals in the Traditional & Cyber-Victims group, while the probability of carrying a weapon was similar for the two groups with high victimization levels (Table 4).

Table 4

Parameterization of weapon on C

Reference Latent Profile		Latent Profile	
Traditional & Cyber-victims		Average	Traditional Victims
	Estimate	-0.859	-0.113
	S.E.	0.310	0.460
	Estimate/S.E.	-2.775	-0.246
	Two Tailed P-Value	0.006	0.806
	Odds ratio	0.424	0.893

Discussion

The goal of the current study was to provide a typology of victimization in the school setting, based on the extent to which students experienced traditional victimization and cyber-victimization, while also taking into account the fear and avoidant behaviors associated with these experiences. The identified profiles differed based on the predominant type of victimization and the most prominent psychosocial consequences. Results showed that most victims experienced "average" levels of victimization, fear, and avoidant behavior. The two

groups with higher levels of victimization were less numerous, but were characterized by extreme levels of fear and avoidance. Adolescents who were both cyber-victims and traditional victims were mostly characterized by avoidance, while individuals who were mostly victims of severe traditional bullying were dominated by fear.

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 children's behavioral patterns; (b) group children 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. Educational psychologists or conselors may provide information on the defining characteristics of each identified type, as well as an inventory of research-based intervention strategies for each category.

The current study contributes to the literature by identifying the victimization latent profiles that are most frequently encountered in the population of U.S. adolescents. These results also increase practitioners' awareness of the negative consequences of cyber- and traditional victimization and may facilitate the early identification of victimization patterns in schools.

When students manifest behaviors that seem to indicate significant levels of fear, or frequently avoid activities and places within the school, the possibility of victimization should be further investigated. Teachers, school counselors, school psychologists, etc. can provide targeted intervention to the students involved in cyber-victimization, 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 and may benefit from counseling services. Further, school representatives may intervene to resolve conflicts among students and to prevent further victimization.

Results showed that effective behavior management at the school level decreases the likelihood of being victimized in the school setting as well as in the cyberspace and, indirectly, of engaging in risky behaviors such as weapon carrying. Specifically, the study showed that the probability of victimization is decreased in schools where (a) students are aware of the school rules, (b) rules are perceived as fair and are strictly reinforced, (c) students know what kind of punishment follows when breaking the rules, and (d) punishment is the same for all students. This information is consistent with previous research on the relationship between victimization and behavior management (Allen, 2010; Gage et al., 2014; Johnson et al., 2011; Klein et al., 2012) and is critical for practitioners because behavior management is a malleable factor and is within the educators' locus of control. For instance, school representatives may implement programs that assist schools in clarifying rules, teaching appropriate social behavior, providing positive reinforcement for desirable behavior, consistently providing appropriate consequences for rule violation, and monitoring data on student behavior (Metzler, Biglan, Rusby, & Sprague, 2001).

Another important finding of the study is that individuals in the Average victimization group were 57.6% less likely to carry a weapon than the individuals in the Traditional & Cyber-Victims group. This estimate indicates that the risky behavior of weapon carrying is significantly more likely to occur as the frequency and severity of victimization increases. This finding is consistent with previous research (Carbone-Lopez et al., 2010; Esselmont, 2014; Nansel et al., 2003; Dukes et al., 2010) and emphasizes the importance of prevention and early identification of victimization. A higher incidence of weapon carrying among adolescents has been identified as a key factor in the increase of youth violence and injury (Page & Hammermeister, 1997; Lowry, Powell, Kann, Collins, & Kolbe, 1998; Pickett et al., 2005). Recently, there has been a significant increase in school violence among U.S. adolescents. The well-publicized school shootings have focused the nation's attention on the risks of weapon carrying in schools. This behavior significantly increases the risk of death or serious injuries to both the carrier and others (Forrest, Zychowski, Stuhldreher, & Ryan, 2000). In fact, suicide and homicide are currently the second and third leading causes of death among adolescents (Heron, 2016). Further, school-related violence has psychological short- and long-term consequences by hindering the ability to concentrate and by causing emotional distress, and even results in post-traumatic stress disorder (Baker & Mednick, 1990).

Limitations

The current study is based on data from the 2011 administration of the School Crime Supplement. Additional research using data from other collection years is needed to determine the extent to which results are consistent across time. Further, the relationships identified in this study only begin to describe the victimization phenomenon. More research using person-oriented classification procedures is needed to describe in more detail the psychosocial characteristics of

traditional victims and cyber-victims and to develop typologies of victimization. Further, the relationships between cyber-victimization profiles 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 of victimization.

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Appendix

SCS Items Included in Composite Variables

Variable	Directions	Item	Response Options and Coding
Behavior management (*bm*)	"I am going to read a list of statements that could describe your school. Thinking about your school, would you strongly agree, agree, disagree, or strongly disagree with the following…"	Everyone knows the school rules. School rules are fair. Punishment is the same no matter who you are. School rules are strictly enforced. If a rule is broken, students know what kind of punishment will follow.	1=Strongly Disagree 2=Disagree 3=Agree 4=Strongly Agree
Traditional victimization (*tv*)	"Now I have some questions about what students do at school that make you feel bad or are hurtful to you. We often refer to this as being bullied. You may include	Made fun of you? Spread rumors about you? Threatened you with harm? Pushed you, shoved you, or spit on you? Tried to make you do things you did not want to do?	0=No 1=Yes

	events you told me about already. During this school year, has any student bullied you? That is, has another student…"	Excluded you from activities on purpose? Destroyed your property on purpose?	
	"What were the injuries you suffered as a result of being pushed, shoved, tripped, or spit on?"	Bruises or swelling Cuts, scratches, or scrapes Black eye/bloody nose Teeth chipped or knocked out Broken bones/internal injuries Knocked unconscious Other	
Cyber-victimization (*cyv*)	"Now I have some questions about what students do that could occur anywhere and that make you feel bad or are hurtful to you. You may include events you told me about already. During this school year, has another student...."	Posted hurtful information about you on the Internet? Threatened or insulted you through email? Threatened or insulted you through instant messaging? Threatened or insulted you through text messaging? Threatened or insulted you through online gaming?	0=No 1=Yes

		Purposefully excluded you from an online community?	
Avoidance (*avoid*)	"During this school year, did you ever STAY AWAY from any of the following places because you thought someone might attack or harm you there?"	Shortest route to school	0=No
		Entrance to the school	1=Yes
		Hallways or stairs in school	
		Parts of school cafeteria	
		School restrooms	
		Other places inside the school building	
		School parking lot	
		Other places on school grounds	
		Did you avoid any activities at your school because you thought someone might harm you?	
		Did you avoid any classes because you thought someone might harm you?	
		Did you stay at home from school because you thought someone might harm you?	

Fear (*fear*)		How often are you afraid that someone will harm you in the school building/property? How often are you afraid that someone will harm you on the way to and from school? Besides the times you are on school property or going to or from school, how often are you afraid that someone will harm you?	0=Never 1=Almost never 2=Sometimes 3=Most of the time
Weapon Carrying (*weapon*)	"In the next series of questions we are going to ask you about weapons at your school. All your responses are strictly confidential and will not be shared with anyone. Some people bring guns, knives, or objects that can be used as weapons to school for protection. During this school year,	A gun A knife brought as a weapon Some other weapon	0=No 1=Yes

did YOU ever bring the

following to school or

onto school grounds?"