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Characterizing Typologies of Polytraumatization: A Replication and Extension Study Examining Internalizing and Externalizing Psychopathology in an Urban Population

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Abstract

A person-centered approach to examining trauma has uncovered typologies of polytraumatization that are differentially associated with psychopathology. However, previous research is limited by narrow conceptualizations of trauma, limited distal outcomes, and underrepresentation of minorities. To address these gaps, we used latent profile analyses to uncover distinct polytraumatization typologies and examine four symptom-based (PTSD, depression, aggression, and substance abuse) and two behavior-based (self-harm, jail counts) outcomes in a sample of low-income adults (n = 7,426, 94% African American). The models were indicated by 19 traumatic experiences (e.g., accident, sexual assault, witnessing/experiencing violence). The best fitting model uncovered five classes: minimal trauma, physical abuse, violence exposure, sexual abuse, and polytrauma. Classes characterized by significant and varied trauma were higher on both internalizing and externalizing psychopathology, while those characterized by specific types of trauma were only higher on one type of psychopathology. Implications for the assessment and treatment of trauma-related disorders are discussed.

Although the diagnosis of posttraumatic stress disorder (PTSD) necessitates the presence of symptoms in relation to any eligible Criterion A trauma (American Psychiatric Association, 2013), trauma characteristics such as the type of trauma and the number of different traumas experienced (i.e., polytrauma) play a crucial role in the development and maintenance of PTSD and other psychopathological symptoms. For example, compared to non-interpersonal traumas (e.g., sudden medical illness), interpersonal traumas (e.g., sexual assault, intimate partner violence) confer greater risk for PTSD (Briere, Agee, & Dietrich, 2016). Additionally, compared to the experience of a single trauma, polytraumatization confers risk for deleterious sequelae across multiple domains, including psychological disorders (Cuevas, Finkelhor, Ormrod, & Turner, 2009), physiological dysfunction (Fox, Perez, Cass, Baglivio, & Epps, 2015; Katz, Sprang, & Cooke, 2012), and functional impairment (Grella, Stein, & Greenwell, 2005; Spilsbury et al., 2007). The heightened severity of posttraumatic, depressive, and somatic symptomatology in polytraumatized...
individuals highlights the need to better understand the effects of different patterns of traumatization as opposed to only the most recent or self-reported most severe trauma (Agorastos et al., 2014; Gustafsson, Nilsson, & Svedin, 2009; McFarlane, 2010). To do so, many researchers have utilized person-centered approaches to effectively capture unique configurations of traumatic experiences and better understand associated consequences.

Whereas variable-centered approaches assume homogeneity in the population and describe relationships between variables, person-centered approaches assume heterogeneity in the population regarding how variables are related to one another and, consequently, identify classifications of individuals on this basis (Laursen & Hoff, 2006). Person-centered modeling techniques cluster either categorical (latent class analysis [LCA]) or dimensional (latent profile analysis [LPA]) data by distributions, resulting in the formation of classes or profiles (Dean & Raftery, 2010). Relative to only examining either the effects of trauma frequency (dose-dependent response) or a pre-determined combination of trauma types (Graham et al., 2016; Wanklyn et al., 2016), person-centered analyses allow for the simultaneous examination of traumatic experiences varying in both type and frequency. The ability to classify individuals on the basis of trauma type and frequency offers several advantages, including the potential to better elucidate associations between patterns of trauma exposure and associated psychopathology, identify unique protective and risk factors unique to specific polytraumatization patterns, and make predictions about the effective targets for intervention based on traumatic experiences (Contractor, Caldas, Fletcher, Shea, & Armour, 2018).

Indeed, a growing body of research using person-centered approaches yields evidence of unique, clinically-relevant patterns of polytraumatization. A systematic review of studies using person-centered approaches on polytraumatization typologies reveals variably proportioned three- and four-class solutions characterized by both frequency of trauma exposure and type(s) of trauma endorsed (Contractor et al., 2018). For example, many studies have found large classes characterized by minimal trauma (e.g., 81% of sample, Burns, Lagdon, Boyda, & Armour, 2016; 63% of sample, Cavanaugh et al., 2012) and smaller classes characterized by high and variable traumas (e.g., 2% of sample, Burns et al., 2016; 3.6% of sample, Holt et al., 2017; 5% of sample, McCutcheon et al., 2010). Some studies have found profiles characterized primarily by single traumatic experiences, such as peer victimization (Holt et al., 2017) or physical assaults (McCutcheon et al., 2010), and others, by multiple traumatic experiences, such as high intimate partner violence (IPV) and childhood abuse (Golder et al., 2012), or high physical and psychological IPV (Burns et al., 2016). The most frequently assessed mental health correlates included depression (e.g., Armour, Elklit, & Christoffersen, 2014; Golder, Connell, & Sullivan, 2012; Holt et al., 2017), PTSD (e.g., Burns et al., 2016; Cavanaugh et al., 2012), and substance use (Young-Wolff et al., 2013). Although these studies have built a strong foundation of evidence supporting the existence and importance of polytraumatization typologies, the extant studies are limited by several factors, including (a) narrow breadth in the conceptualization of trauma, (b) restricted developmental range of trauma timing, (c) limited examination of distal outcomes, and (d) overreliance on primarily White samples. Each of these limitations may obfuscate our understanding of polytraumatization typologies in important ways.
Regarding breadth in the conceptualization of trauma, most studies use dichotomously-assessed childhood experiences of trauma and maltreatment as opposed to a wider breadth of lifetime traumatic experiences assessed continuously (Contractor et al., 2018). Indeed, with the exception of McCutcheon et al. (2010), who assessed a diverse array of traumatic experiences (e.g., natural disasters, accidents not interpersonal in nature, interpersonal traumas), most studies have focused on likelihood of experiencing an interpersonal trauma, most commonly sexual and physical assault, childhood abuse and neglect, and IPV. This narrow focus on interpersonal traumas ignores the potential impact and risk for psychopathology associated with other Criterion A traumas, including natural disasters (Najarian, Goenjian, Pelcovitz, Mandel, & Najarian, 2001) and accidental physical injuries (Zatzick et al., 2008). Given that the identification of profiles characterized by particular types of trauma is contingent on the indicators included in the analyses, having a limited scope may underestimate and mischaracterize true typologies (Wurpts & Geiser, 2014). For example, only studies that include witnessing of family or community violence as an indicator typically uncover a profile characterized by high likelihood of witnessing violence (e.g., Cavanaugh et al., 2013; McCutcheon et al., 2010; Walsh et al., 2012). Further, it is important to extend beyond likelihood of experiencing various types of trauma (e.g., dichotomous assessments), and instead use numerous continuous indicators of frequency both for conceptual reasons (e.g., to minimize the risk of losing relevant information regarding trauma load) as well as statistical reasons (e.g., to optimize convergence and accuracy of typologies; Contractor et al., 2018). Thus, breadth in the quantification of traumatic experiences and inclusion of trauma types as indicators is necessary for accurate characterizations of polytraumatization across the lifespan.

Breadth in the developmental timing of traumatic experiences is important to consider when examining polytraumatization given that timing of trauma exposure has been identified as a salient risk factor for subsequent negative outcomes (Dunn, Nishimi, Powers, & Bradley, 2017; Kaplow & Widom, 2007). Consistent with this, polytraumatization studies that include both childhood and adulthood trauma often uncover profiles that vary by developmental period of trauma. For example, Burns et al. (2016) identified a class characterized mostly by childhood traumatic experiences, another by adult victimization, and a third, by a combination of both. Importantly, the class characterized by both adult and childhood trauma had the highest likelihood of various types of psychopathology. Similarly, Golder et al. (2012) found that a class characterized by interpersonal and childhood trauma reported more PTSD, substance abuse, and self-harm compared to one characterized by only high childhood trauma. Thus, the interactive impact of traumas across the lifespan necessitates the inclusion of both childhood and adulthood traumatic experiences in the identification of polytraumatization typologies which may, in turn, correspond to differential patterns of psychopathological symptoms and subsequent impairment.

Although PTSD is the most frequently studied outcome in studies examining trauma typologies, a broader focus is warranted given its co-occurrence with a wide array of both internalizing (e.g., depression) and externalizing (e.g., aggression, substance abuse) psychopathology (Humphreys et al., 2012). Additionally, traumatic experiences are associated with a host of functional and behavioral outcomes that decrease safety and autonomy (Copeland et al., 2018), such as suicidal behaviors (Ford et al., 2008; Stein et al.,...
2010) and criminal justice involvement (Grella et al., 2005; Spilsbury et al., 2007). Thus, examining a range of psychopathology and behaviors is necessary to gain an understanding of the wide-ranging impact of traumatic experiences on outcomes.

To date, polytraumatization research has lacked racially diverse samples, with many studies describing the characterization of trauma in White individuals (e.g., Burns et al., 2016; Cavanaugh et al., 2013; Holt et al., 2017). This represents a crucial area for growth, as data suggests not only that African American individuals account for the highest prevalence of PTSD compared to other racial groups in the United States (Himle et al., 2009; Roberts, et al., 2011), but also because epidemiological studies show that African Americans are more likely to experience particular types of traumatic experiences (Breslau, 2002). Furthermore, racial and ethnic minority individuals are underrepresented in research examining various mental health outcomes (e.g., Carrington, 2006) making it particularly important to examine associations between trauma and various mental health outcomes.

Given the limitations in previous research – including narrow operationalization of trauma, limited distal outcomes, and underrepresentation of racial minorities – the current study aims to advance the literature by examining polytraumatization typologies using a wide array of traumatic experiences in a large sample of low-income, predominately African American adults. To do so, we utilized LPA models based on 19 different potentially traumatic Criterion A experiences (e.g., accident, sexual assault, experiencing violence) across the lifespan. Given that most studies describe classes differentiated by high or low trauma load and specific trauma exposure, we hypothesized that at a minimum, previously identified classes (e.g., minimal trauma, witnessing violence, global victimization) would emerge in the present analyses. As a function of the variety of the traumatic experiences assessed as well as our use of continuous (versus dichotomous) indicators, we also expected to find more nuanced polytraumatization patterns compared to what has been reported to date. We compared distal psychological and behavioral outcomes falling in both internalizing (e.g. PTSD, depression, suicidality) and externalizing dimensions (e.g. substance abuse, aggressive behaviors, criminal justice involvement) across subgroups. In accordance with previous research, we predicted that profiles characterized by high frequency and variability of trauma exposure will report more severe internalizing psychopathology (e.g., PTSD, depressive symptoms) and associated outcomes (e.g., self-harm) as well as more severe externalizing psychopathology (e.g., aggression, substance abuse) and associated outcomes (e.g., frequency of criminal justice involvement).

**Method**

**Participants**

A total of 9,385 participants recruited from a large, urban community hospital were initially enrolled in the study (see Table 1). From the total sample of participants who started the study, we retained participants who had complete data for our main indicator variables (frequency of traumatic experiences), which resulted in a total of 7,426 participants. This was done because the data was not missing at random (Little’s MCAR test: $\chi^2 (3,939) = 5695.731, p < .01$) likely due to changes in the form throughout the years of the study (e.g., some questions removed and then re-added, new questions added). In addition, due the
nature of the study recruitment (i.e., in the waiting room of a hospital) some data toward the end of the measure may be missing due to related circumstances (e.g., being called into appointment). The age of participants ranged from 18 to 65, with a mean of 40.47 (SD = 13.97). The majority of participants were women (78.8%), African-American (93.5%), and high school (or equivalent) graduates (60.3%). About half (53.5%) reported their monthly household income as being $999 or less. Participants reported experiencing an average of 6.16 (SD = 3.53) different types of traumatic experiences.

Procedure

As part of a large study of risk and resilience factors for PTSD (Gillespie et al., 2009), participants were approached in a random manner by trained undergraduate and postbaccalaureate interviewers in various clinics in a non-profit healthcare system in Atlanta, Georgia. Interviewers administered a battery of self-report measures to participants and recorded responses with a tablet. The duration of the interview ranged from 1 to 2 hours depending on the extent of participants’ trauma histories. Participants met eligibility criteria if they were between 18 and 65 years of age, were able to provide informed consent, and had not been hospitalized for psychiatric reasons within the last month. They were compensated $15 for their time. All procedures were approved by the university and hospital institutional review boards and were carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki.

Measures

The Traumatic Events Inventory (TEI) (Schwartz, Bradley, Sexton, Sherry, & Ressler, 2005) is a 19-item screening instrument for lifetime history of traumatic experiences (see Table 1 in supplementary materials). Interviewers asked participants to indicate the number of times they experienced various traumatic incidents, including physical and sexual abuse (by age), experiencing violence (by romantic and non-romantic partners and with and without a weapon), witnessing violence (family and non-family and with and without a weapon) and other traumatic incidents (e.g., being confronted with murder of a family or friend). For each traumatic event, participants indicated frequency on a scale of 0 (zero times) to 8 (greater than 20 times). The TEI was developed using a similar procedure to other commonly used trauma assessment tools, such as the Life Events Checklist (Gray et al., 2004) and Traumatic Life Events Questionnaire (Kubany et al., 2000), in that experts in the field of traumatic stress thoroughly examined the previous literature and used consensus processes to determine the key items that should be included to establish content validity. In addition, similar to the convergent validity methods used to establish these other trauma assessment tools, the TEI has been shown to be associated with related constructs (e.g., PTSD symptoms) in previous work (Gillespie et al., 2009) as well as in this study (see Supplemental Table 1 for associations between TEI items and psychopathology).

Although the inclusion of so many items is not a parsimonious approach, such highly detailed indicators is warranted given the limitations documented in prior LCA and LPA studies. For example, we did not collapse intimate partner violence and interpersonal violence frequencies, as some evidence suggests that women are more likely to experience intimate partner violence and may also experience more severe outcomes than males.
who experience this type of trauma (Carbone-López, Kruttschnitt, & Macmillan, 2006; Stockman, Hayashi, & Campbell, 2015). Similarly, because there may be more risk for negative psychological outcomes associated with witnessing violence at home or involving a known individual as opposed to violence between strangers (e.g. community violence) (Kilpatrick et al., 1989; Zinzow et al., 2009), we did not collapse indicators for the general category of witnessing violence. Finally, because the current sample represents a high-risk group, including events with low base rate (e.g. witnessing murder) in the general population enhances our understanding of polytraumatization typologies.

The Modified PTSD Symptom Scale (mPSS; Falsetti, Resnick, Resick, & Kilpatrick, 1993) is a 17-item self-report measure of frequency and severity of DSM-IV PTSD symptoms ($\alpha = 0.92$). Items reflect the three PTSD symptom clusters of re-experiencing, avoidance/numbing, and hyper arousal. Participants were instructed to report frequency of these symptoms related to any trauma referenced on the TEI, and not in reference to a specific index trauma. Individuals who did not endorse trauma in their lifetime (7.7% of the sample) were not administered the mPSS. Items were scored by frequency on a scale from 0 (not at all) to 3 (5 or more times a week) in the past two weeks from the date of their screening. There is significant psychometric support for this measure (Coffey, Dansky, Falsetti, Saladin, & Brady, 1998) and it has shown excellent internal consistency and reliability in similar samples (Dunn et al., 2017).

The Beck Depression Inventory, Second Edition (BDI-II) (Beck, Steer, & Brown, 1996) is a 21-item psychometrically validated inventory of current depressive symptoms ($\alpha = 0.93$). The BDI assesses the presence and severity of continuous depression symptoms over the two-week period prior to testing using a scale of 0 (never) to 3 (every day). Total score was calculated by summing the ratings for the 21 items, with a maximum score of 63. The BDI-II shows high reliability, and construct validity in diverse samples (Wang & Gorenstein, 2013).

The Suicide and Self-Harm (SSH) scale contained 4 items to assess the frequency of the following behaviors: intentionally putting oneself in harm’s way (recklessness), non-suicidal self-injury, being hospitalized for suicidal ideation, and attempting suicide ($\alpha = 0.68$). The total score was computed as the sum of the frequency of those items.

The Drug Abuse Screening Test (DAST) (Skinner, 1982) is a 20-item self-report measure of current and lifetime substance use (excluding alcohol) and associated problems ($\alpha = 0.88$). The utility and psychometric properties of the DAST as a measure of substance abuse and dependence have been widely supported across a variety of samples, including non-clinical samples, psychiatric outpatient samples, trauma-exposed samples, and low-income African-American samples (Armour & Sleath, 2014; Cocco & Carey, 1998; French, Roebuck, McGeary, Chitwood, & McCoy, 2001; Wingo, Ressler, & Bradley, 2014).

The Behavior Questionnaire-Short (BQ-S) is an internally constructed 5-item scale designed to assess aggressive behavior frequency. This measure was developed by Dr. Bekh Bradley ($\alpha = 0.76$) based on the Conflicts Tactics Scale (Straus, Hamby, Boney-McCoy, & Sugarman, 1996), a measure commonly used to assess conflict behaviors. Items from
the BQ-S ask participants how often they have perpetrated violent acts (e.g. “punched or hit someone with something that could hurt”), and respond using a graded scale: “never”, “once”, “several times”, “more times than I can count”. Each answer was scored between 0 (“Never”) to 4 (“More times than I can count”), and the sum was computed to attain the total score.

**Demographic** information, including sex, age, race and ethnicity, household monthly income, and legal history (e.g., whether they have been to jail and if yes, how many times) was ascertained using an internally-developed form.

**Data Analytic Plan**

The latent profile analyses were conducted using Version 8.2 of Mplus (Muthén & Muthén, 2018) using maximum likelihood estimation with robust standard errors (MLR). We followed standard procedures for the initial development of our models and selection of an optimal solution (Masyn, 2013). In the first step, one to \( k \) profiles were run until the best fitting model was determined. The number of profiles was determined by evaluating the Loglikelihood (LL), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), Bayesian Information Criterion (BIC), Sample-Size Adjusted Bayesian Information (SABIC), Approximate Weight of Evidence Criterion (AWE), the Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT), the BLRT (bootstrapped LRT), correct model probability (cmP), and entropy (Muthén & Asparouhov, 2008; Nylund et al., 2007; Masyn, 2013). Smaller approximate fit indices, including the AIC, CAIC, BIC, SABIC, and AWE indicate superior model fit (D’Unger, Land, McCall, & Nagin, 1998; Nylund-Gibson & Choi, 2018). The likelihood based tests, including the LMR-LRT and the BLRT, compare a \( k-1 \) versus \( k \)-profile model, with significant \( p \)-values indicating that the \( k \)-class model should be favored over the \( k-1 \) profile model and nonsignificant \( p \)-values indicating that the addition of another class does not improve the fit (Asparouhov & Muthén, 2014). The \( cmP \) uses the Schwarz Information Criterion (SIC; Schwarz, 1978) to examine the probability of each model being correct among the models being considered. Finally, although entropy is not a fit index and thus should not be used for model selection, it summarizes the levels of posterior probabilities across classes and individuals and is therefore a useful indicator of classification certainty (Masyn, 2013). Entropy values range from 0 to 1, with higher values (particularly > .8) indicating higher classification certainty (Celeux & Soromenho, 1996).

To predict distal outcomes from latent class membership, we used the Lanza, Tan, and Bray (LTB) method (Lanza, Tan, & Bray, 2013), which examines the conditional distribution of a distal outcome given a latent class variable and has been found to be robust across a variety of indicators. Asparouhov and Muthén (2014) identified the LTB method as being superior in terms of coverage (percentage of times population values fall within confidence intervals of parameter estimates), bias (parameter estimates across various conditions), and mean squared error. In comparison to other procedures such as Vermunt’s (2010) method or Bandeen-Roche et al. (1997) pseudo-class method, Collier and Leite (2017) found that the LTB method produced higher power and the most acceptable Type 1 error rate, particularly when the sample size was over 500 and the entropy values were above .80. Thus, the LTB method was chosen to estimate a model where the distal outcomes (internalizing and
externalizing psychopathology and behavior) were used as latent class predictors inside a multinomial logistic regression in addition to the latent class model. This method is appropriate for use of both continuous and count variables, which was particularly important due to the nature of our distal outcomes. Then, the conditional distributions of the indicators given class membership were determined using the auxiliary model by applying Bayes’s theorem, with Chi-square tests used to determine statistical significance in the final step (Asparouhov & Muthén, 2014).

Results

Preliminary Analyses

We first examined basic demographic variables of our sample (Table 1), examined correlations between the frequency of each traumatic experience and each of our distal outcomes (see Supplemental Table 2), and examined the distribution of traumatic events (see Supplemental Table 3). The associations between traumatic experiences and PTSD were all significant and positive, ranging from $r = .11$ (e.g., natural disaster) to $r = .29$ (e.g., attacks by romantic partner without a weapon). The associations with depression and self-harm were similarly all significant and positive, ranging from $r = .04$ to $.27$ and $r = .09$ to $.28$, respectively. For both substance abuse and aggression, the associations were positive and significant, though they deviated from the previous distal outcomes in that the strongest associations were with frequency of attacks by someone who was not a romantic partner using weapons ($r = .26$ and $r = .31$, respectively) and without weapons ($r = .36$ and $r = .35$, respectively). In terms of frequency of going to jail, all correlations were positive and significant with the exception of frequency of life-threatening illness, which was nonsignificant. The magnitude of the correlations with jail frequency was generally smaller compared to the other distal outcomes, ranging from $r = .03$ to $r = .24$. Overall, the internalizing symptoms and behaviors appeared more strongly associated with the traumatic incidents characterized by directly experiencing sexual and non-sexual violence, whereas the externalizing symptoms and behaviors appeared more strongly associated with incidents characterized by witnessing violence. Both internalizing and externalizing symptoms and behaviors had relatively weaker associations with non-violent incidents such as natural disasters or serious illness. Next, we extended these variable-centered analyses by characterizing our sample based on frequency of experiencing these traumatic incidents.

Latent Profile Analyses

We completed a series of latent profile analyses using Mplus Version 8.2 (Muthén & Muthén, 2018). As per recommendations (Masyn, 2013), we specified 600 initial stage random starts and 120 final stage optimizations. First, we started with $k = 1$ models and added classes until the $k + 1$ models no longer evidenced a superior fit as indicated by the bootstrapped tests (see Table 2). Although the BLRT was significant for all models, which is reportedly common in applied work (Masyn, 2013), the $p$ value for the LMR-LRT test was consistently statistically significant until $k = 6$, indicating that the $k – 1$ model was a better fit. We then examined the fit indices and found that the AIC, BIC, CAIC, SABIC, and AWE consistently decreased with the addition of classes. The large magnitude of change in fit indices precluded us from calculating the exponential function of the SIC difference scores,
and thus we were unable to calculate the $cmnP$. Upon closer examination of the classes, we found that in the $k = 5$ model, there were two high trauma-endorsing classes comprising <5% of the sample, which raised concerns about the stability and separation of our classes (Nylund-Gibson & Choi, 2018). We therefore closely examined the average latent class probabilities to determine whether the existence of the small classes as separate classes was justifiable. A high probability of falling in more than one class would suggest that our ability to distinguish between these classes was weak and that it may be best to subsume some individuals into another class or remove them from our analysis. However, we found high (> .96) average probabilities for the most likely latent class membership corresponding to their respective class and low (< .04) average probabilities for the most likely latent class membership corresponding to other classes. More specifically, the average latent class probabilities were as follows: Class 1 = .99, Class 2 = .99, Class 3 = .98, Class 4 = .96, and Class 5 = 1.0. We interpreted this to mean that individuals in each class, including the small classes, had a very high probability of being classified into their assigned class, and a low chance of being classified into a different class (Nagin, 2005). In addition, we calculated the Odds of Correct Classification (OCC) and because each of the average latent class probabilities were very close to zero, the results (OCC > 5) indicated that a high degree of accuracy regarding class assignment. Furthermore, other person-centered research focusing on polytraumatization has also uncovered classes that are less than 5% of the sample (e.g., Burns et al., 2016; Holt et al., 2017), which, as argued by Contractor et al. (2018), offsets concerns about stability of the classes by demonstrating replicability across samples. Thus, on the basis of fit indices, fit with previous literature, and classification quality, we selected the $k = 5$ model and interpreted the classes in more detail (see Figure 1). For analyses examining how race and gender differentially predicted assignment to these classes, please see supplementary materials.

The largest emergent class (75.8%, $n = 5,830$) was characterized by relatively infrequent trauma. This is consistent with previous large-scale studies, who found similarly low levels of trauma were characteristic of their largest class (e.g., 81.4%, Burns et al., 2016; 71.5%, Cavanaugh et al., 2013). Given their relatively low prevalence of experiencing traumatic incidents or witnessing violence, we named this class Minimal Trauma.

The second largest class (9.9%, $n = 732$) was characterized by the highest levels of childhood physical abuse ($M = 6.98$, $SE = 0.05$) and relatively lower levels of sexual abuse in childhood and sexual assault in adulthood. Individuals in this class reported witnessing some violence in their family, but otherwise reported relatively infrequent experience or witnessing of violence as adults. We named this the Physical Abuse class.

The third largest class (7.6%, $n = 567$) was characterized by high frequency of witnessing violence as well as serious accidents. Relative to other classes, they reported particularly high frequency of witnessing non-family violence both with a weapon ($M = 3.91$, $SE = .34$) and without a weapon ($M = 5.05$, $SE = .19$). They reported experiencing some violence, though it appeared to be perpetrated mostly by nonromantic partners (i.e., not an interpersonal violence context). Given the notably high levels of exposure to violence across domains, this was named the Violence Exposure class.
The fourth largest class (2.9%, \( n = 213 \)) reported the highest frequency of childhood sexual abuse during both preadolescence (\( M = 4.61, SE = .27 \)) and adolescence (\( M = 6.79, SE = .18 \)) and similar levels of witnessing family violence as the Physical Abuse and Violence Exposure classes. They also reported somewhat higher frequency of being attacked by a romantic partner. Despite the notably high levels of sexual abuse in childhood, participants in this class reported very low exposure to sexual violence in adulthood. Therefore, we named this the *Sexual Abuse* class.

The fifth and smallest class (1.1%, \( n = 84 \)) was characterized by relatively high trauma across several domains. They had the highest exposure to sexual assault in adulthood (\( M = 6.59, SE = .22 \)) and attacks by a romantic partner (\( M = 4.47, SE = .40 \)). Individuals in this class had relatively higher rates of sexual abuse (second only to the Sexual Abuse group) and relatively higher rates of Physical Abuse (second only to the Physical Abuse class). Given the relatively high prevalence of reported trauma across domains and across both childhood and adulthood, this class was named *Polytrauma*.

**Distal Outcomes**

We then examined PTSD, depression, self-harm, substance abuse, aggression, and jail count as latent class predictors inside a multinomial logistic regression to determine whether the conditional distributions of the outcomes differed by class membership (Asparouhov & Muthén, 2014). The available data for each distal outcome differed and thus models were run separately, with the sample size indicted for each analysis (see Table 3). For ease of interpretation and visual representation of our results, means were converted to standardized scores (see Figures 2a–2f). For the raw means and standard deviations by class, see Supplemental Table 4.

Our PTSD analysis revealed that the distribution of PTSD symptoms differed by class membership \( \chi^2 (4, n = 6,661) = 730.44, p < .01 \) (see Figure 2a). Both the Polytrauma and Sexual Abuse classes reported higher PTSD symptoms compared to the Physical Abuse, Violence Exposure, and Minimal Trauma classes, but did not differ from each other. The Physical Abuse and Violence Exposure classes reported more severe PTSD symptoms compared to the Minimal Trauma class but did not differ from each other.

The distribution of depressive symptoms also differed by class membership \( \chi^2 (4, n = 6,726) = 467.70, p < .01 \) (see Figure 2b). The Polytrauma class reported higher levels of depression relative to all other classes. The Physical Abuse and Sexual Abuse classes reported higher levels of depression relative to the Violence Exposure and Minimal Trauma classes but did not differ from each other. The Violence Exposure class, in turn, also reported higher levels of depression relative to the Minimal Trauma class.

For self-harm and suicidal behaviors, the class membership effect was also significant \( \chi^2 (4, n = 1,973) = 127.46, p < .01 \) (see Figure 2c). The Polytrauma class reported higher levels of suicidal behaviors compared to all classes except the Sexual Abuse class. The Sexual Abuse, Violence Exposure and Physical Abuse classes reported more suicidality behaviors relative to the Minimal Trauma classes but did not differ from each other.
The severity of substance abuse symptoms also differed by class membership $\chi^2 (4, n = 3,969) = 343.74, p < .01$ (see Figure 2d). The Violence Exposure class reported higher substance abuse symptoms compared to the Sexual Abuse, Physical Abuse, and Minimal Trauma classes, but did not differ from the Polytrauma class. The Polytrauma, Sexual Abuse, and Physical Abuse classes all reported more severe substance abuse symptoms compared to the Minimal Trauma class but did not differ from each other.

The distribution of aggressive behaviors differed by class membership $\chi^2 (4, n = 3,855) = 616.94, p < .01$ (see Figure 2e). The Violence Exposure class reported higher aggressiveness relative to all other classes. The remaining classes all had higher aggressiveness scores compared to the Minimal Trauma class but did not differ from each other.

Finally, we found that the distribution of jail count was also contingent on class membership $\chi^2 (4, n = 5,167) = 87.32, p < .01$ (see Figure 2f). Similar to the findings for substance abuse, the Violence Exposure class reported going to jail more frequently compared to the Sexual Abuse, Physical Abuse, and Minimal Trauma classes (but not the Polytrauma class). The Polytrauma, Sexual Abuse, and Physical Abuse classes all reported more instances of going to jail compared to the Minimal Trauma class but did not differ from each other.

**Discussion**

Building on the polytraumatization typology literature, the goals of the current study were to (a) identify patterns of polytraumatization based on a developmentally and ontologically diverse array of traumatic experiences in an urban sample of low-income, predominately African American adults and (b) determine the degree to various psychological outcomes differ based on typology. The current analyses revealed five traumatization profiles, which we characterized as follows: 1) Minimal Trauma, 2) Physical Abuse, 3) Violence Exposure, 4) Sexual Abuse, and 5) Polytrauma. We also found that for PTSD symptoms, the Polytrauma and Sexual Abuse classes reported similarly severe symptoms, followed by the Physical Abuse and Violence Exposure classes. For depression, the Polytrauma class was highest relative to all other classes, followed by the Physical Abuse and Sexual Abuse classes, who reported similar levels of depression that were both higher than the Violence Exposure class. The Polytrauma class reported the highest incidence of suicidal behaviors, followed by the Sexual Abuse class, Physical Abuse, and Violence Exposure classes. For both substance abuse and jail incidents, the Violence Exposure class was higher compared to the Sexual Abuse and Physical Abuse classes, but not the Polytrauma class. On aggressiveness, however, the Violence Exposure class was higher compared to all other classes, including the Polytrauma class. The uncovered differences in psychological and behavioral outcomes may inform the assessment, etiology, and treatment of trauma-related symptoms and disorders in the future.

Consistent with other studies (Burns et al., 2016; Cavanaugh et al., 2012, 2013; McCutcheon et al., 2010), the majority of the current sample was assigned to the Minimal Trauma class. Of note, this class still exhibited an average of four lifetime trauma types, which is consistent with evidence that the population represented by our sample (i.e., predominantly low-income, urban) is exposed to elevated rates of trauma as compared to other demographic
groups (Gillespie et al., 2009). The experiences of the Minimal Trauma class were primarily comprised of exposure to intimate partner violence, either witnessed between caregivers or experienced personally. In contrast, within all other trauma profiles, individuals reported experiencing an average of eight to ten traumas across the lifespan. The remaining classes were characterized by exposure to different types of trauma and were less distinguishable by overall frequency. Although each profile demonstrated evidence of polytrauma, the Physical Abuse class was characterized by particularly high rates of physical abuse in childhood, the Violence Exposure class by high rates of witnessing violence, and the Sexual Abuse class by high rates of sexual trauma in childhood. In contrast, individuals assigned to the Polytrauma class demonstrated relatively even rates of trauma across multiple domains, with high rates of both childhood and adulthood sexual violence in addition to violence exposure.

The profiles identified in the present study align with and extend prior literature on polytraumatization (Contractor et al., 2018). As was hypothesized, we identified profiles represented by minimal trauma, violence exposure, and polytrauma. Unique to the present study, however, were those profiles characterized by particularly high rates of sexual and physical abuse, which in prior studies have typically been grouped within the polytrauma profile (e.g., Cavanaugh et al., 2012; McCutcheon et al., 2010). Although these classes each made up a small proportion of the sample (particularly the sexual abuse [3%] and polytrauma [1%] profiles), which some consider too small to warrant a distinct latent profile (Hipp & Bauer, 2006), differentiation between these classes was supported by the LPA tests of best fit as well as the low probability of misclassification demonstrated by the selected model. These results are also consistent with other person-centered studies that have identified at least one small but meaningfully different profile that comprises individuals with exceptionally high trauma loads (Contractor et al., 2018). Notably, such studies that do isolate these smaller, more specific classes have also found that high rates of sexual or physical abuse characterize these profiles (Burns et al., 2016; Holt et al., 2017; McCutcheon et al., 2010).

Although the present study is the first to isolate three profiles based on specific types of abuse (in addition to the Minimal Trauma and Violence Exposure classes), there are a number of important factors that likely contribute to these differences. First, the present sample differs from previous samples in both its racial composition as well as its diversity of reported traumas. Previous studies have typically utilized dichotomous LCA approaches to examine predominantly White samples (e.g., Burns et al., 2016; Cavanaugh et al., 2013; Cavanaugh et al., 2012), with many focusing on specific populations, such as college students or women with a history of intimate partner violence (e.g., Holt et al., 2017; Young-Wolff et al., 2013). The current study, on the other hand, examined a community sample of urban, predominantly low-income individuals using continuous indicators (i.e., LPA), thus allowing for a more robust and comprehensive examination of trauma profiles. Further, previous studies often excluded certain Criterion A traumas (particularly those non-interpersonal in nature, such as accidents or injuries), included non-Criterion A traumas (e.g., emotional abuse), and/or grouped traumas by timing or category (Contractor et al., 2018). Naturally, these differences impact the identification of latent profiles. Considering our primary aim to identify trauma-exposure profiles at risk for PTSD, we considered only and all Criterion A traumas in order to identify relevant latent profiles. Further, we did
not consolidate traumas by category (e.g., combining *attacked with a weapon* with *attacked without a weapon*) or timing (e.g., *childhood sexual abuse* with *childhood physical abuse*), as there is no empirically-supported taxonomy for doing so and psychological outcomes have been shown to differ with respect to subtle differences in traumatic experiences (Kilpatrick et al., 1989; Zinzow et al., 2009). This level of nuance subsequently allows for the examination of how different polytraumatization patterns map on to psychopathology patterns.

In line with previous research, the five trauma profiles identified in the current study demonstrated varying patterns of risk for all distal outcomes examined. Notably, the pattern of differences examined generally maps onto existing hierarchical models of psychopathology, and consequently, may inform such models by identifying unique and shared trauma-specific factors associated with the development of psychopathology. For example, according to the Hierarchical Taxonomy Of Psychopathology (HiTOP), the outcomes PTSD, depression, and suicidality may be considered part of the internalizing spectrum, drug abuse may be part of the disinhibited externalizing spectrum, and aggressive behaviors may be part of the antagonistic externalizing spectrum. Jail counts is ambiguous because the precipitating event leading to being in jail is unknown. However, given that the behaviors conceptualized in the HiTOP model as being part of the disinhibited externalizing factor constitute the majority of offenses leading to jail (e.g., drug use, theft; Moore & Elkavich, 2008), it may be reasonable to assume that jail counts is more likely to be consistent with the disinhibited (rather than antagonistic) externalizing spectrum. Although all trauma classes were higher on the measured outcomes compared to the minimal trauma group, the patterns of differences between the trauma classes appeared to map onto these spectra.

First, in terms of the internalizing spectrum, the profile differences for PTSD, depression and suicidality exhibited a similar pattern. For example, those profiles characterized by childhood abuse, including the Polytrauma, Sexual Abuse, and Physical Abuse classes, had higher depressive symptoms compared to the Violence Exposure group. Those characterized by relatively higher childhood sexual abuse in particular, including the Polytrauma and Sexual Abuse classes, also reported higher depressive symptoms than the Physical Abuse class. The Polytrauma class also had higher suicidal behaviors compared to the Violence Exposure and Physical Abuse class, but had similar rates to the Sexual Abuse class. This is consistent with evidence that among individuals with PTSD, experiences of sexual assault were specifically associated with higher rates of suicidality (LeBouthillier, McMillan, Thibodeau, & Asmundson, 2015). In line with this, both the Polytrauma and Sexual Abuse classes had higher PTSD symptoms compared to the Violence Exposure and Physical Abuse classes, which is consistent with previous findings that risk for PTSD increases incrementally with compounding traumas, particularly traumas of varying types (Suliman et al., 2009). Taken together, these results suggest that the internalizing spectrum, and in particular, the distress components, appear to be most strongly predicted by various forms of childhood abuse. Childhood abuse may be particularly relevant to the etiology of the internalizing spectrum through its association with known risk factors for the development of internalizing psychopathology, such as altered physiological stress responses (Yang et al., 2017) and interpersonal attachment (Widom et al., 2018). Further, the highest level of
internalizing symptoms appeared to be among those subgroups characterized by childhood and adulthood sexual abuse, suggesting a potentially important role of these types of traumas. One possibility is that childhood sexual abuse may be more likely to happen in the context of other types of abuse (English et al., 2013) and be particularly likely to illicit emotions such as shame (Feiring et al., 2009). The presence of adulthood trauma may be particularly exacerbating in terms of risk because it signifies the lack of “corrective” interpersonal experiences in adulthood. Although these effects seem to be the strongest for depression, the similar patterns for PTSD symptoms and suicidal behaviors suggest some shared risk for the distress components of the internalizing spectrum.

Second, with regard to the disinhibited externalizing spectrum, there also appeared to be a consistent pattern. The Violence Exposure class was higher in substance abuse and jail counts compared to all classes except the Polytrauma class. Although the Polytrauma class was not significantly higher in substance abuse or jail counts compared to any other trauma class, the elevated rates and lack of differentiation from the Violence Exposure class is notable. Specifically, these results suggest that the classes characterized by adulthood trauma may be particularly at risk for disinhibited externalizing behaviors characterized by impulsivity, suggesting a shared risk pathway. Despite this similarity, however, it is possible that individuals in the Violence Exposure and Polytrauma group engage in disinhibited behaviors such as substance abuse for very different reasons (Bresin & Mekawi, 2019). Individuals in the Violence Exposure class, for example, may engage in drug use for enhancement reasons which would be consistent with underlying impulsivity tendencies, whereas individuals in the Polytrauma class may engage in drug use to cope with distress or negative affect, which would be consistent with the higher rates of PTSD and depressive symptoms.

The differences in patterns of substance abuse and jail counts differ from those found for aggressive behaviors, which were higher in the Violence Exposure class compared to all other classes, including the Polytrauma class. Thus, in contrast to the disinhibited externalizing findings, this suggests that high violence exposure is specifically associated with antagonistic externalizing symptoms. This delineation provides some modest support for categorization described in the HiTOP model, and also suggests potentially unique pathways to these two spectra. Furthermore, these results were consistent with prior evidence that exposure to violence is associated with later perpetration of aggression (e.g., Scarpa & Ollendick, 2003). One possibility is that such behaviors are “learned” as a result of exposure to violence both in the community and also in the home. There may also be a reciprocating cycle, wherein engaging in aggression leads to more consequences (e.g., incarceration), which then results in further exposure to violence (Carlson & Shafer, 2010). Another possibility is that individuals in the Violence Exposure class live in disenfranchised neighborhood contexts where aggressive behaviors may be a means to survival. Thus in some ways, and consistent with the lower psychological distress, these behaviors may be considered “adaptive” in that they allow for survival. Regardless of the specific mechanism, one implication of these findings is that attempting to establish etiological pathways to HiTOP spectra should include a thorough examination of various traumatic experiences.
A final implication for etiology is that, in general, we found that the most consequential traumas were those characterized by experiencing and being exposed to physical and sexual violence. Non-interpersonal traumas (e.g., natural disasters, serious accidents and life-threatening illnesses), at least in the context of a high trauma exposure sample, did not differentiate traumatization profiles, nor did they differentially predict outcomes. These results are consistent with prior evidence that non-interpersonal traumas confer less risk for PTSD and other adverse outcomes compared to interpersonal traumas (Breslau, Peterson, Poisson, Schultz, & Lucia, 2004; Howgego et al., 2005). Little is known about the potential cumulative impact of these traumas in the context of interpersonal traumas. Given evidence that PTSD symptoms may vary following exposure to non-interpersonal versus interpersonal traumas (Alisic et al., 2014), gaining a better understanding of this differential risk in the context of polytraumas is an important future direction.

The current research has important implications for programs and providers serving populations exposed to elevated rates of trauma across the lifespan. Our finding that patterns of trauma exposure vary across demographic groups may be useful in identifying individuals at risk for certain traumatic experiences, which in turn may inform targeted evaluation or prevention efforts. Further, given our findings that outcomes differ between minimal and high trauma classes, an assessment of all lifetime traumas – rather than a focus on any single trauma – may better inform clinical intervention. Historically, interventions for PTSD and other trauma-related outcomes (e.g., Prolonged Exposure, Cognitive Processing Therapy) have focused narrowly on a single traumatic experience (Foa, Chrestman, & Gilboa-Schechtman, 2008; Resick & Schnicke, 1992). Given our findings that individuals with higher rates of trauma demonstrate greater severity and comorbidity of psychopathology, it may be valuable to take a more holistic transdiagnostic approach (e.g., Ellard et al., 2010) to treating trauma-related symptoms in the context of polytrauma. Further, given our finding that outcomes not only vary with respect to trauma load but also trauma type (e.g., high rates of sexual abuse versus physical abuse), it is important to comprehensively evaluate trauma types in addition to trauma load. This information may then be leveraged to provide more tailored interventions for individuals at higher risk for internalizing versus externalizing psychopathology.

Our findings must be interpreted with consideration of certain limitations. The study was cross-sectional and retrospective in design and utilized interviewer-administered measures designed for self-report rather than in-depth clinical interviews. It is possible that participant responses were impacted by recall bias or underreporting which is of particular concern given prior evidence that African-American individuals tend to underreport experiences of victimization or symptoms of psychopathology (Sawyer, Bradshaw, & O’Brennan, 2008). Related to this point, more psychometric support is needed for the TEI beyond the construct validity evidence reported in the supplemental materials. The lack of test re-test reliability or other psychometric support designed for this type of measure (e.g., multidimensional scaling) is particularly relevant given that the TEI is the basis for the polytraumatization profiles. Given that trauma assessment is unique compared to other psychological constructs (e.g., depression) in that trauma does not represent a hypothetical construct, we would not expect trauma assessment tools to adhere to common assumptions (e.g., internally consistent, represented in a latent context/indicated by manifest variables).
Thus, it is important for future research to develop specialized methods for assessing the psychometric validity of these types of measures. The generalizability of our findings may also be limited by the data-driven nature of LPA, which can result in model overfitting (Lanza & Rhoades, 2013; Nylund et al., 2007). Although our results largely aligned with findings from other LPA and LCA studies that examined a variety of demographic groups (Contractor et al., 2018), future research is needed to corroborate our finding that a five-profile model best explains observed differences in trauma exposure and outcomes. Finally, although our sample reflected demographic characteristics typically underrepresented in clinical psychology research, it was nonetheless homogenous in many respects (e.g., lower socioeconomic stress, predominantly African American women).

Despite these limitations, our results demonstrate the utility of using a continuous, person-centered approach to examine the cumulative impact of different categories of trauma. By focusing on a population that is exposed to disproportionately high rates of trauma, we were able to identify the differential impact of minimal versus cumulative trauma as well as the impact of varied types of trauma exposure on polytraumatization typologies. Furthermore, the differences in psychological and behavioral outcomes lay the groundwork for further research designed to inform the assessment, etiology, and treatment of trauma-related symptoms and disorders.

**Supplementary Material**

Refer to Web version on PubMed Central for supplementary material.

**Acknowledgements**

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**References**


McCutcheon VV, Heath AC, Nelson EC, Bucholz KK, Madden PAF, & Martin NG (2010). Clustering of trauma and associations with single and co-occurring depression and panic attack over
twenty years. Twin Research and Human Genetics, 13(1), 57–65. 10.1375/twin.13.1.57 [PubMed: 20158307]


Figure 1.
Plot of estimated means of traumatic experience frequencies by class
Figure 2a.
PTSD severity scores based on latent class membership (% of sample)

Note. *p < .05
Figure 2b.
Depression severity scores based on latent class membership (% of sample)
*Note. *p < .05
Figure 2c.
Suicidal behaviors scores based on latent class membership (% of sample)

Note. *p < .05
Figure 2d.
Substance abuse severity scores based on latent class membership (% of sample)

Note. * $p < .05$
Figure 2e.
Aggression severity scores based on latent class membership (% of sample)

Note. *p < .05
Figure 2f.
Average jail count based on latent class membership (% of sample)

Note. *p < .05
### Table 1

Demographics for Total Sample and By Class

<table>
<thead>
<tr>
<th></th>
<th>Total Sample ( (n = 7,496) )</th>
<th>Minimal Trauma ( (n = 5830) )</th>
<th>Physical Abuse ( (n = 732) )</th>
<th>Violence Exposure ( (n = 567) )</th>
<th>Sexual Abuse ( (n = 213) )</th>
<th>Polytrauma ( (n = 84) )</th>
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<tr>
<td>Sample (%)</td>
<td>100</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
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<td>18–68</td>
<td>18–67</td>
<td>18–65</td>
<td>21–64</td>
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<td>41.77 (12.46)</td>
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<td>Gender (%)</td>
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<td>Men</td>
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<td>22.7</td>
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<td>45.7</td>
<td>86.9</td>
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<td>Race (%)</td>
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<td></td>
<td></td>
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<td></td>
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<td>African American</td>
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<td>87.7</td>
<td>93.1</td>
<td>86.9</td>
<td>86.9</td>
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<td>2.2</td>
<td>5.2</td>
<td>2.0</td>
<td>7.5</td>
<td>7.1</td>
</tr>
<tr>
<td>Other</td>
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<td>3.2</td>
<td>7.1</td>
<td>5.0</td>
<td>5.6</td>
<td>6.0</td>
</tr>
<tr>
<td>Education (%)</td>
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<td></td>
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<tr>
<td>Less than 12th</td>
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<td>12th Grade/High School Graduate</td>
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<td>GED or equivalent</td>
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<td>6.5</td>
<td>5.3</td>
<td>10.8</td>
<td>11.9</td>
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<td>26.5</td>
<td>25.8</td>
<td>27.4</td>
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<td>Technical school graduate</td>
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<td>College graduate</td>
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<td>Monthly Household Income (%)</td>
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<td></td>
<td>Total Sample (n = 7,496)</td>
<td>Minimal Trauma (n = 5,830)</td>
<td>Physical Abuse (n = 7,32)</td>
<td>Violence Exposure (n = 5,67)</td>
<td>Sexual Abuse (n = 213)</td>
<td>Polytrauma (n = 84)</td>
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<td>$500 – 999</td>
<td>26.0</td>
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<td>22.7</td>
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<td>$1,000 – 1,999</td>
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<td>$2,000 or more</td>
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<td>14.7</td>
<td>18.7</td>
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Overall Number of Traumas

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<th>Range</th>
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<th>0–16</th>
<th>1–18</th>
<th>4–18</th>
<th>2–17</th>
<th>3–18</th>
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<tbody>
<tr>
<td>Mean (SD)</td>
<td>5.16 (3.53)</td>
<td>4.05 (2.74)</td>
<td>8.41 (3.15)</td>
<td>10.23 (2.59)</td>
<td>8.76 (3.49)</td>
<td>10.16 (3.39)</td>
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Table 2

LPA Fit Indices

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<tr>
<th>k</th>
<th>LL</th>
<th>npar</th>
<th>AIC</th>
<th>BIC</th>
<th>CAIC</th>
<th>SABIC</th>
<th>AWE</th>
<th>LMR-LRT</th>
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<td>487887.78</td>
<td>488150.47</td>
<td>488151.46</td>
<td>488029.71</td>
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<tr>
<td>2</td>
<td>−26332.59</td>
<td>58</td>
<td>472781.18</td>
<td>473182.11</td>
<td>473183.12</td>
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<td>3</td>
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<td>462985.50</td>
<td>463524.69</td>
<td>463525.69</td>
<td>463276.83</td>
<td>464221.39</td>
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<tr>
<td>4</td>
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<td>98</td>
<td>456452.87</td>
<td>457130.32</td>
<td>457131.32</td>
<td>456818.89</td>
<td>458005.27</td>
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<tr>
<td>5</td>
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<td>451747.98</td>
<td>452563.68</td>
<td>452564.68</td>
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<td>449515.17</td>
<td>449075.64</td>
<td>450745.63</td>
<td>0.58</td>
<td>0.950</td>
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Note: Loglikelihood (LL), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), Bayesian Information Criterion (BIC), Sample-Size Adjusted Bayesian Information (SABIC), Approximate Weight of Evidence Criterion (AWE), the Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT), the BLRT (bootstrapped LRT), correct model probability (cmP), and entropy (Muthén & Asparouhov; 2008, 2012; Nylund et al., 2007, Masyn, 2013). Smaller approximate fit indices, including the AIC, CAIC, BIC, SABIC, and AWE indicate superior model fit (D’Unger, Land, McCall, & Nagin, 1998; Nylund-Gibson & Choi, 2018).
### Table 3: Chi-Square Estimates for Equality Tests of Means Across Classes

<table>
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<tr>
<th></th>
<th>PTSD</th>
<th>Depression</th>
<th>Self-Harm</th>
<th>Substance Abuse</th>
<th>Aggression</th>
<th>Jail</th>
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<tr>
<td>Overall Test</td>
<td>730.44*</td>
<td>672.61*</td>
<td>1973</td>
<td>3969</td>
<td>5167</td>
<td></td>
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<tr>
<td>PTSD vs. Depression</td>
<td>164.83*</td>
<td>82.44*</td>
<td>11.65*</td>
<td>37.215*</td>
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Note: 
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