The Typology of Peer Victimization in College: A Network Science Perspective

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CHAPTER I

Introduction

Despite considerable research into the types of peer victimization (PV) that occur in middle and high-school settings, almost no research has identified the myriad types of PV that students experience in post-secondary educational settings. In college-age populations, researchers have typically relied upon PV typologies and structures that were validated for younger populations. One exception is Cole et al.'s (2020) recent work, which empirically identified 10 subtypes of PV that are prevalent among college students. Still unknown, however, is how these subtypes relate to and influence one another. The overarching goals of the current study seek to identify higher-order clusters of the 10 college level PV subtypes, to examine which PV subtypes are more central to and predictive of others, and to ascertain which types and subtypes of PV are especially harmful, particularly with respect to victim's levels of stress, anxiety, and depression.

We start with two important concepts. First, in the current study, we use the term *peer victimization* to mean any type of hurtful behavior perpetrated upon a college student by a fellow student (e.g., Cole et al., 2020). Studying PV in college students is critical as it is both highly prevalent (e.g., Franklin, 2008) and linked to serious outcomes, including stress, emotional dysregulation, depression, anxiety, hostility, problem drinking, substance abuse, eating disorders, dysfunctional coping, relationship problems, chronic physical symptomatology, and even suicide (e.g., Chen & Huang, 2015; Klomek, Sourander, & Gould, 2010; Kwan, Gordon, Minnich, Carter, & Troop-Gordon, 2017; Tennant, Demaray, Coyle, & Malecki, 2015). Understanding the structure of PV and its associations with internalizing symptoms can inform counseling-related

interventions, both within therapeutic relationships and as part of broad-based, college-wide support programs. Second, we use the term *centrality* as defined in psychological network modeling (Costantini & Perugini, 2012). Although several kinds of centrality exist, the general concept refers to the degree that a particular PV subtype is statistically close to, correlated with, or predictive of other PV subtypes. If some PV subtypes have high centrality, they may represent high-value targets for intervention (Haslbeck & Waldorp, 2018). That is, intervening with them could affect many other subtypes of PV, as well.

The types of, reasons for, and sequelae to victimization may be more complex in college students than they are for younger students (cf. Cole et al., 2020; Pina & Gannon, 2012; Rivers & Smith, 1994). Most child and adolescent researchers have divided PV into the following broad binary subtypes: relational versus physical (Crick & Grotpeter, 1995), overt versus covert (Kazdin, 1992), online versus offline (e.g., Sumter, Valkenburg, Baumgartner, Peter, & van der Hof, 2015), bias-based versus non-bias-based (e.g., Jones, Mitchell, Turner, & Ybarra, 2018; Mulvey, Hoffman, Gönültaş, Hope, & Cooper, 2018), and verbal versus nonverbal (e.g., Blake, Kim, Sohn McCormick, & Hayes, 2011). A few studies have identified as many as four or five subtypes of PV (e.g., Hunt, Peters, & Rapee, 2012; Mynard & Joseph, 2000). In college students, however, Cole et al. (2020) empirically identified 10 distinct subtypes: hazing/peer pressure, sabotage, belittlement, broken trust, online, stereotyping, social exclusion, physical, verbal aggression, and sexual PV.

Preliminary evidence suggests that different types of PV may be associated with different risk factors and different kinds of problematic outcomes. With respect to risk, genetic factors convey greater risk for physical and social victimization at younger ages, but environmental risk factors play a greater role with respect to verbal, physical, social, and property-related PV in later

adolescence (Eastman, Moore, Cecilione, Hettema, & Roberson-Nay, 2018). With respect to outcomes, Casper, Card, Bauman, and Toomey's (2017) meta-analysis showed that overt victimization was more strongly related to externalizing outcomes in the victims, whereas relational victimization was more related to internalizing problems. Unfortunately, these studies examined only two to four subtypes of PV, and none considered all of the kinds of PV that occur in college. Further examination of the structure and consequences of college PV could inform both individual-level interventions and institution-wide prevention efforts (Finkelhor, Ormrod, & Turner, 2007; Ostrov & Kamper, 2015).

In our examination of PV structure, we utilized psychological network analysis instead of factor analysis. We based this decision on the compatibility of statistical assumptions with our conceptualization of PV. Factor analytic and latent class analyses rest on the assumption that the observed behaviors reflect an underlying latent attribute. Such a latent attribute is sometimes referred to as a *reflective construct* and the observed behaviors are referred to as its *effect indicators* (K. Bollen & Lennox, 1991). In many areas of research, this assumption is completely reasonable. For example, one would easily assume that an underlying illness "causes" its various symptoms. Furthermore, if a single illness factor underlies a set of symptoms, then the symptoms only correlate with each other because of that factor (and they no longer correlate after controlling for the factor; Bollen & Lennox, 1991; Borsboom, Mellenbergh, & van Heerden, 2003).

In the PV arena, however, the assumption of a latent reflective construct is less tenable. For example, we would not assume that all types of verbal micro-aggressions occur for the same underlying reason. A more defensible conceptualization of PV is to regard one's level of PV as formed from all such PV behaviors. The overall PV level in this case is a *formative construct* and

the observed behaviors are *cause indicators* (Bollen & Lenox, 1991). To some extent, this view allows two people to have the same level of PV for completely different underlying reasons. For example, one person might be subjected to racial slurs whereas another person might be subjected to homophobic insults. Consequently, in the current paper, we utilized non-factor-analytic methods such as gaussian graphical models, cluster analysis, and principal component analysis that avoid the questionable assumptions underlying factor analysis.

In the application of these methods, we anticipated that the structure of college PV would be complex. Previous research (admittedly conducted with younger populations and with different statistical methods) has highlighted a variety of overlapping types and subtypes. For example, relational victimization can be either overt or covert (Bradshaw, Waasdorp, & Johnson, 2015; Crick & Grotpeter, 1995), and covert victimization can be either relational or physical (Kaukiainen et al., 2001). This kind of complexity highlights the need to consider higher- and lower-order aspects of PV simultaneously, as in research on poly-victimization, where a common risk factor for high-level types of PV may help explain the occurrence of multiple subtypes of PV (Eastman et al., 2018; Finkelhor et al., 2007). For example, coming out as gender queer could create risk for higher-order personal/relational PV, which could manifest in multiple specific ways such as stereotyping, social exclusion, and verbal aggression. We anticipated that, simultaneously studying higher- and lower-order subtypes of PV could have synergistic effects.

In the current study, we opted to use psychological network modeling, a collection of methods that has gained popularity for emphasizing pairwise interconnections between explicit, observable, non-latent variables (Hofmann, Curtiss, & McNally, 2016). In this effort, we define lower-order "subtypes" as the clusters of specific PV behaviors identified by Cole et al. (2020), and we define "types" as higher-order clusters of victimization subtypes. Approaching PV types

and subtypes from a system-science view avoids the causal latent variable assumption and instead examines structure via simultaneous consideration of all pairwise relations. Psychological network analysis also provides graphical visualizations as an intuitive way to understand the structure of PV structure and highlight the proximity of specific subtypes.

PV networks emphasize specific subtypes of PV through "nodes" and the pairwise relations among the nodes through "edges" (Costantini & Perugini, 2012). One set of network metrics, called *centrality* metrics, can help characterize the relative importance of specific subtypes of PV. Several types of centrality exist. *Strength centrality* reflects how strongly one form of PV immediately connects to other forms (Barrat, Barthelemy, Pastor-Satorras, & Vespignani, 2004). *Closeness centrality* reflects the average distance for linking one subtype of PV to all other PV subtypes (Bavelas, 1950). *Betweenness centrality* reflects how frequently the form serves as a connector between other forms of PV (Freeman, 1977). Effecting change in a high-centrality PV subtype would be expected to affect many other subtypes of PV.

A second network metric is *predictability*, which quantifies how much variance in one node is explained by immediately connected nodes (Haslbeck & Waldorp, 2018). Predictability reflects how a specific subtype of PV may change because of changes in other subtypes of PV. High predictability would suggest that one subtype of PV is strongly statistically linked to other types of PV, which in the current study could reflect avenues for poly-victimization. Subtypes with high predictability may change in response to improvements in other PV subtypes. Consequently, predictability may provide clues as to the malleability of PV in response to broadband institutional interventions. Conversely, PV subtypes with low predictability may be resistant to broadband interventions and may require a more targeted approach.

A third metric is *small-worldedness*, a measure of network stability (Humphries & Gurney, 2008). A small-world network is robust against removal of the variable within the network. The small-worldedness index can show how subtypes of PV cohere to form a cohesive system. High stability of the identified network may reflect the generalizability of the network model across domains where one or more variable may not be relevant.

In psychological network modeling, the term *community* refers to a set of variables (e.g., PV subtypes) that are very closely related (and relatively less related to other subtypes). Identifying homogenous communities can help define superordinate types of PV. Community detection methods, such as hierarchical clustering, can identify clusters within which all constituents offer similar information (Golino & Epskamp, 2017)[1]. Such clusters are different from factors, as clusters allow the manifest variables to correlate after controlling for an underlying latent variable. Studying within- and between-community relations can reveal how sets of PV subtypes constitute a superordinate type, and how specific subtypes show cross-type connectivity.

Using these methods, we had four primary goals for the current study. First, we examined the relations between empirically derived PV subtypes in college (using gaussian graphical model). Second, we identified higher-order PV types under which PV subtypes might be nested (using cluster analysis). Third, we elucidated the nature of the relation between PV types and

[1] Variable cluster methods here are qualitatively different from latent class analysis. The methods in the current study help to reveal variable-centered typologies, in which types are identified as clusters of variables. Latent class analysis identifies person-centered typologies, in which types are identified as clusters of people. We acknowledge that latent class analyses have played an important role in identifying homogeneous subgroups within which people would share more homogeneous experiences of peer victimization (e.g., Bradshaw, Waasdorp, & O'Brennan, 2013; Nguyen, Bradshaw, Townsend, Gross, & Bass, 2020; Nylund, Bellmore, Nishina, & Graham, 2007; Williford, Brisson, Bender, Jenson, & Forrest-Bank, 2011). Our cluster analyses, in contrast, aim to identify "clusters" of peer victimization within which peer victimization subtypes are similar to or correlated with each other. We caution against the juxtaposing the results of these two procedures, as these methods and their results are not directly comparable.

subtypes, clarifying whether the subtypes are better regarded as cause or effect indicators of their higher-order PV types (using tetrad analysis; Bollen & Lenox, 1991; Bollen & Ting, 2000). Finally, we investigated the relation of higher-order PV types to various mental health outcomes (using principal components analysis and regression).

CHAPTER II

Participants and Procedures

The university IRB approved all procedures. We recruited participants using Qualtrics Survey Panels with email invitations. Participants were full-time, in-person college students in the United States, who were at least 18 years old and fluent in English. We used validity checks recommended by DeSimone and Harms (2018) to exclude participants who likely provided careless or dishonest responses. We excluded respondents in our final sample if they gave incorrect answers to any of three quality control questions: e.g., "For us to check that this online survey is functioning properly, please select '4' as your answer to this question" (n = 13, approximately 2.4% of all recruits). We also examined protocols for speed of responding; however, no respondent completed the survey faster than recommended cutoff speeds (Wood, Harms, Lowman, & DeSimone, 2017). Through Qualtrics Survey Panels, participants received compensation of approximately $5 value for completing the survey. The final sample consisted of 520 participants. Because we included nontraditional students (i.e., older students going back to school) as long as they were full-time students, the with mean age was 24.47 years (SD = 7.60, range from 18 to 60). Regarding race/ethnicity, our sample was 9.81% Asian, 14.04% Black/African American, 12.50% Hispanic/Latinx, 71.15% White/Caucasian, 1.15% Middle Eastern, and 1.35% other. Regarding gender, the sample was 48.46% male, 50% female, .02% transgender, and 1.35% gender variant/nonbinary. Regarding sexuality, the sample was 79.42% straight/heterosexual, 6.54% gay/lesbian, 9.04% bisexual, 3.27% pansexual, 1.15% queer, 1.92% asexual, and 1.54% questioning. (Note: percentages do not sum to 100% because demographic categories were not mutually exclusive.)

Measures

Peer Victimization in College (*PVIC*; Cole et al., 2020) is a 60-item checklist that measures ten specific subtypes of college PV: hazing/peer pressure (e.g., “Other students made me do embarrassing/disgusting things in order to join a group”), sabotage (e.g., “Another student tried to humiliate me or put me down in front of my professor”), belittlement (e.g., “A student acted as though I were inferior”), broken trust (e.g., “I found out someone was saying negative things about me behind my back”), online PV (e.g., “A student publicly posted a mean message about me on social media”), stereotyping (e.g., “A student made ignorant comments about some aspect of who I am”), social exclusion (e.g., “Other students ignored or overlooked me, either online or in-person”), physical PV (e.g., “A student was physically aggressive towards me”), verbal aggression (e.g., “Rude comments were directed at me by another student”), and sexual PV (e.g., “A student groped, kissed, or touched me sexually without my consent”). Subscale scores are proportions of endorsed items within a given subtype. The item and subscale constructions of PVIC relied upon reports from nationally representative college student samples. The PVIC has good convergent, divergent, and construct validity (Cole et al., 2020).

The Depression and Anxiety Stress Scale (DASS; Lovibond & Lovibond, 1995) is a 42-item self-report measure of respondents’ emotional states concerning symptoms of depression, anxiety, and stress. Respondents rate the extent to which various statements applied to them over the past week on four-point Likert scales (0 = "did not apply to me at all" to 3 = "applied to me very much, or most of the time"). Exploratory and confirmatory factor analyses support the existence of three factors: depression, anxiety, and stress (Lovibond & Lovibond, 1995). Sample items include "I felt down-hearted and blue” (depression), "I found it difficult to relax" (anxiety), and "I found myself getting upset by quite trivial things" (stress). Each subscale consists of 14

items. In the current study, coefficient alphas were .97 for the depression subscale, .95 for the anxiety subscale, and .95 for the stress subscale.

Data Analyses

Graphical Network Analysis

Using the R package `qgraph` (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012), we estimated a LASSO-regularized gaussian graphical model using EBIC as the selection criterion with ten subscales of PVIC as nodes. Given nonnormality, we incorporated nonparanormal transformation (Liu, Lafferty, & Wasserman, 2009). To improve robustness, we adopted a bootstrap procedure where observations are bootstrapped, and edges are retained only if the 95% bootstrap confidence interval of the edge magnitude does not contain zero. We applied the bootstrap criterion as the study is exploratory in nature and we decided to focus on network edges that showed the least sampling variability per bootstrap samples.

To perform community detection on the variables, we used the hierarchical clustering algorithm from the R package `clustofvar` (Chavent, Kuentz, Liquet, & Saracco, 2011). The algorithm seeks to maximize homogeneity within clusters, defined as the sum of squared correlations between each variable with the first principal component of all variables within the cluster. As per Chavent et al. (2011), we first determined the number of clusters by performing bootstrap procedures to evaluate the stability of different numbers of partitions. Second, we selected the partition with high similarity within clusters both on average and with consistency. Third, we represented average similarity as the mean-corrected rand index and consistency as the standard deviation of the corrected rand index across bootstrap samples.

To quantify the network structure, we computed various graph metrics. Strength centrality reflects the overall connections of a specific PV to other related subtypes, quantified

by summing the correlation-based weights of a node to other connected nodes. Closeness centrality depends on the path distances from a node to all other nodes and is defined as the inverse total length. Closeness centrality shows how a PV subtype connects to all other subtypes. directly or indirectly. Betweenness depends on the number of shortest paths that pass through a node. The shortest paths between nodes indicate the edges with the smallest inverse weights; therefore, betweenness can show how a subtype of PV may be intermediary to connections between other subtypes (Opsahl, Agneessens, & Skvoretz, 2010). Hybrid centrality fuses degree, betweenness, and closeness centrality to summarize the overall centrality (Abbasi & Hossain, 2013). Impact of a node measures how much the average distance in the network changes with each node removed (Kenett, Kenett, Ben-Jacob, & Faust, 2011). Moreover, we estimated the predictability of each node (i.e., the explained variance of a node by its immediately connected nodes). Given identified community membership, we utilized bridge centrality and diversity metrics to characterize the connection of each node to nodes outside its own community (Jones, Ma, & McNally, 2019; Rubinov & Sporns, 2010).

Tetrad Analysis

To test the hypothesis that PV subtypes are causal indicators, we used a tetrad test. A tetrad refers to the difference between products of a pair of covariances. Common factor-analytic models make the "vanishing tetrads" assumption (i.e., population tetrads should be zero). From a causal indicator perspective, the exogeneity of observed variables implies no constraints on the covariances between causal indicators (Bollen & Ting, 2000). When a cause-indicator model is better justified than an effect-indicator model, principal components analysis can serve as an alternative to factor analysis for constructing indices of the identified higher-order PV types.

We used STATA to perform tetrad tests for each identified cluster. The procedure first identifies independent tetrads within the specified structure. Then it tests all tetrads against zero. Statistical significance indicates absence of vanishing tetrads, providing evidence against the effect-indicator assumption in traditional factor analytic models. Finally, a joint test determines whether a causal indicator or an effect indicator approach is more plausible.

Principal Components Analysis and Regression

Based on results of the tetrad tests, we used principal component analyses to construct indices for identified communities. Using regression analyses, we examined the utility of the resultant indices to predict stress, anxiety, and depression symptom severity. It is worth noting that the current study uses exploratory data analyses, and we tested no inferential hypotheses beyond the tetrad tests. Consequently, power analyses were not applicable.

CHAPTER III

Results

Graphical Network Analysis

Table 1 presents the means, standard deviations, and various graph metrics for the estimated network. Based on pairwise partial correlations, Figure 1 shows the estimated network depicting the stable relations between different subtypes. The estimated network shows small-worldedness = 1.13 > 1, indicating robustness against random perturbation or node deletion in the estimated network.

Centrality metrics in Table 1 indicate the relative importance of different forms of PV. Across degree, betweenness, closeness, and hybrid centralities, the most central PV forms in the estimated network were online, verbal aggression, and stereotyping. Impact can be both positive and negative. Positive impact indicates that removal of the node increases the average interconnection, whereas negative impact indicates that removal of the node decreases the average interconnection. Ranking the absolute values reveals that the three most impactful PV subtypes are broken trust (.10), social exclusion (-.09), and verbal aggression (.07).

Predictability may signify how a subtype of PV may change due to changes in other connected subtypes of PV. Overall, PV in college showed good predictability (M = .54, SD = .089, range = .38 to .66). The most predictable forms were stereotyping (R^2 = .66), broken trust (R^2 = .64), and verbal aggression (R^2= .62), suggesting potentially good responsiveness to a broadband intervention. The sexual PV subtype may require a more targeted intervention, as indicated by its smaller predictability (R^2 = .38).

Stability analyses for hierarchical clustering yielded a two-cluster structure, average corrected rand index = .96 with a standard deviation of .126. The high average rand index indicates that the structure shows good within-cluster homogeneity. The low standard deviation indicates that the homogeneity of the identified clusters is relatively stable across bootstrapped samples. We named the two clusters *personal/relational PV* and a*busive/exploitative PV*. Personal/relational PV consisted of belittlement, broken trust, stereotyping, social exclusion, and verbal aggression (order determined by hybrid centrality). Abusive/exploitative PV peer pressure/hazing, sabotage, online, physical, and sexual behaviors (order determined by hybrid centrality). On average, personal/relational and abusive/exploitative PV respectively show hybrid centrality of .66 (*SD* = .33) and .40 (*SD* = .21), absolute impact of .071 (*SD* = .027) and .023 (*SD* = .017), and predictability of .60 (*SD* = .054) and .48 (*SD* = .071). Figure 1 depicts cluster membership whereas Figure 2 uses structural paths.

Bridge centrality and diversity statistics reveal how nodes facilitate cross-cluster connections. Broken trust, physical aggression, and verbal aggression are the greatest contributors to cross-cluster connections among PV subtypes, based on rankings within the top three bridge statistics.

Tetrad Analysis

Tetrad test results showed sufficient evidence to reject the vanishing tetrads hypothesis for both personal/relational PV, $\chi^2(15) = 46.69$, bootstrap test $p = .029$, and for abusive/exploitative PV, $\chi^2(15) = 47.22$, bootstrap test $p = .022$. Results supported our hypotheses that all subtypes of PV are determinants, rather than manifestations of their respective higher-order types. Figure 2 illustrates the structure of the PV types and subtypes under the causal-indicator assumption. Our data did not support the effect-indicator assumption

underlying factor-analytical methods (Bollen & Ting, 2000). The tetrad test results did not support the common assumption that higher-order types are common causes of the lower-order PV subtypes. Instead, data support our hypothesis that lower-order PV subtypes combine to form higher-order PV types.

Principal Components Analysis and Regression

Given tetrad test results, we proceeded with principal components analyses. Figure 2 includes parameter estimates with respect to the first components, which we used as the index scores. The contributions to the personal/relational PV index score in percentages were 25.4 for belittlement, 21.9 for social exclusion, 18.6 for verbal aggression, 17.9 for stereotyping, and 16.2 for broken trust. The contributions to the abusive/exploitative PV index score in percentages were 28.1 for online, 22.9 for sabotage, 22.7 for sexual, 15.9 for peer pressure, and 10.3 for physical PV.

Using constructed indices, we regressed stress, anxiety, and depression subscales from DASS onto personal/relational PV and abusive/exploitative PV to test the utility of the identified higher-order types (see Table 2). Personal/relational PV significantly predicted depression (β= .15, 95% CI [.032,.259]), anxiety (β= .12 [.008,.229]), and stress (β= .23 [.121,.345]). Abusive/exploitative PV significantly predicted depression (β= .23 [.117,.343]), anxiety (β= .32 [.206,.426]), and stress (β= .16 [.049,.273]).

CHAPTER IV

Discussion

The current study generated four major findings. First, we identified two broad, higher-order PV types: personal/relational PV and abusive/exploitative PV. Second, predictability analyses suggested that many subtypes of PV in college are strongly connected to other PV subtypes. On one hand, these connections provide clues about processes that may underlie poly-victimization. On the other hand, the connections revealed clusters of PV subtypes that may be responsive to a single, broadband social intervention. Third, these higher-order PV types statistically predicted symptoms of depression, anxiety, and stress. And fourth, college student reports of PV behaviors jointly served as causal indicators of higher-order personal/relational and abusive/exploitative PV types, rather than serving as effect indicators of common underlying latent variables. We discuss each of these findings and their implications below.

First, analyses supported the existence of two broad, superordinate types of PV. One was personal/relational PV, which consisted of belittlement, broken trust, stereotyping, social exclusion, and verbal aggression. The other was abusive/exploitative PV, which consisted of peer pressure, sabotage, online, physical, and sexual victimization subtypes. Technically, personal/relational PV consisted of subtypes that showed high connectivity to other subtypes with stereotyping clearly at its center. Conversely, abusive/exploitative PV exhibited a more distributed structure without a clear center. Moreover, PV subtypes within the personal/relational cluster were more cohesively connected to other subtypes than were the abusive/exploitative PV subtypes. Collectively, these results yield several important counseling-

related implications. Personal/relational PV may expose the victim to a wider variety of PV subtypes than does abusive/exploitative PV, which consists of PV subtypes that are somewhat more insular. Consequently, personal/relational PV may have high potential for responding to general, broad-band, social intervention. Such an intervention might focus on challenging students' stereotypic conceptualizations of others and fostering an appreciating diversity (Lin & Israel, 2012; Salzman & D'Andrea, 2001; Soble, Spanierman, & Liao, 2011). Alternatively, abusive/exploitative subtypes of PV may require multiple, distinct intervention strategies, each with a discrete focus: e.g., sexual exploitation, physical assault, peer pressure/hazing, or cyberbullying (e.g., Frazier, Valtinson, & Candell, 1994; Roark, 1987).

A second set of results has implications for poly-victimization and for intervention. Our new understanding of the structure of PV reveals that some subtypes are especially central or more highly connected to other subtypes, such that being subjected to those central subtypes increases the likelihood of experiencing other subtypes. For example, verbal aggression and broken trust were among the strongest connectors, suggesting that being subjected to verbal aggression or broken trust (both are subtypes of personal/relational PV) may represent a risk factor for exposure to other kinds of PV both within and across superordinate types of PV.

Previous studies on verbal aggression support the idea that verbal aggression increases the likelihood of both personal/relational and abusive/exploitive PV. For example, Schumacher and Leonard (2005) found verbal aggression to predict physical aggression in early marriage. (Wang, Iannotti, Luk, & Nansel's (2010) study of 2,812 individuals suffering from verbal victimization revealed that 20–48% also suffered from physical, exclusion, rumor, or cyber victimization. Bradshaw, Waasdorp, and Johnson (2015) also reported overlap between verbal bullying and both physical and electronic bullying. Other examples of highly connected subtypes

include broken trust, physical victimization, and stereotyping. Broken trust connects to subtypes in both broad types, highlighting its broad relevance. Physical PV, despite being low on overall centrality, was a key connection between both types of PV. The discovery that physical victimization increases risk for cross-type victimization demands attention from both practitioners and researchers. Stereotyping, as one of the most central subtypes, is a particularly important aspect of personal/relational PV. Its high centrality within personal/relational PV, coupled with its low connectivity to abusive/exploitative PV, suggests that stereotyping plays a key role in the differentiating between these broad types.

Our new understanding of PV structure also has implications for intervention. The fact that many PV subtypes were highly predicted by other subtypes suggests that most PV subtypes could respond well to the same general social intervention program. On average, changes in immediately connected PV subtypes account for 54% of the variability in PV subtypes. Given these strong interconnections, changes in any subtype may bring about changes in most other PV subtypes. The centrality of verbal aggression, online PV, and stereotyping suggests that focusing social interventions on these subtypes might be especially effective. Among these, verbal aggression was one of the more predictable subtypes (suggesting that it is among the more malleable) and one of the more deleterious subtypes (suggesting that its interruption may be especially important). Similarly, stereotyping (as the center of personal/relational PV victimization) could be an important social intervention target as well.

Intervention programs should also take low predictability subtypes into account. The low predictability of sexual and physical PV suggests that these subtypes may be relatively resistant to broadband intervention. More specialized and focused interventions may be needed instead. However, such interventions require attention to certain complexities inherent in these PV

subtypes. For example, although sexual PV shares immediate connections to physical PV, online PV, peer pressure/hazing within abusive/exploitative PV, and broken trust within personal/relational PV, its connections are of low magnitude. Similarly, physical PV is only weakly connected to other subtypes, suggesting that changes in these other subtypes may have little influence on physical PV. However, the connectivity of physical PV to verbal, online, and sexual PV adds intricacy to physical PV. The complexity and resistance to change through other subtypes suggest that researchers and practitioners should consider sexual and physical PV as targets for specialized intervention.

Our third major finding focuses on psychological consequences of PV. Both personal/relational PV and abusive/exploitative PV victimization uniquely predicted self-reported symptoms of depression, anxiety, and stress. However, the two types of PV differed with respect to the magnitude and precision of their predictions. In the prediction of depression and anxiety symptoms, although personal/relational PV victimization was associated with smaller effects than abusive/exploitative PV victimization, its influence was much more consistent (i.e., more precise). One possible explanation derives from the structural cohesion of personal/relational PV victimization as compared to abusive/exploitative PV victimization. Greater cohesion of personal/relational PV may imply consistency and homogeneity of its consequences, whereas the weaker cohesion of abusive/exploitative PV victimization may lead to more heterogeneous reactions to specific subtypes. In the prediction of stress, personal/relational PV and abusive/exploitational victimization show similar impact on stress, (although the effect of personal/relational PV was more consistent).

Our fourth major finding was that PV subtypes are better conceptualized as cause indicators of formative constructs rather than as effect indicators of latent attributes. In other

words, our results lead us to reject the fundamentalist understanding that college PV subtypes share underlying latent causes. Instead, we embrace a coherentist view of PV where subtypes connect to each other and together form cohesive systems. The rejection of the fundamentalist understanding means that in research and practice related to PV, we should not regard one subtype of PV as more basic or foundational. Instead, each PV subtype is an important member of a system and deserves careful study in its own right. That is, one must simultaneously examine victimization in terms of both its types and subtypes to avoid losing valuable information.

Several limitations of the current study suggest avenues for future research. First, the current study is cross-sectional in nature. Implications about causal relations and the efficacy of possible interventions require longitudinal research and experimental validation. Second, to discover robust connections, we adopted the regularized graphical model with bootstrapping. This approach risks omitting potentially important connections. Future studies should attempt to replicate our findings and to uncover potential connections between PV subtypes that the current study may have overlooked. Third, we want to emphasize that our findings are based on PV among college students. Further research is required before generalizing to other age groups and settings. Fourth, and importantly, our analyses do not account for the potential effects of cultural or individual differences. Given prior research (e.g.,Friedman et al., 2011) that highlights certain minority groups (e.g., sexual minorities) experience high levels of PV, future work should investigate more specifically how the structure of PV might change due to other multicultural and contextual factors.

In conclusion, we identified important PV subtypes that present risk for poly-victimization. We also identified two types of PV that have distinct characteristics. Results led us

to recommend a system science approach to studying PV in college, where no one particular subtype or type is foundational or derivative and all connections deserve careful consideration. Results also lead to potential intervention targets. We encourage researchers to replicate and validate our results in both experimental and quasi-experimental settings.

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Table 1

Descriptive and Importance Statistics of Specific Peer Victimization (PV) Subtypes.

PV subtype	Mean (SD)	Degree	Betweenness	Closeness	Hybrid	Predictability	Impact	Bridge strength	Bridge betweenness	Bridge closeness	Diversity
Peer Pressure	0.11 (0.184)	0.81 (5)	4 (4)	1.2 (4)	0.57 (6)	0.55 (5)	-0.01 (5)	0.14 (6)	0 (6)	0.09 (4)	0.67 (7)
Sabotage	0.12 (0.233)	0.43 (10)	0 (7)	0.9 (10)	0.18 (9)	0.47 (7)	-0.01 (5)	0.17 (5)	0 (6)	0.07 (9)	**0.97 (2)**
Belittlement	0.44 (0.349)	0.85 (4)	4 (4)	1.18 (6)	0.67 (4)	0.56 (4)	0.04 (4)	0.09 (9)	**2 (3)**	0.08 (8)	0.47 (9)
Broken Trust	0.32 (0.284)	**1.07 (1)**	**18 (1)**	**1.43 (1)**	**1 (1)**	**0.64 (2)**	**0.1 (1)**	**0.48 (1)**	**9 (1)**	**0.12 (1)**	**0.99 (1)**
Online	0.15 (0.232)	0.77 (6)	0 (7)	1.13 (7)	0.65 (5)	0.54 (6)	0.04 (4)	**0.22 (2)**	0 (6)	0.09 (5)	0.86 (4)
Stereotyping	0.27 (0.287)	**0.94 (2)**	**6 (3)**	1.19 (5)	**0.76 (3)**	**0.66 (1)**	0.04 (4)	0.1 (8)	**2 (3)**	0.08 (7)	0.5 (8)
Social exclusion	0.30 (0.331)	0.59 (9)	0 (7)	1 (9)	0.11 (10)	0.54 (6)	**-0.09 (2)**	0 (10)	0 (6)	0.07 (10)	0 (10)
Physical	0.08 (0.169)	0.65 (7)	4 (4)	**1.23 (3)**	0.36 (7)	0.44 (8)	-0.01 (5)	**0.19 (3)**	**2 (3)**	**0.11 (2)**	**0.87 (3)**
Verbal aggression	0.27 (0.302)	**0.94 (2)**	**14 (2)**	**1.27 (2)**	**0.78 (2)**	**0.62 (3)**	**0.07 (3)**	0.19 (3)	**6 (2)**	**0.1 (3)**	0.72 (6)
Sexual	0.14 (0.236)	0.64 (8)	0 (7)	1.07 (8)	0.22 (8)	0.38 (9)	-0.04 (4)	0.13 (7)	0 (6)	0.09 (6)	0.74 (5)

Note. Except for the first column, ranks are included in parentheses. The PV subtypes with highest three importance are bolded.

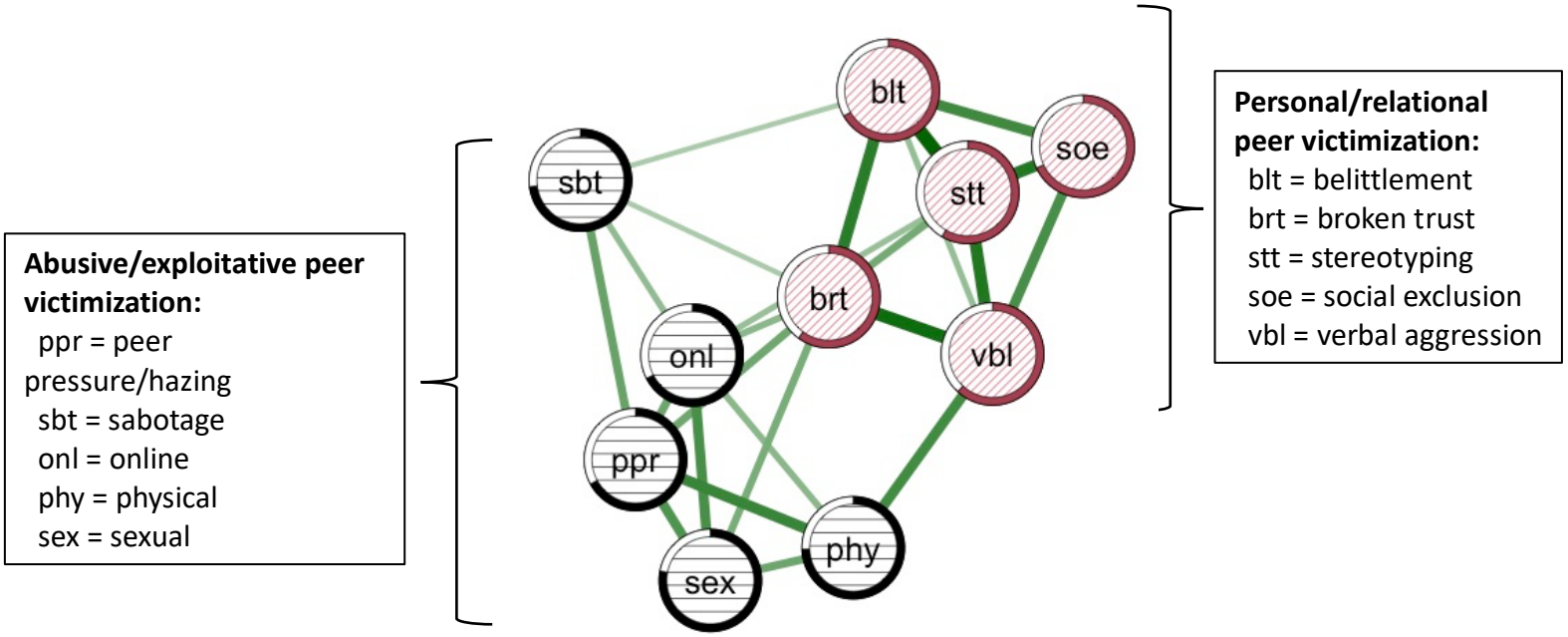
Table 2

Regression Analyses of Personal/relational and Abusive/exploitative Peer Victimization (PV) Predicting Depression, Anxiety, and Stress Scale (DASS) Scores

Predictor	B	SE (B)	*t*	Partial R^2	*p*
Model 1: DV = Depression, $F(2,517) = 35.5$, $p < .001$, $R^2=.121$					
Abusive/exploitative PV	7.17	1.80	3.99	0.11	<.001
Personal/relational PV	2.89	1.14	2.54	0.01	.012
Model 2: DV = Anxiety, $F(2,517) = 51.4$, $p < .001$, $R^2=.166$					
Abusive/exploitative PV	8.13	1.44	5.63	0.16	<.001
Personal/relational PV	1.94	0.92	2.12	0.01	.035
Model 3: DV = Stress, $F(2,517) = 39.5$, $p < .001$, $R^2=.133$					
Abusive/exploitative PV	4.44	1.58	2.82	0.1	.005
Personal/relational PV	4.09	1.00	4.08	0.03	<.001

Figure 1

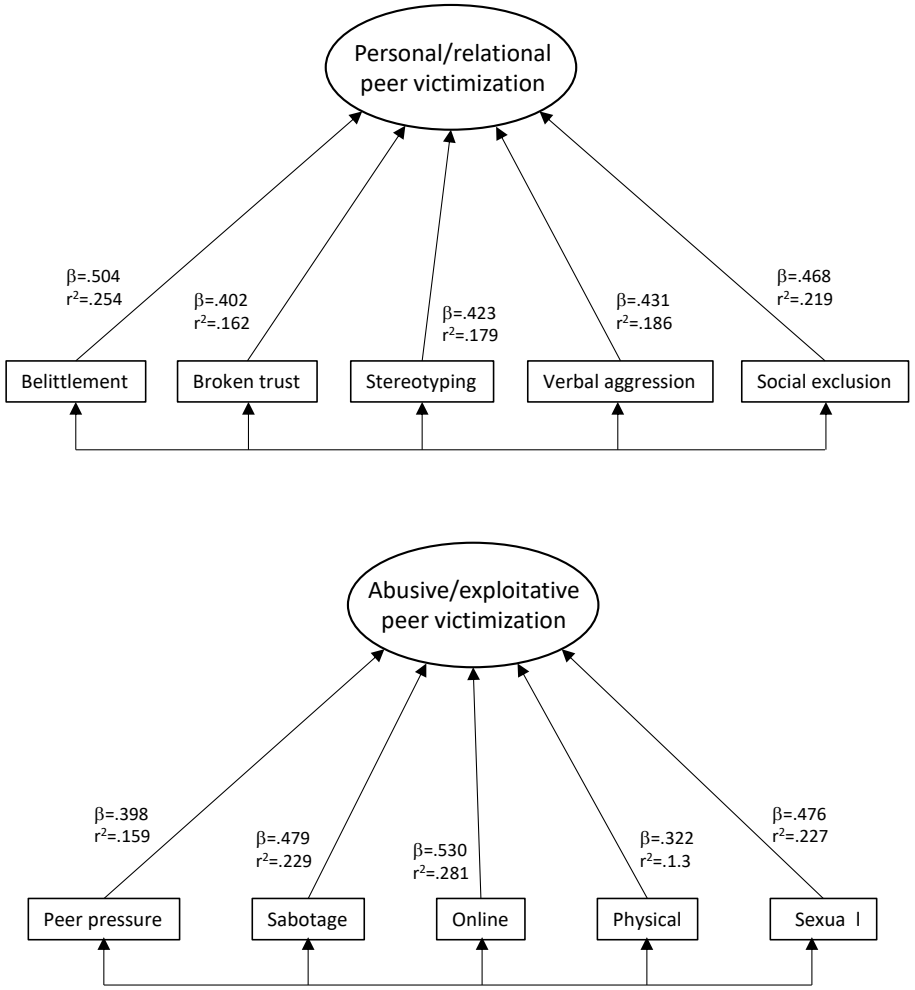
Network Displaying the Relations between PV Subtypes.



Note. Edges constituting positive partial correlations between variables. Shaded rings within pie graphs around the nodes represent variance explained in one node by the connecting nodes.

Figure 2

Path Diagram Illustrating Causal Indicator Assumption.



Note. Principal component analysis parameter estimates indicate the contribution of each PV subtype to the first principal component.