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Addressing Disaster Exposure Measurement Issues With Latent Class Analysis

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Abstract

Disaster exposure can put survivors at greater risk for subsequent mental health (MH) problems. Within the field of disaster MH research, it is important to understand how the choice of analytic approaches and their implicit assumptions may affect results when using a disaster exposure measure. We compared different analytic strategies for quantifying disaster exposure and included a new analytic approach, latent class analysis (LCA), in a sample of parents and youth. Following exposure to multiple floods in Texas, a sample of 555 parents and 486 youth were recruited. Parents were predominantly female (70.9%) and White (60.8%). Parents were asked to have their oldest child aged between the ages of 10 and 19 years old participate (M = 13.74 years, SD = 2.57; 52.9% male). Participants completed measures on disaster exposure, posttraumatic stress, depression, and anxiety. The LCA revealed four patterns of exposure in both parents and youth: high exposure (15.5% parent, 9.5% child), moderate exposure (19.8% parent, 28.2% child), community exposure (45.9% parent, 34.4% child), and low exposure (18.8% parent, 27.8% child). In terms of MH, there were similarities across analytic approaches, but the LCA highlighted a threshold effect, with the high exposure class doing worse than all others, d = 1.12. These results have important implications in understanding the different exposure experiences of survivors and the linkage to MH outcomes. The findings are also informative in the development and use of screening tools used in postdisaster contexts in determining who may or may not need MH services.

Natural disasters are rapid, massively disruptive events that lead to prolonged alterations in the social and material environment. Several literature reviews (e.g., Bonanno, Brewin, Kaniasty, & La Greca, 2010; Norris et al., 2002) and meta-analyses have supported an increased risk for postdisaster posttraumatic stress disorder (PTSD; Furr, Comer, Edmunds,

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& Kendall, 2010), as well as other internalizing (e.g., anxiety, depression) and externalizing (e.g., oppositional behavior, aggression) symptoms (Rubens, Felix, & Hambrick, 2018). However, measurement and statistical issues related to quantifying disaster exposure have plagued the field, affecting researchers' ability to adequately analyze the effect of exposure on mental health (MH; McFarlane & Norris, 2006). In this study, we used a disaster exposure checklist to measure disaster exposure and applied different statistical approaches to understand the effects of exposure on MH outcomes. We used the standard statistical methods described in the extant disaster literature—regression and multivariate analysis of variance (MANOVA)—and latent class analysis (LCA) as a modeling approach. Although LCA has previously been used to classify outcomes of disaster exposure (Rosellini, Coffey, Tracy, & Galea, 2014), to our knowledge, LCA has not been applied to classify disaster exposure. We highlighted what each method assumes about disaster exposure and compared results across methods. Implications for understanding the association between disaster exposure and MH are discussed. This comparative analysis is an important methodological step forward to help advance disaster exposure measurement and quantification.

Disaster exposure measurement needs to consider how to: (a) measure the emotional reactions of terror and horror at the time of impact and recoil, which vary across disasters and individuals, but are highly predictive of MH postdisaster; (b) capture domains of loss, such as home, work, relationships, and community resources; (c) accommodate scaling and validity issues; and (d) address challenges associated with individual interactions with community exposure (McFarlane & Norris, 2006). Meta-analyses of disaster MH research have identified similar issues and noted that the types of questions asked to assess disaster exposure have varied greatly across studies (Furr et al., 2010; Rubens et al., 2018). Some researchers have determined geographic proximity and may or may not have asked individual exposure questions (e.g., Goenjian et al., 2001). Others have created a checklist of objective exposure experiences—what the person saw, heard, or experienced (e.g., Vernberg, La Greca, Silverman, & Prinstein, 1996). Measuring subjective peritraumatic reactions, such as experiencing fear or horror, and perceived life threat have also been common. Finally, prospective studies have compared pre- and postdisaster MH mean outcomes and may have included a measure of disaster exposure (e.g., Scaramella, Sohr-Preston, Callahan, & Mirabile, 2008). In addition to different measurement approaches, a variety of statistical options for describing the impact of exposure on postdisaster MH have been used.

There are considerations specific to postdisaster event checklists that make them different than the measurement of psychological constructs, like self-esteem (see Netland, 2001, 2005). For example, drawing from research on political violence but applicable to natural disasters, Netland (2001) argued that the effect indicator model (Bollen & Lennox, 1991) commonly used in many psychological constructs to create a scale (e.g., self-esteem) does not fit with experiences of political violence or disaster exposure. This approach makes the assumption of an underlying, normally distributed latent variable, which fits with classical test theory and confirmatory factor analysis (CFA). It assumes that items will correlate with one another—an assumption that does not apply to checklists used in disaster research. One experience does not necessarily correlate with another experience in consistent patterns across exposed individuals.

Instead, Netland (2001) suggested that a causal indicator model would be more appropriate for many potentially traumatic events because the objective events to which the individual was exposed determine the construct. With this model, event checklists are used, often to create a composite variable or sum score. Each item is an important part of understanding the experience and may or may not be correlated with other items on the checklist in a consistent manner across survivors. Event checklists need to be thorough, capture the full range of experiences, and items must fit the definition of what is intended to be measured. Further, Netland (2001) argued that factor-analytic techniques are inappropriate for defining the construct with event-checklist data. However, disaster researchers are still commonly asked to do this.

Researchers now need to consider person-centered analytic approaches, such as LCA, as a statistical model that can be used to group disaster survivors based on shared experiences. Even though LCA is technically considered an effect indicator model, it assumes that the underlying latent variable is categorical rather than continuous, like CFA, which provides a way to group individuals based on disaster experiences. Also, researchers must consider how different statistical approaches may affect our understanding of the association between disaster exposure and MH.

A simple sum score of experiences based on an event checklist is a common method for quantifying disaster exposure. The sum score is an aggregate of the items endorsed, whereby a higher score indicates more disaster exposure. For example, Vernberg et al. (1996) used a hurricane exposure sum score in a regression and found more disaster exposure was associated with a higher level of MH symptoms. Although the sum score is a practical way to quantify disaster exposure, there are several assumptions made when a sum score is used. First, with sum scores, all items on a checklist are given the same weight, which assumes equal associations with the MH outcome (Netland, 2005). This is contrary to the knowledge that certain experiences (e.g., injury or death) will have a stronger impact than others (e.g., seeing flames from a wildfire). A score of 6 indicates that six items from the checklist were endorsed, regardless of which items were endorsed. This assumes that all items on the checklist are interchangeable and equally good indicators; thus, the combination of particular items is not important. In addition, the sum score assumes that there is one dimension being captured by the set of items. As such, the difference between a 5 and a 6 on the total score is expected to be equivalent to the difference between a 14 and a 15. There may be contexts in which these sets of assumptions about sum scores are true, but there are likely times where they are not (Netland, 2005). The convenience of creating, using, and interpreting sum scores has made them very appealing, and they are one of the most practical and commonly used approaches to date.

An alternative is the “critical item” approach. Instead of creating a continuous sum score, critical experiences from the disaster, such as death of a loved one or time displaced from one’s home, are used to examine differences between groups of exposed individuals. For example, Liao, Chen, Chen, and Chien (2014) used this approach, identifying death or injury of a family member and time until the home was restored following a massive earthquake in Taiwan. These authors compared MH outcomes for children who experienced each of these items and those who did not. This approach avoided the set of assumptions of the sum score, as death of a loved one, injury, or prolonged displacement are considered more severe disaster experiences than losing utilities or temporary evacuation. However, by potentially not exploring interrelationships with other disaster experiences, some important differences may be overlooked, which may put some respondents at higher risk for negative postdisaster outcomes. Individuals who lost their homes may be more likely to have had a loved one injured or killed, compared to those whose home was undamaged. It also may underestimate the complexity of survivors' disaster experiences by only focusing on a limited range of experiences (McFarlane & Norris, 2006; Netland, 2001). This method assumes the researchers know which events are critical. Although some events, such as death of a loved one, are universally critical, there may be context-dependent issues that make some experiences more critical in one disaster over another. Critical items could vary by type, timing, and severity of the disaster; thus, their selection could be arbitrary and miss important considerations.

The means or proportion approach is used under several circumstances. For example, this approach might be used when disaster researchers have a prospective study and can compare pre- to postdisaster MH (e.g., Scaramella et al., 2008); when researchers are comparing low, medium, and high exposure groups, often based on geographical location with relation to the disaster (e.g., Goenjian et al., 2001) or through creating groups based on quartiles or a similar approach; or when using cutoffs with a sum score to divide a sample into nondisaster exposed and exposed groups for comparisons (e.g., Felix et al., 2011). Many of the same assumptions that apply to sum scores apply here; additionally, categorizing loses variability in the sample. With a categorical grouping, individuals within a given group may be drastically different from one another, with one having lost a loved one and another with less severe exposure (e.g., loss of utilities). Categorization based on quartiles or above or below the mean is arbitrary and will vary across disaster studies.

In sum, there are important considerations with respect to the measurement of disaster exposure. First, it is not reasonable to assume that disaster exposure is continuous—for each added item on the exposure checklist, researchers would not expect the same increase in exposure level. Not all of the ways survivors experience a disaster hold equal weight in contributing to survivors' overall exposure and their reactions to this exposure. Differences between objective events and subjective experiences may not be adequately captured in a sum score. Methods used to measure disaster exposure must be sensitive to this idea; however, thus far, the current measurement and statistical approaches typically used in disaster research have been unsatisfactory in one assumption or another. Given these issues and Netland's (2001, 2005) recommendations and cautions, we believe that considering other statistical methods not commonly used in disaster research may help the field better understand the experiences of disaster survivors and how they relate to adjustment.

Latent class analysis is a person-centered analytic approach that provides a different way of identifying groups that is sensitive to the need to adequately capture different experiences of disaster exposure. Person-centered analytic approaches are still relatively new to the field of trauma research, as evidenced by their low usage (Contractor, Caldas, Fletcher, Shea, & Armour, 2018), but they are growing as useful tools in understanding patterns in trauma exposure (O'Donnell et al., 2017). With LCA, researchers can group individuals based on their patterns of endorsing certain disaster exposure events, which may be a way to move the field forward, as this approach can help researchers identify groups of disaster-exposed individuals that are not based on linear, additive assumptions about exposure. Additionally, LCA provides a way to explore how the combinations of disaster exposure indicators are important. It goes beyond the "more is worse" assumption, which at times is true but is dependent upon the types of exposure indicators endorsed. "More is worse" is the assumption that underlies regression models, and it is the only outcome that can emerge from these models, as the approach relies on correlations. When comparing LCA-derived groups based on disaster exposure to explore MH outcomes, we can ascertain if there is a "threshold effect"—is there a grouping of disaster experiences that are most associated with subsequent negative MH outcomes? This can help in postdisaster screening to discern priority for critical supportive services. Using a comprehensive event checklist of disaster exposure with adults and youth, we address: (a) what differences in MH outcomes, if any, emerge when we compare results from commonly used statistical methods to study the impact of disaster exposure?; (b) how do the results of LCA on the disaster checklist help us understand how to quantify disaster exposure?; and (c) what do differences across the methods tell us about disaster exposure and MH?

Method

Participants and Procedure

The U. S. Federal Emergency Management Association (FEMA) made six major disaster declarations for the state of Texas between May 2015 and May 2016 (the period of this study), with 159 out of 254 counties receiving FEMA declarations for individual and/or public assistance. Initially, the current research began as a study following the May 2015 Memorial Day weekend flood, which affected 44.5% (113) counties in Texas. After we received Institutional Review Board (IRB) approval, recruitment began in October 2015. Very shortly after recruitment began, another devastating flood occurred (Halloween Weekend Flood in October 2015). IRB was modified to ask about both floods (only one person had participated before this modification). Over the course of recruitment, additional flooding and storms occurred, including the April 2016 flood that affected Houston and surrounding areas. This made it prohibitive, in terms of participant time and survey fatigue, to ask exposure questions repeatedly for each flood, as families could have been affected by multiple floods. Therefore, IRB was modified to ask about the "flood most stressful to you," and participants could indicate "Memorial Day Weekend 2015," "Halloween Weekend 2015," "April 2016," or "Other" and specify which flood.

Recruitment included distributing flyers at local schools, community events, and shopping centers; advertising in electronic newsletters from local schools and through a university; posting flyers in libraries and community centers; door-to-door recruitment in affected neighborhoods; advertising in social media forums, newspapers, and online ads; and telephone recruitment. To reach the desired dyadic sample size, we also used an opt-in panel obtained through Qualtrics (Provo, UT) following the April 2016 flood and severe weather. Recruitment ended in March 2017. The average time since disaster at survey completion was

406.33 days (*SD* = 162.79). All participants completed their surveys online and received a small incentive for participation.

A sample of 581 parents and 510 children, aged 10–19 years, were recruited from flood-affected areas in Texas. We excluded 26 parents and 24 children who reported their most stressful flood experience was "other" because of the wide range of past floods reported (e.g., a 2010 flood, Hurricane Katrina, none were stressful, etc.). The final sample included parents (*N* = 555) and youth (*N* = 486) whose most stressful flood occurred during the period of May 2015 through May 2016. Parent participants were predominantly female (70.9%), and the primary relationship to the child was mother (68.2%), father (24.5%), or other family relationship (e.g., stepparent, grandparent; 7.3%). Parents' ethnicity was 60.8% White, 19.5% Latinx, 9.1% African American, 7.5% Asian or Pacific Islander, 1.6% Native American, and 1.5% mixed. United States Census data for Texas adjusted for 2016 showed the population to be 42.6% White (non-Hispanic), 39.1% Latinx, 12.6% African American, 4.8% Asian, 0.1% Pacific Islander, and 1.0% Native American. Parents' highest level of completed education was some college education (25.5%), graduated college (30.1%), or graduate school (17.0%). Median income was $60,001–70,000 (USD). Parents were asked to have their oldest child who was within the eligible age range of 10–19 years complete the youth survey. The mean child age was 13.74 years (*SD* = 2.57). Child participants were 52.9% male, and ethnicity was 57.2% White, 18.8% Latinx, 9.0% African American, 7.9% Asian/Pacific Islander, 1.0% Native American, and 6.1% biracial/multiethnic.

Measures

Flood impact.—The authors developed the Flood Impact Questionnaire (FIQ) from established measures of disaster exposure (Felix et al., 2011; Ginexi, Weihs, Simmens, & Hoyt, 2000; La Greca, Silverman, Vernberg, & Prinstein, 1996). Parents and youth completed separate FIQs; see Table 1 for items. Participants completed the FIQ in regards to the flood they reported to be most stressful to them. Response options were 0 = *no* and 1 = *yes*. One item on damage to participants' home was answered on a 5-point scale from 0 (*no damage*) to 4 (*total loss or destruction*). This was converted to a dichotomous scale (0 = *no damage* and 1 = *any damage*) following an analysis that demonstrated it was "no" versus "any damage" that distinguished between MH outcomes.

Depending upon the statistical model being employed, exposure scores were computed in different ways. For the sum score, the dichotomized items were summed to create a total score. For quartiles, the sum score was divided at approximately 25% intervals, which represented for parents: 0–2 items for low, 3–4 items for medium low, 5–6 items for moderate, and 7–13 items for high. For children, the following four quartiles emerged: 0–1 items for low, 2 items for medium low, 3–4 items for moderate, and 5–10 items for high. Three critical-item indicators were used (having someone close to you killed, having someone close to you get injured or sick, and having your home damaged) to determine their effect on MH outcomes. These were chosen based on their common use in extant disaster research that has used the critical-item method.

Posttraumatic stress symptoms (PTSS).—Parents completed the Impact of Events Scale (IES-6; Thoresen et al., 2010), and children completed the Children's Revised Impact of Events Scale–8 (CRIES-8; Yule, 1997). Participants were asked to indicate, with respect to the flood that was most stressful to them, how distressed or bothered they were during the past 7 days by each listed difficulty. Response options were 0 (*not at all*) to 4 (*extremely*), with a total score representing the sum of responses. The IES-6 is a six-item measure of PTSS that is derived from the IES-Revised (Weiss & Marmar, 1997). It contains two items each assessing intrusion (e.g., "other things kept making me think about it"), avoidance ("I tried not to think about it"), and hyperarousal ("I had trouble concentrating"). The IES-6 has correlated highly (pooled correlation = 0.95) with the IES-R in four different samples of individuals exposed to a traumatic event, across gender, age, type of trauma, and trauma severity, and has demonstrated good internal consistency (Cronbach's $\alpha = .80$; Thoresen et al., 2010). The CRIES-8 is used with children aged 8 years and older and measures intrusion and avoidance. Studies have supported the validity and reliability of the CRIES-8 (e.g., Yule, 1997). Our data yielded reliability estimates of Cronbach's $\alpha = .95$ for both the parent and youth scales.

Depression and anxiety.—The Hopkins Symptom Checklist (HSCL-25; Hesbacher, Rickels, Morris, Newman, & Rosenfeld, 1980) measures symptoms of anxiety (10 items; e.g., "suddenly scared for no reason," "feeling fearful") and depression (15 items; e.g., "feeling low in energy, slowed down," "crying easily"). Parents and youth reported how much each symptom bothered them in the last week. Responses ranged from 1 (*not at all*) to 4 (*extremely*) and were averaged to create an anxiety and a depression score, per scoring guidelines. Due to IRB recommendations, one depression item ("thoughts of ending your life") was not included in the youth version of the checklist used in this study. The HSCL-25 has demonstrated good validity and reliability (Hesbacher et al., 1980). In our study, internal consistency for the Anxiety and Depression subscales was excellent, with Cronbach's alpha values of .93 and .95, respectively, for parents and .96 and .97, respectively, for children.

Data Analysis

To demonstrate the impact of different statistical approaches on understanding the influence of disaster exposure on MH, we used multiple regressions and MANOVA, which are the statistical methods commonly found in the literature, as well as LCA. Using a sum score of disaster exposure, several linear regressions investigated whether disaster exposure significantly predicted MH and examined the strength of the association. Next, we also used linear regression to test the critical-items approach by entering each item as a predictor into the regression equation. We used MANOVAs to identify significant mean differences in MH between the exposure quartiles for parents and youth. This approximates the methods used when researchers divide samples based on geography assumed to indicate high, medium, and low exposure groups.

Latent class analysis provides the opportunity to empirically group participants based on observed response patterns across multiple disaster exposure items (Collins & Lanza, 2010) instead of grouping participants based on cut-off scores. Two separate series of LCAs on parents and youth were conducted using M*plus* 8.0 (Muthén & Muthén, 1998–2017) to empirically identify latent classes based on subpopulations of flood exposure. A total of six LCA models were run for both the parent and child LCAs, starting with a one-class model and followed by models that included one additional class until adding classes achieved little or no improvements in fit. Mplus uses full information maximum likelihood (FIML) estimation under the missing at random assumption (MAR).

Several fit indices were examined to detect improvements in model fit because no single statistical criterion identifies the best fitting LCA model (Nylund, Asparouhov, & Muthén, 2007). The fit statistics we considered included the Bayesian information criterion (BIC), which has been shown to most often identify the best fitting model (Nylund et al., 2007), and the sample size–adjusted BIC (ABIC). Smaller values on these fit indices indicate a preferred model. Likelihood-based tests were also examined to compare models, including the bootstrap likelihood ratio test (BLRT) and the Lo–Mendell–Rubin (LMR) test. These provide p values comparing a model with k classes and a model with k–1 classes. A nonsignificant p value for the k class model indicates the k–1 class model is preferred.

In addition to fit indices, we examined entropy, which measures how well participants are classified into the emergent latent classes. Entropy values range from 0 to 1; higher values indicate better classification of individuals into groups and classes that are clearly delineated from one another (Nylund et al., 2007), where values around 0.8 are considered to have good classification. Once the best-fitting unconditional model was identified, item probability plots were interpreted to give descriptive names to the classes based on response patterns across all indicators. Finally, the auxiliary variables (i.e., distal outcomes) of indices of MH were included to examine differences across the derived latent classes.

Distal outcomes were examined using the three-step approach, which is a best practice for this analysis, specifically the Bolck, Croon, & Hagenaars (2004) method to explore whether the means of MH indicators were significantly different across classes. The BCH method allows for the identification of significant mean differences between all pairwise comparisons of latent classes. This approach prevents auxiliary variables from influencing emergent latent classes, thus avoiding shifts in the latent classes when distal outcomes are added. Pairwise mean differences were assessed, and effect sizes, reported as standardized differences (Cohen's d), are reported and should be interpreted in standard effect sizes (c.f., Cohen, 1998).

Results

Descriptive statistics are presented in Table 1. For parents, the most commonly endorsed flood experience was having their neighborhood affected, and for youth, it was that places they went for fun were affected by the floods (e.g., restaurants, parks, play areas). For both parents and youth, the least common experience was that someone close to them was killed because of the flood.

Comparison of Commonly Used Statistical Approaches

Regression with sum scores.—For parents, more flood exposure significantly predicted greater anxiety, $F(1, 537) = 95.26$, $\beta = .389$, $p < .001$, $R^2 = .15$; depression, F(1,

535) = 69.67, $\beta = .339$, $p < .001$, $R^2 = .12$; and PTSS, $F(1, 506) = 198.39$, $\beta = .532$, $p < .001$, $R^2 = .28$. Similar results were found for youth for anxiety, $F(1, 477) = 84.05$, $\beta = .389$, $p < .001$, $R^2 = .15$; depression, $F(1, 478) = 82.40$, $\beta = .383$, $p < .001$, $R^2 = .15$; and PTSS, $F(1, 473) = 197.14$, $\beta = .546$, $p < .001$, $R^2 = .30$.

Regression with critical items.—Collinearity was assessed with variance inflation (VIF; O'Brien, 2007). For parents, VIF ranged from 1.05–1.15, and for youth, it ranged from 1.07–1.21, which indicates no collinearity. When the critical items were treated as individual predictors, anxiety—$F(3, 526) = 18.57$, $p < .001$, $R^2 = .10$ for parents and $F(3, 468) = 39.04$, $p < .001$, $R^2 = .20$ for children—was significantly predicted by having someone close get sick and/or injured, $\beta = .124$, $p = .005$ for parents and $\beta = .183$, $p < .001$ for children; having someone close get killed, $\beta = .161$, $p < .001$ for parents and $\beta = .280$, $p < .001$ for children; and having home damage, $\beta = .169$, $p < .001$ for parents and $\beta = .151$, $p < .001$ for children. Similar results were found for depression—$F(3, 526) = 13.56$, $p < .001$, $R^2 = .07$ for parents and $F(3, 469) = 39.79$, $p < .001$, $R^2 = .20$ for children—which was predicted by having someone close get sick/injured, $\beta = .129$, $p = .003$ for parents and $\beta = .206$, $p < .001$ for children; having someone close get killed, $\beta = .119$, $p = .006$ for parents and $\beta = .257$, $p < .001$ for children; and having home damage, $\beta = .143$, $p = .001$ for parents and $\beta = .157$, $p < .001$ for children. Additionally, PTSS—$F(3, 495) = 35.23$, $p < .001$, $R^2 = .18$ for parents and $F(3, 464) = 62.63$, $p < .001$, $R^2 = .29$ for children—were predicted by having someone close get sick and/or injured, $\beta = .133$, $p = .002$ for parents and $\beta = .294$, $p < .001$ for children; having someone close get killed, $\beta = .236$, $p < .001$ for parents and $\beta = .175$, $p < .001$ for children; and having home damage, $\beta = .253$, $p < .001$ for parents and $\beta = .281$, $p < .001$ for children.

Quartile approach.—We tested MANOVAs for mean differences on the outcomes with respect to the quartiles from sum scores. The means and standard deviations of parent and youth outcome measures by quartiles (low, medium, moderate, high) are presented in Table 2. For both youth and parents, the high quartile consistently exhibited greater MH symptoms whereas the low quartile consistently reported the best MH outcomes. For parents, significant mean differences were found across all outcome variables, Wilks' λ, $p < .001$, which included anxiety, $F(3, 495) = 22.61$, $p < .001$, $\eta^2 = .12$; depression, $F(3, 495) = 17.33$, $p < .001$, $\eta^2 = .10$; and PTSS, $F(3, 495) = 49.24$, $p < .001$, $\eta^2 = .23$. Bonferroni post hoc tests revealed that the means for anxiety, depression, and PTSS for the high quartile group were significantly higher than all other groups, $p < .001$. The means for anxiety and PTSS for the moderate quartile group were significantly higher than the low quartile group, with $p = .042$ for anxiety and $p < .001$ for PTSS. Among youth, significant mean differences were found, Wilks' λ, $p < .001$, for anxiety, $F(3, 471) = 27.39$, $p < .001$, $\eta^2 = .15$; depression, $F(3, 471) = 27.70$, $p < .001$, $\eta^2 = .15$; and PTSS, $F(3, 471) = 60.20$, $p < .001$, $\eta^2 = .28$. Bonferroni post hoc tests revealed that the means for anxiety, depression, and PTSS for the high quartile group were significantly higher than all other quartile groups, $p < .001$. In addition, the mean for PTSS for the moderate quartile group was significantly higher than the low, $p < .001$, and medium groups, $p = .008$.

Latent Class Analysis of Parent and Youth Flood Exposure

Two separate series of LCA models were conducted, one for the parent flood exposure and another for youth flood exposure. Fit information is presented in Table 3. In the parent LCA, the BIC value reached a minimum value at four classes, which supported a four-class model. The ABIC did not reach a minimum value and thus was not informative. The *p* values for the LMR showed support for both the two- and four-class models. The entropy for the four-class model was 0.79, which suggests the classes were clearly delineated and that participants were grouped into these classes well. Thus, given the decent entropy and the support from the BIC and LMR *p* value, we picked the four-class model for the parents.

Considering fit for the LCA of the youth outcomes, the BIC was lowest for the three-class model although it was only very slightly larger for the four-class model, which provided support for both the three- and four-class models. The ABIC did not reach a minimum value and thus was not informative. Although the small increase in BIC value at the four-class solution provided some evidence for the three-class model, this increase was only by 0.65 points. An increase of 29.08 points appeared between the four- and five-class models. Furthermore, the first nonsignificant *p* value of the LMR was found with the five-class model, providing evidence that the four-class solution was preferred by the LMR. Based on the substantial increase in BIC value between the four- and five-class models, the nonsignificant LMR *p* value at the five-class model, and substantive interpretation, the four-class solution was chosen as the final model. The entropy for this model was 0.77, which indicates well-delineated classes.

Item-probability plots (see Figures 1 and 2 for parent and child) were used to describe the classes. Among parents, the class labeled high exposure (15.5% of parents) reported the largest number of types of flood exposure. Specifically, members in this group had a greater than 50% chance of endorsing all items, except for one item (someone close to you was killed). Based on the conditional item probabilities, the items that best differentiated this group from the others (especially the moderate exposure group) included personally getting sick or injured as a result of the flood; someone close to the participant getting sick or injured due to the flood; being afraid of dying in the flood; and having an animal lost, hurt, or killed in the flood. Although the probability for endorsing knowing someone who was killed in the flood was below 50% for all groups, it was highest for the high exposure group. The moderate exposure class (19.8%) endorsed eight of 13 items above 50% probability, indicating they had to temporarily move, and their neighborhood, work, child’s school, home, utility, finances, and items of value were affected by the flood. The community exposure class (45.9%) indicated their neighborhood, work, child’s school, home, and utility service were impacted by the flood, but they did not endorse fear of dying in the flood; injury or illness to self or loved ones; or having an animal lost, hurt, or killed. They were less likely than the moderate exposure group to endorse financial losses, destruction of personal belongings, and having to temporarily move. The class labeled low exposure (18.8%) had a low probability of endorsing any of the flood exposure items.

Among youth, four similar classes emerged. A high exposure class (9.5% of youth) reported the most types of flood exposure, having a greater than 60% chance of endorsing eight of 10 items. Similar to parents, the youth high exposure group was more likely than the other groups to endorse feeling afraid they would die in the flood; having someone close to them get sick or injured in the flood; and having an animal lost, hurt, or killed. Although the probability for endorsing knowing someone who was killed in the flood was below 50% for all groups, it was highest for the high exposure group. A moderate exposure class (28.2%) endorsed half of the items at greater than 50% probability, indicating they had to temporarily move, and their school, areas of entertainment, home, and items of value were impacted by the flood. The community exposure class (34.4%) indicated their school, areas of entertainment, and home were affected by the flood. As with parents, youth in the moderate exposure were more likely to endorse having their home or belongings damaged in the flood, losing important belongings, and having to temporarily move due to the flood than those in the community exposure group. Youth in the low exposure class (27.8%) had a low probability of endorsing any of the flood exposure items.

Several MH outcomes were included to examine the predictive validity of the latent classes that emerged for both parents and youth (Figures 3 and 4). For both parents and youth, across depression and anxiety, there appeared to be a threshold effect, as the high exposure class had a significantly higher mean score compared to the other three classes, $p < .001$ across all three comparisons. Among youth, the low exposure class reported significantly lower levels of anxiety, $p = .001$, $d = 0.37$; and depression, $p = .002$, $d = 0.34$, compared to the moderate exposure class. In addition, youth in the low exposure class reported significantly lower levels of anxiety compared to those in the community exposure class, $p = .049$, $d = 0.21$. Among parents, the low exposure class reported significantly lower levels of anxiety, $p = .005$, $d = 0.27$; and depression, $p = .013$, $d = 0.26$, compared to the community exposure class. Finally, parents in the low exposure class reported significantly lower levels of anxiety compared to those in the moderate exposure class, $p = .015$. This pattern supports a nonlinear trend in depression and anxiety in that there was a jump in symptoms from low exposure to any other exposure class but then a sharp incline in symptoms for the high exposure class, $d = 1.12$. Thus, the combination of the items predominantly associated with the high exposure group represents critical experiences to consider. Regarding PTSS, a more linear trend appeared. For youth and parents, all possible pairwise comparisons were significantly different from each other, as the high exposure class endorsed significantly higher levels, followed by the moderate exposure class, community exposure class, and finally the low exposure class.

Discussion

Critical issues have been raised in disaster MH about how to best capture the experiences of disaster survivors that relate to ongoing postdisaster MH. The costs and benefits of various approaches for measurement and statistical analysis have been recognized (e.g., Furr et al, 2010; McFarlane & Norris, 2006; Netland, 2005; Rubens et al., 2018), but these investigations have lacked a full exploration of alternatives and a comparison of the approaches. With advances in statistical techniques that allow us to better model real world experiences, we explored how LCA may address limitations to understanding disaster exposure that are known to exist with the use of sum scores, quartiles, or critical items. This person-centered approach is becoming more popular in trauma research, with a high trauma exposure group and a low trauma exposure group commonly found (Contractor et al., 2018; O'Donnell et al., 2017).

In commonly used statistical techniques, such as ANOVA or regression models, there is an assumption of a linear association between disaster exposure and MH. Our LCA results suggest that this linear pattern exists for PTSS for parents and youth, in which similar increases in symptoms were found at each level of exposure. The LCA results were consistent with the other statistical approaches explored, which suggests that each is useful for PTSS. However, the linear assumption did not hold for depression and anxiety. Our parent and youth LCAs showed that not all items were created equal in that certain thresholds of disaster experiences led to a sharp increase in depression and anxiety symptoms. Further, although our emergent classes were somewhat ordered in that they seemed to be increasing in the number of disaster challenges, in this exploratory analysis, we did not know if that would emerge. Additionally, the classes were associated in a nonlinear way to depression, and we could see the combination of items that differentiated groups. This supports consideration of alternate statistical models, at least for these outcomes.

Using LCA revealed that the only class (high exposure) that endorsed personally getting sick or injured, someone close to them getting sick or injured, someone close getting killed, being afraid that they would die, and having an animal lost or injured demonstrated significantly worse outcomes than the other groups. Although the regression and ANOVA approaches with sum scores or quartiles also demonstrated that a high exposure group was at the greatest risk for distress, they did not reveal what experiences led to this risk. Indeed, these analyses suggested a higher number of items endorsed—any items—was associated with the increase in symptoms. The LCA indicated that individuals in the high exposure class not only experienced more flood exposure items, but they were the only participants who had a high probability of experiencing the aforementioned events. This has implications for postdisaster screening efforts that include a questionnaire about disaster experiences. Adults and youth who endorse this combination of items are at greater risk for long-term distress; thus, it may be important to flag these individuals for priority when offering supportive services and rescreening to monitor MH over time. Results from regression or ANOVA models would only suggest that the total number on the screening form matters; this might include people from the moderate or community exposure groups who may not be the priority for support and could unintentionally exclude people in the high exposure group.

With the critical-item approach, certain experiences would also be flagged over other experiences in postdisaster MH screening efforts. However, these exposures would be explored in isolation. The results from the LCA suggest that there are critical items that co-occur with one another, which factors into the number of disaster experiences endorsed. It was the totality of these experiences that led to a sharp increase in risk for depression and anxiety symptoms. The fact that we saw a "threshold" effect, with almost no difference in depression and anxiety symptom levels among all exposure classes except the high exposure group, suggests that disaster exposure may be nonlinear in its influence on some MH outcomes. This information may be missed in some types of regression that only indicate that more exposure is worse as well as in a MANOVA, which uses preexisting cutoff scores that cannot identify existing thresholds.

This study was cross-sectional and the sample may not be representative of the population of Texas; additionally, it might not generalize to other disaster survivors. Our study occurred about a year after the disaster, and results could be different in the short-term aftermath or over an extended period of time. Finally, we focused on the most commonly used statistical approaches in disaster research to date, which meant excluding other approaches that are viable but not yet regularly used in this subfield, such as the cumulative score approach (as presented in Shevlin, Houston, Dorahy, & Adamson, 2008). Nevertheless, our exploration of measurement and statistical issues with our data has helped highlight some potential solutions to disaster measurement issues.

Our conclusion is not that LCA is best. Our analyses support the utility of each statistical method that has been used in prior research. However, we suggest that LCA is an option for researchers to consider to better understand the diversity of experiences within a disaster, especially when the MH outcomes being assessed are not PTSS and the research questions are aimed at finding groups of individuals with differences on the set of outcomes. Future research should replicate this study across different disasters and at earlier postdisaster time points to see if similar classes are found and how they relate to MH. For practice, we noted earlier that these results have implications for postdisaster MH screening efforts. How researchers and clinicians set up and interpret screening forms and scores would change based on the knowledge from LCA. Practitioners would want to check for a combination of experiences that confer risk and prioritize that group for support. Simply summing a screening form would potentially identify different people to serve, including those who may not be the highest priority in terms of risk for subsequent depression and anxiety. With these suggestions, we hope to move forward disaster MH research and practice.

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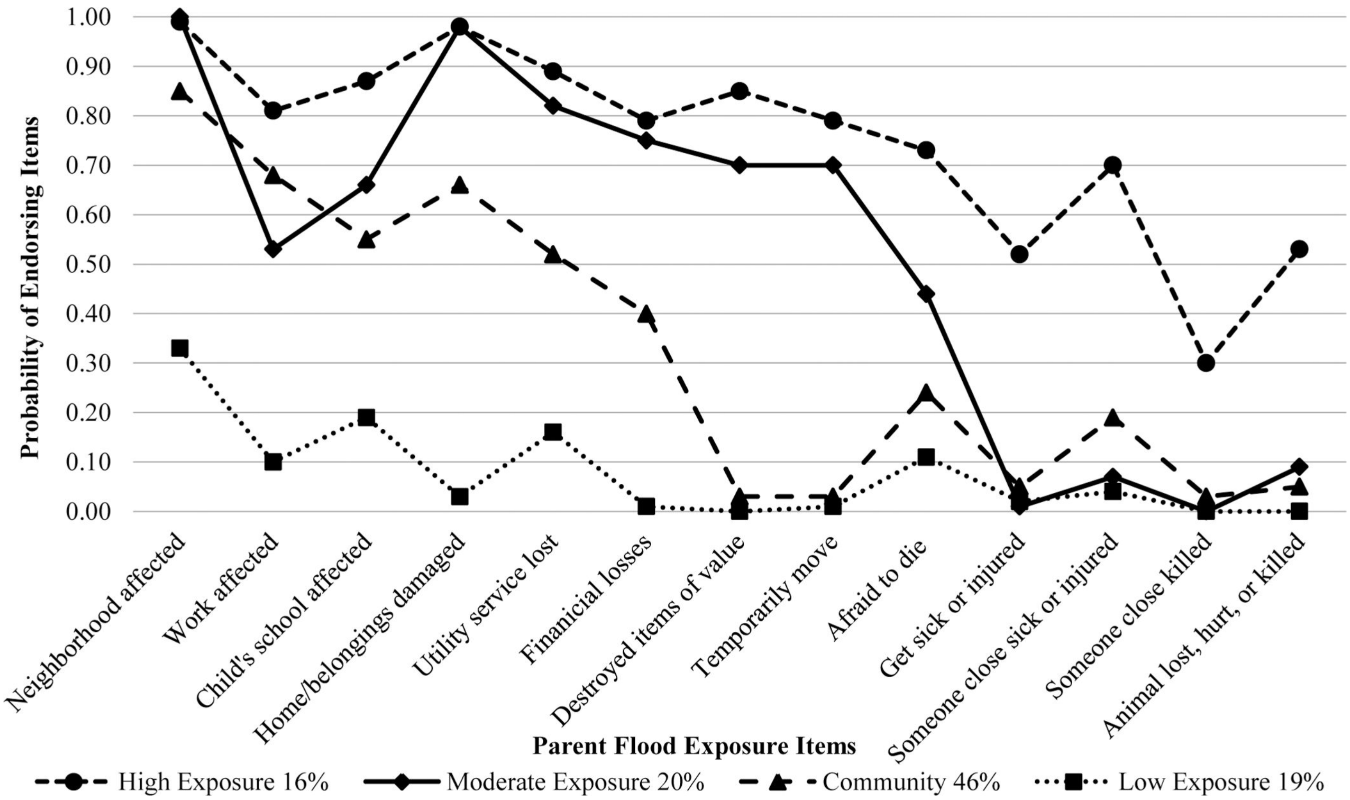

Figure 1.
Item probability plots for parent latent class analysis (LCA) using the flood exposure items.

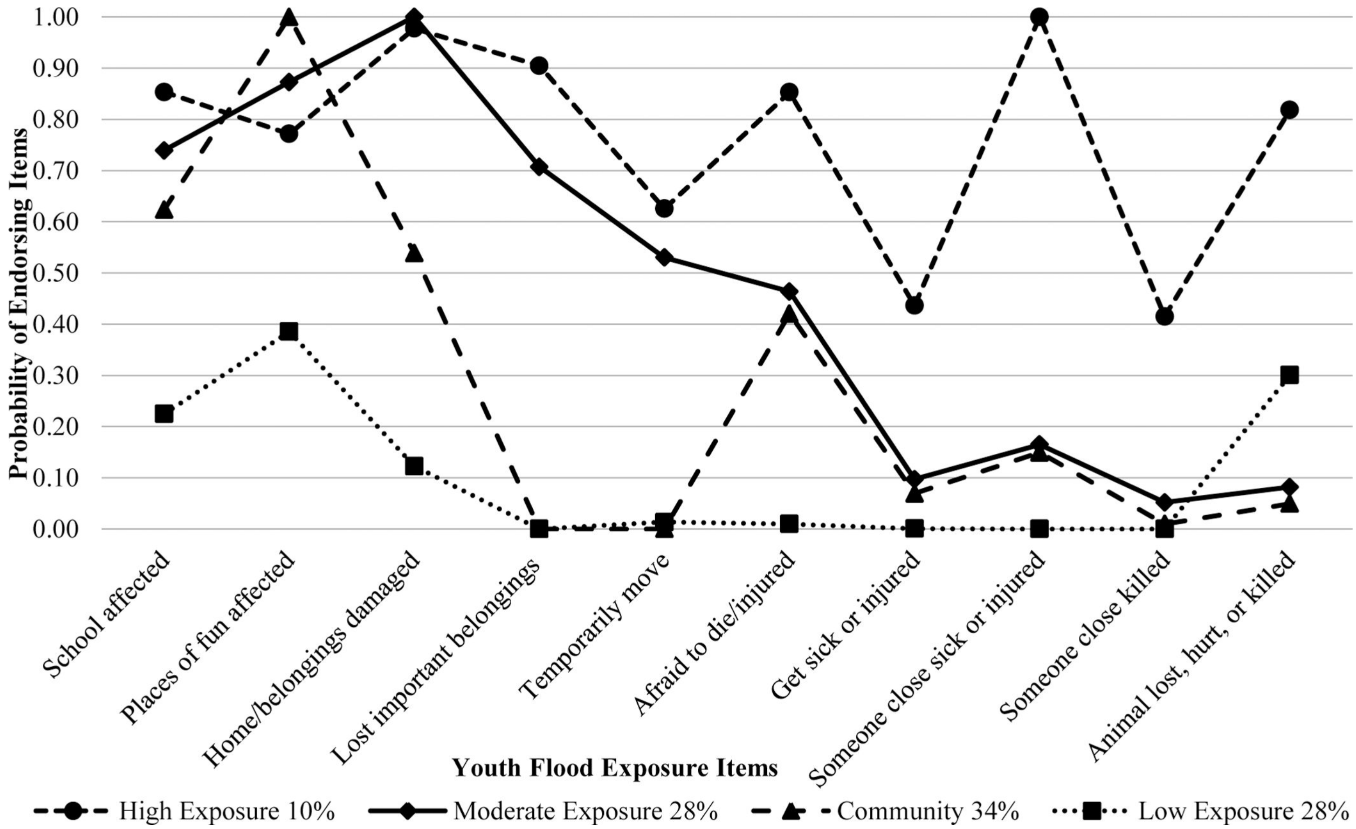

Figure 2.
Item probability plots for youth latent class analysis (LCA) using the flood exposure items.

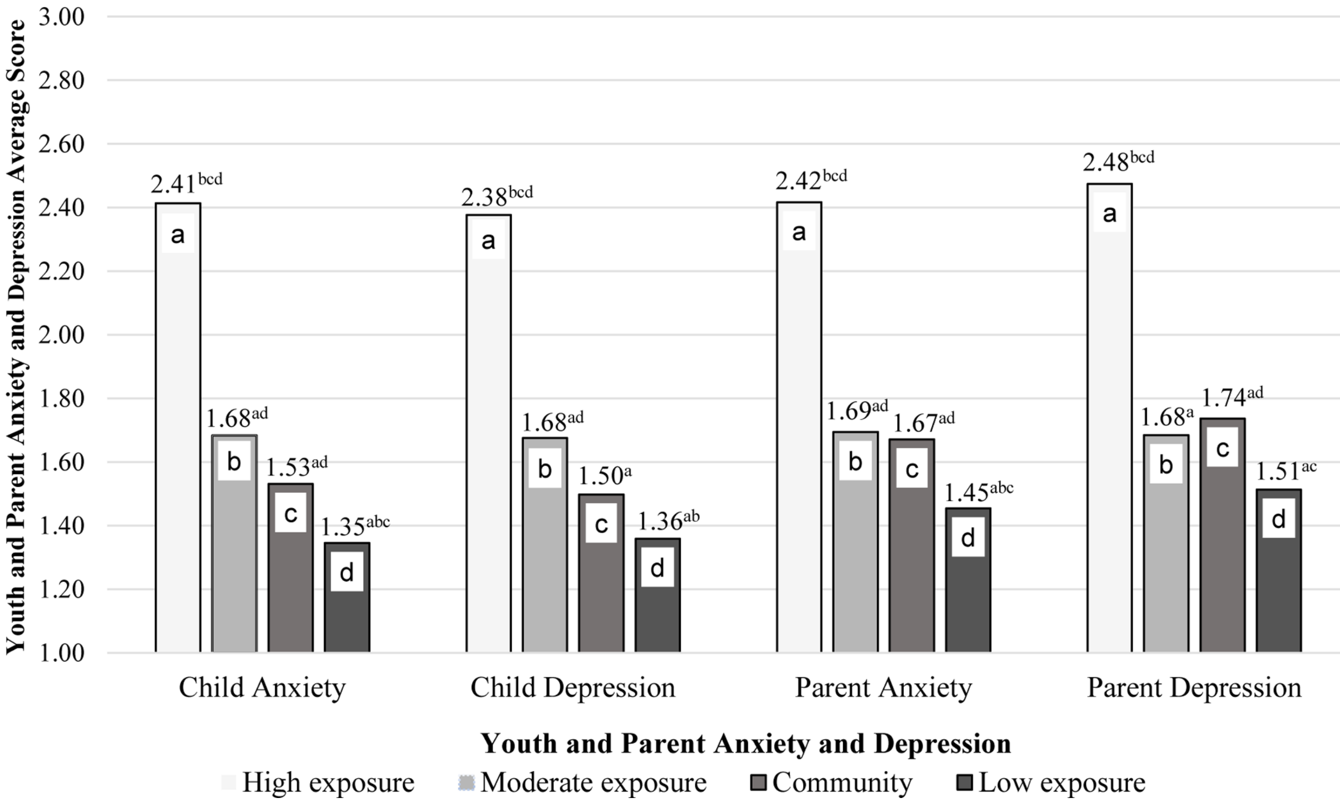

Figure 3.

Youth and parent mental health outcomes by flood exposure classes. Superscripts correspond to the letter on the bars and indicate which classes have distal means that are significantly differences at $p < .05$.

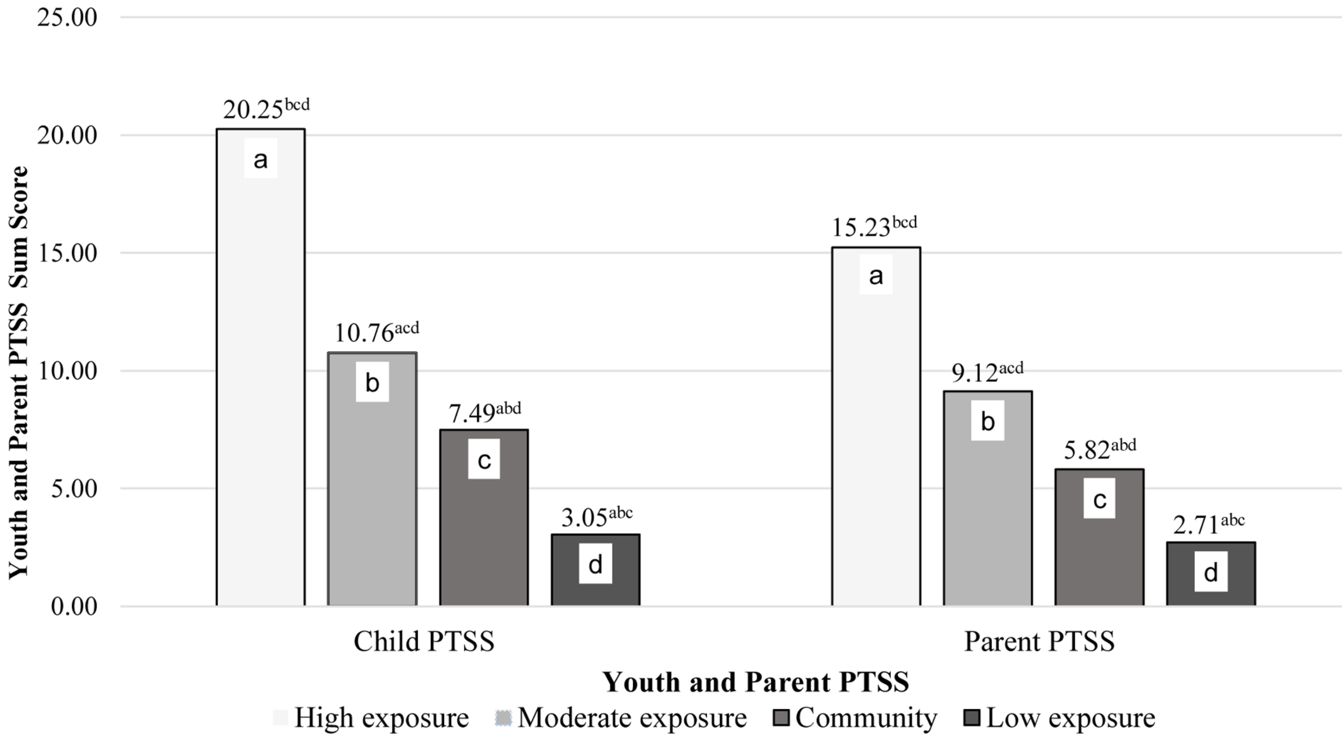

Figure 4.

Youth and parent posttraumatic stress symptom (PTSS) by flood exposure classes. Superscripts correspond to the letter on the bars and indicate which classes have distal means that are significantly differences at $p < .05$.

Table 1

Descriptive Statistics for the Flood Exposure Items and Distal Outcomes

Variable	Parent				Youth			
	n	%	*M*	*SD*	*n*	%	*M*	*SD*
Flood exposure experiences								
Neighborhood was affected	446	80.4			N/A	N/A		
Place of work was affected	306	55.1			N/A	N/A		
Child's school was affected	306	55.1			274	56.4		
Places for fun were affected (e.g., restaurants, parks)	N/A	N/A			374	77.0		
Utility service was lost	315	56.8			N/A	N/A		
Important belongings were lost	N/A	N/A			137	28.2		
Items of sentimental value were damaged/destroyed	157	28.3			N/A	N/A		
Home and belongings were damaged	364	65.6			313	64.4		
Had to move temporarily	153	27.6			101	20.8		
Was afraid of dying or getting injured	183	33.0			190	39.1		
Got sick or injured	62	11.2			45	9.3		
Someone close to them got sick or injured	122	22.0			95	19.5		
Someone close to them was killed	33	5.9			28	5.8		
An animal they love was lost, hurt, or killed	67	12.1			56	11.5		
Experienced financial losses	252	45.4			N/A	N/A		
Mental health outcomes								
Anxiety			1.76	0.69			1.61	0.76
Depression			1.81	0.73			1.59	0.77
PTSS			7.24	7.13			8.47	8.75

Note. PTSS = posttraumatic stress symptoms. N/A indicates item was not asked of that group or not included in the LCA.

Table 2

Results of the MANOVA Comparing Parent and Youth Outcomes Across Quartile Groups of Disaster Exposure

	Youth		Parent	
Outcome and quartile	***M***	***SD***	***M***	***SD***
Anxiety				
Low[a]	1.37	0.53	1.47	0.46
Med[b]	1.42	0.54	1.59	0.59
Moderate[c]	1.48	0.63	1.71[a]	0.61
High[d]	2.09[a,b,c]	0.95	2.09[a,b,c]	0.81
Depression				
Low[a]	1.37	0.54	1.54	0.57
Med[b]	1.37	0.54	1.65	0.63
Moderate[c]	1.47	0.66	1.76	0.71
High[d]	2.08[a,b,c]	0.95	2.12[a,b,c]	0.79
PTSS				
Low[a]	3.22	5.83	3.42	5.04
Med[b]	4.95[a]	6.96	5.06	5.60
Moderate[c]	8.24	7.50	7.07[a]	6.48
High[d]	15.43[a,b,c]	8.72	12.27[a,b,c]	7.44

Note. Superscripts indicate which groups have significant differences at $p < .05$. PTSS = posttraumatic stress symptoms.

Table 3

Fit Information for Parent and Youth Latent Class Analysis Models

Model	Log-likelihood	BIC	ABIC	*p* LMRT	*p* BLRT
Parent LCA Models					
1 class	−3,963.89	8,009.93	7,968.66	-	-
2 class	−3,466.08	7,102.77	7,017.06	< .001	< .001
3 class	−3,358.49	6,976.06	6,845.91	.076	< .001
4 class	−3,309.60	6,966.75	6,792.15	.039	< .001
5 class	−3,274.47	6,984.95	6,765.91	.183	< .001
6 class	−3,248.20	7,020.88	6,757.40	.165	< .001
Youth LCA Models					
1 class	−2,456.28	4,974.50	4,942.76	-	-
2 class	−2,141.86	4,413.64	4,346.99	< .001	< .001
3 class	−2,079.46	4,356.87	4,255.31	< .001	< .001
4 class	−2,045.76	4,357.52	4,221.04	< .001	< .001
5 class	−2,026.27	4,386.60	4,215.21	.107	< .001
6 class	−2,007.90	4,417.89	4,211.59	.030	< .001

Note. BIC = Bayesian information criteria; ABIC = adjusted Bayesian information criterion; BLRT = bootstrapped likelihood ratio test; LMR = Vuong–Lo–Mendell-Rubin likelihood ratio test.