Characterizing the dimensional structure of early-life adversity in the Adolescent Brain Cognitive Development (ABCD) Study

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Abstract

Early-life adversity has profound consequences for youth neurodevelopment and adjustment; however, experiences of adversity are heterogeneous and interrelated in complex ways that can be difficult to operationalize and organize in developmental research. We sought to characterize the underlying dimensional structure of co-occurring adverse experiences among a subset of youth (ages 9-10) from the Adolescent Brain Cognitive Development (ABCD) Study (N = 7,115), a community sample of youth in the United States. We identified 60 environmental and experiential variables that reflect adverse experiences. Exploratory factor analysis identified 10 robust dimensions of early-life adversity co-occurrence, corresponding to conceptual domains such as caregiver substance use and biological caregiver separation, caregiver psychopathology, caregiver lack of support, and socioeconomic disadvantage / neighborhood lack of safety. These dimensions demonstrated distinct associations with internalizing problems, externalizing problems, cognitive flexibility, and inhibitory control. Non-metric multidimensional scaling characterized qualitative similarity among the 10 identified dimensions. Results supported a nonlinear three-dimensional structure representing early-life adversity, including continuous gradients of “perspective”, “environmental uncertainty”, and “acts of omission/commission”. Our findings suggest that there are distinct dimensions of early-life adversity co-occurrence in the ABCD sample at baseline, and the resulting dimensions may have unique implications for neurodevelopment and youth behavior.

Keywords: early-life adversity; dimensions; ABCD Study; psychopathology; cognitive control

Highlights:

- Data-driven methods can elucidate heterogeneity in early-life adversity (ELA)
- ELA could be reduced to 10 dimensions of co-occurrence in a large population-based (i.e., not enriched for adversity) sample of youth
- ELA dimensions of co-occurrence were differentially associated with mental health and cognitive control outcomes
- ELA dimensions of co-occurrence predicted child outcomes in an independent replication sample
- Nonlinear multidimensional representation revealed three continuous ELA gradients

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Exposure to early-life adversity (ELA) is common, with more than half of youth experiencing at least one adverse event prior to age 18 (McLaughlin, 2016; Merrick et al., 2018). It is well established that these adverse experiences can have far-reaching consequences for mental health (Alisic et al., 2014; Copeland et al., 2011; McLaughlin et al., 2012) and cognitive functioning (Hostinar et al., 2012; Mueller et al., 2010). ELA exposures vary qualitatively across a wide range of experiences such as emotional abuse or neglect, caregiver substance use, caregiver separation, and physical abuse or neglect, and these experiences also vary along other key features, such as chronicity, timing, and severity (Cohodes et al., 2021; Ellis et al., 2009; Fox et al., 2010; Gee & Casey, 2015; McLaughlin & Sheridan, 2016; Teicher et al., 2018; Tottenham & Sheridan, 2010). Increasing evidence suggests that different dimensions and features of early-life adversity are associated with unique outcomes (McLaughlin et al 2021; Ellis et al., 2022). However, given the complexity of these factors and the frequent co-occurrence of adverse experiences (Gee, 2021; Smith & Pollak, 2020), it has been challenging to account precisely for heterogeneity in ELA, precluding a clear understanding of how, why, and when ELA shapes brain and behavior across development. Data-driven efforts to characterize the co-occurring nature of ELA is one important approach to advancing this understanding. Given the increasing use and necessity of large-scale developmental neuroimaging studies that often recruit from the general population (e.g., Hoffman et al., 2019; Rosenberg et al., 2018; Somerville et al., 2018), there is clear need to apply these data-driven approaches in community-based samples that are not necessarily enriched for adversity exposure.

Given the wide range of possible adversity exposures and variability across individuals, ELA researchers face challenging decisions about how to meaningfully conceptualize or organize data on these exposures. Rich and heterogeneous data on ELA must be statistically reduced in some way to enhance interpretation and predictive power. To this end, a number of approaches have been adopted to structure ELA data. For example, cumulative risk models capture the summation of adverse experiences across different domains, aggregating all data into an overarching metric of total adversity exposure (Evans et al., 2013; Rutter, 1983). Alternatively, dimensional approaches have sought to identify distinct mechanistic dimensions of adversity (Wade et al., 2022) such as threat and deprivation (McLaughlin et al., 2014), harshness and unpredictability (Ellis et al., 2009), and proximity of experiences (Ellis et al., 2022). Empirical support suggests that different ELA dimensions have at least partially distinct effects on neurodevelopment and child behaviors (McLaughlin et al., 2019; VanTieghem & Tottenham, 2018). However, clearly identifying robust dimensions of adverse experiences is challenging, and it has been argued that researcher-defined, mechanistic dimensions may be ambiguous and can generate conflicting evidence (Pollak & Smith, 2021; Smith & Pollak, 2020). Moreover, real-world occurrences of adversity are multifaceted and co-occur in complicated ways, resulting in highly complex data. Data-driven methods to delineating heterogeneity in ELA may balance the benefits of predominant approaches while emphasizing naturally-occurring patterns of ELA in a given sample (e.g., Hong & Sisk et al., 2021).

Recent work applying data-driven methods, often in samples enriched for significant adversity, has characterized meaningfully distinct ELA dimensions. For example, Nikolaidis et al. (2022) identified three stable dimensions of caregiving-related early adversities in school-age children via factor analytic and machine learning methods. The resulting factors included

"Additive Caregiving-Related Early Adversity Exposure", "Caregiver Emotional Maltreatment without Domestic Violence", and "Physical/Supervisory Neglect". These dimensions transcend traditional socio-legal categories, highlighting the utility of factor analytic methods in characterizing the dimensional nature of ELA. Similarly, Ford et al. (2014) identified a three-factor model in adults who retrospectively reported on ELA exposure. By assessing a wide range of adversities, they identified "Household Dysfunction", "Emotional/Physical Abuse", and "Sexual Abuse" factors, which were validated with confirmatory factor analysis. Similar studies have identified even more dimensions, such as "Parental Absence" (Mersky et al., 2017), "Instability" (Cohen-Cline et al., 2019), "Social Environment" (Zinn et al., 2020), and "Community Adversity" (van Zyl et al., 2022). The variability of these identified dimensions across studies likely stems from a number of factors such as differences in sample ages, ELA measures, and sample size. Large-scale developmental datasets provide an important opportunity to identify stable, population-level dimensions of ELA spanning diverse features of the environment that may be more generalizable.

While prior work has illustrated the promising utility of data-driven approaches to characterizing adversity, much of this work has relied on small or relatively homogenous samples that are often enriched for adversity exposure. Identifying ELA dimensions in a community sample of youth (i.e., not enriched for adversity exposure) is necessary to advance our knowledge about the co-occurrence of ELAs in a 'typically' developing sample, which likely differs from the co-occurrence in high adversity-exposed youth. For example, observed dimensions of adversity may be contingent on the characteristics of a given sample, and patterns of co-occurrence may differ in samples that have especially high adversity exposure, relative to normative, community samples of youth. Identifying stable ELA dimensions in large-scale developmental datasets may also help to facilitate reproducibility across studies and advance our understanding of the developmental sequelae of ELA.

The Adolescent Brain Cognitive Development (ABCD) Study (Casey et al., 2018) offers a valuable opportunity to characterize the nature of ELA in a large and diverse community sample of youth across the United States. With nearly 12,000 participants and measures of environment and experience across different domains, the ABCD Study presents a valuable opportunity to clarify how adverse experiences relate to mental health and cognitive functioning among typically-developing youth. However, these rich data also come with challenging decisions on how to organize and reduce ELA data. Research that thoroughly characterizes co-occurring patterns of adversity in the ABCD Study will help users of this dataset navigate heterogeneity in the data. Furthermore, delineating the dimensional structure of ELA, especially within racially and economically diverse samples such as ABCD, is critical to understanding effects on youth mental health and cognitive functioning. Thus, our primary aims were to 1) characterize dimensions of ELA among youth in the ABCD Study at baseline (ages 9-10), and 2) examine associations between ELA dimensions and youth mental health and cognitive functioning. Given the value of prediction as a complement to explanation in developmental neuroscience (Rosenberg et al., 2018), we also sought to evaluate the degree to which the ELA-behavior associations were reproducible in a separate replication dataset. In addition, it may be useful to understand complex adverse environments by emphasizing the similarity amongst specific ELA exposures as opposed to their co-occurrence, which is a common approach to characterizing bioecological systems in other fields such as environmental science (Kenkel & Orloci, 1986). An exploratory aim, therefore, was to examine the extent to which ELA is characterized by nonlinear environmental gradients based on the similarity (vs. co-occurrence) among specific ELA experiences/items.

Method

Sample

Participants were recruited from 21 sites across the U.S. as part of the ABCD Study (Casey et al., 2018) through presentations and emails delivered to caregivers of youth in local schools. Interested caregivers underwent a telephone screening to determine whether their children were eligible to participate in the study. Participants were excluded if they had MRI contraindications, no English fluency, uncorrected vision or hearing, sensorimotor impairments, major neurological disorders, low gestational age, low birth weight, birthing complications, or unwillingness to complete assessments. Parental consent and assent were obtained from all participants. The current study used the baseline data provided by the ABCD consortium in the fourth annual release (DOI:10.15154/1523041) and included participants with complete data across all ELA measures (excluded N = 2,739). Twins, triplets, and if applicable, one sibling from a family were excluded (N = 2,022) from this analysis to limit multicollinearity. This resulted in a final sample of 7,115 youth (48% female) with a mean age of 9.90 years (*SD* = 0.62). Median household annual income fell between $50,000 and $100,000. Participants identified as Asian (2%), Black (12%), Hispanic (19%), White (56%), and Other Race (11%).

Measures and Variable Selection

Early-Life Adversity

ELA variables were identified from the range of ABCD baseline measures (Barch et al., 2021; Hoffman et al., 2019). A total of 139 potential item-level variables were selected given their relevance to ELA constructs such as caregiving disruption, caregiver psychopathology, maltreatment, neighborhood safety/violence, family/community support, socioeconomic disadvantage, and physical trauma exposure. Responses to these items were reported by the child, their parent, or rated/calculated by research personnel. The items selected for use in the current study are all from validated scales widely used in the literature, though the versions administered by ABCD were modified for some of the scales (Barch et al., 2021; see Table S1). Variables with >50% missing data (e.g., family history of depression) or <0.05% endorsement (e.g., caregiver self-report of clinical inattention problems) were removed. Following procedures from Michelini et al. (2019), in cases where variables had very high intercorrelations (*r*s >.75), conceptually similar variables were aggregated to avoid inflation in the factor structure resulting from high collinearity in the data. Twenty total items were identified as having high intercorrelations with at least one other item (e.g., traumatic event items on sexual abuse by 1) an adult at home, 2) an adult outside the family, or 3) a peer) and were aggregated with highly correlated items to create six different composite scores. In this way, we retained key ELA constructs based on prior work while minimizing potential statistical bias from high collinearity. Following these criteria, 60 total ELA variables were selected for final analysis. See Figure 1 and Table S1 for details on the ELA variable selection process. The final variables included binary, polytomous, and continuous variables. To facilitate interpretation of results, all variables were coded such that higher scores reflected greater adversity.

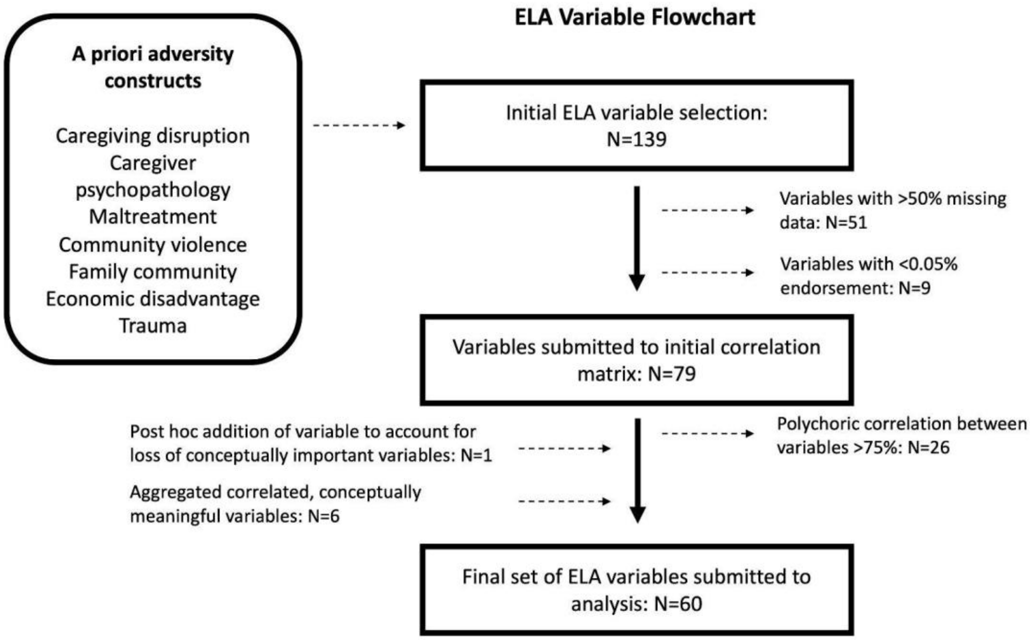

Figure 1. Selection process for early-life adversity variables from the ABCD baseline data

Psychopathology and Cognitive Function

Psychopathology and cognitive function variables were used to assess the associations between ELA dimensions and youth outcomes. Psychopathology variables included T-scores for internalizing and externalizing behaviors from the caregiver-report Child Behavior Checklist (CBCL). The CBCL is a standardized, well-established instrument (Achenbach & Rescorla, 2001) that provides continuous measures of externalizing problems (rule-breaking and aggressive behaviors) and internalizing problems (withdrawn/anxious/depressed behaviors and somatic complaints). Cognitive functioning was assessed using the uncorrected standard composite scores of two tasks from the NIH Toolbox: the Flanker Task and the Card-Sorting Task. The Flanker Task measures inhibitory control and attention, whereas the Card-Sorting

Task measures cognitive flexibility (Thompson et al., 2018; Casaletto et al., 2015). Prior work has found that inhibition and flexibility are two key constructs of executive functioning (Miyake & Friedman, 2012) in which inhibitory control is the voluntary control (inhibition) of goal irrelevant information and responses (Nigg, 2000; Tiego et al., 2018) and cognitive flexibility is the ability to shift a strategy to changing conditions or demands (Dajani & Uddin, 2015). These two domains were chosen for use in the current study given prior work linking ELA to both inhibition and cognitive flexibility domains (Johnson et al., 2021).

Analytic Plan

Aim 1: Identifying ELA dimensions

Analyses were conducted in Mplus version 8.7 (Muthen & Muthen, 2022). The 60 ELA variables were entered into an exploratory factor analysis (EFA), specifying continuous versus binary/categorical variables accordingly, with 1 to 15 possible factors and 10,000 iterations. We used weighted least squares mean- and variance-adjusted estimation (WLSMV). The optimal solution was determined based on 1) model fit statistics (i.e., chi-square, RMSEA, CFI, TLI), 2) number of factors with eigenvalues greater than 1 (Kaiser, 1960), and 3) theoretical and conceptual interpretability. RMSEA values of less than .05 and CFI and TLI values of greater than .95 were considered an excellent fit (Bentler, 1990; Browne & Cudeck, 1992). Next, in order to obtain factor scores, we ran an exploratory structural equation model (ESEM) specifying the number of factors identified in the EFA and with an oblique rotation. Following procedures from Michelini et al. (2019), ELA items were considered meaningful for interpretation of a factor when the loadings were greater than .35.

Supplementary Analysis. Given the possibility that various demographic, clinical, and ELA variables may differ by ABCD site, we repeated the EFA when leaving out one site each time, for a total of 21 supplementary analyses. We compared the factor solutions (i.e., model fits and factor loadings) of each analysis to determine whether the absence of one site changed the factor structure of the analysis.

Aim 2: Associations between ELA dimensions and youth behavior

ELA factor scores were calculated for each participant in Mplus by multiplying the ELA factor loadings from each dimension with the participant's original ELA scores. To test associations between these factor scores and youth outcomes, we conducted a Bayesian multivariate multilevel model with non-informative priors using the *brms 2.16.3* package in R 4.1.2 (Bürkner, 2017, 2018; Carpenter et al., 2017; R Core Team, 2021). Bayesian approaches tend to outperform frequentist approaches and are more likely to reach convergence when estimating many parameters in complex multivariate multi-level models with fixed and random effects (Hackenberger, 2019). Furthermore, Bayesian approaches allow for the discussion of the probability that an alternative hypothesis is true given the available data and prior information (Lecoutre & Poitevineau, 2014). An additional benefit is that future investigations of ELA-behavior links using ABCD data from forthcoming releases will be able to incorporate the current results into a subsequent model as priors (Hackenberger, 2019). After participants with missing psychopathology or cognitive measures were dropped (n = 432), random sampling stratified by study site split the dataset into discovery (70%; n = 4,687) and replication (30%; n = 1,996) sets to examine reproducibility.[1]

All ELA factor scores were included as independent variables (grand mean-centered). The covariates were age (grand mean-centered) and sex (dummy-coded as -0.5 = male and 0.5 = female). Individuals were nested within each study site. The model included internalizing

[1] There were no discovery/replication set differences in age, sex, site distribution, ELA factor scores, or child behavior scores.

behaviors, externalizing behaviors, cognitive flexibility, and inhibitory control as the dependent variables. All variables were scaled (mean-centered and unit variance of 1) to facilitate comparison of effects. Random intercepts and residual correlations were modeled. Models converged using four chains with 2,000 iterations per chain. The models were trained on the discovery set and then used to predict youth behaviors in the independent replication set. Prediction accuracy was assessed with non-parametric Spearman correlations between the predicted and actual youth behavior scores.

Exploratory Aim: Multidimensional ELA Representation

Non-metric multidimensional scaling (NMDS) analysis was conducted to visualize the similarity/dissimilarity of the identified ELA dimensions. This method projects the ELA items in a nonlinear, lower-dimensional space. NMDS preserves the original topology (similarity represented as a distance metric) of the pairwise distances between ELA items. This approach differs from other dimension reduction methods that rotate items to identify linear combinations to maximize the amount of variance explained and minimize the number of items that load onto each dimension (e.g., factor analysis). NMDS analyses were conducted with the *vegan 2.5.7* package (Oksanen et al., 2020) in R 4.1.2 (R Core Team, 2021). ELA items were scaled and Spearman correlation matrices were computed for each participant. Item dissimilarity matrices were computed for each participant and then submitted to Kruskal's NMDS (1964a, 1964b). Inspection of goodness-of-fit indices (i.e., stress and Pseudo-R2) determined the number of dimensions. Stress is a measure of rank-order disagreement between the observed and fitted distances, with lower values indicating that the observed model fits the patterns observed in the raw distance patterns. Pseudo-R2 values reflect the degree to which the NMDS model fits the patterns in the raw data, with higher values indicating stronger fit. Stress values less than .01 and

Pseudo-R2 greater than .80 indicate a good fit between the NMDS solution and actual data, suggesting that we can be confident in the inferences being drawn (Kruskal, 1964a, 1964b). Ordination plots were then generated for the optimal *k*-dimensional model to highlight the similarities between ELA items, such that ELA items that are more similar are closer together on the plot.

Data availability

Data for the ABCD Study are available through the National Institutes of Health Data Archive (NDA; nih.nda.gov). The participant IDs included in these analyses, as well as further details on the measures used, can be found in this project's NDA study (DOI:10.15154/1527711). The scripts and outputs for analyses are included on the Open Science Foundation project for this study at: https://osf.io/28cb7/?view_only=b7789e2eb92d40d290358a5ad623ac65.

Results

Aim 1: Identifying ELA Dimensions

Results from the EFA identified 14 factors with eigenvalues greater than 1. The 1-factor model demonstrated poor model fit ($\chi^2 = 61825.83$, $df = 1710$, $p < .001$, RMSEA = 0.07, CFI = .39, TLI = .37). Model fit improved as the number of factors increased (Table S2) and demonstrated an excellent fit with 10 or more factors (i.e., RMSEA < 0.05, CFI and TLI > .95). Thus, we compared the 10-factor solution ($\chi^2 = 4260.83$, $df = 1215$, $p < .001$, RMSEA = 0.02, CFI = .97, TLI = .96) with the 11-14 factor solutions. The 11-14 factor models were rejected due to limited interpretability (e.g., factors with no significant factor loadings). Thus, when testing the ESEM in order to obtain factor scores, we specified 10 total factors (see Table 1 for factor loadings).

Table 1. *Factor loadings for the ten early-life adversity dimensions*

Early-Life Adversity Variables	Factor 1 Caregiver psycho-pathology	Factor 2 Socio-economic disadvantage and neighbor-hood safety	Factor 3 Secondary caregiver lack of support	Factor 4 Primary caregiver lack of support	Factor 5 Youth report of family conflict	Factor 6 Caregiver substance use and separation from biological parent	Factor 7 Family anger and arguments	Factor 8 Family aggression	Factor 9 Trauma exposure	Factor 10 Lack of supervision
Caregiver ADHD symptoms (CG)	0.720									
Caregiver antisocial symptoms (CG)	0.551									
Caregiver anxiety symptoms (CG)	0.728									
Caregiver avoidant symptoms (CG)	0.704									
Caregiver depression symptoms (CG)	0.910									
Caregiver somatic problems (CG)	0.557									
Caregiver makes feel better when worried* (Y)				0.842						
Caregiver smiles* (Y)				0.581						
Caregiver makes feel better when upset* (Y)				0.775						
Caregiver shows love* (Y)				0.650						
Caregiver easy to talk to* (Y)				0.682						
Secondary caregiver makes feel better when worried* (Y)			0.758							
Secondary caregiver smiles* (Y)			0.597							
Secondary caregiver makes feel better when upset* (Y)			0.772							
Secondary caregiver shows love* (Y)			0.793							
Secondary caregiver easy to talk to* (Y)			0.596							
Household income* (CG)		0.947								
Inability to pay for necessities (rent, food, utilities) (CG)		0.600								
Inability to pay for necessities (healthcare) (CG)		0.473								
Caregiver marital separation (CG)		0.608								
Separation from biological caregiver (CG)						0.668				
Caregiver(s) level of education* (CG)		0.736								
Family fights a lot (CG)							0.500			
Family members rarely angry* (CG)							0.822			
Family throws things when angry (CG)								0.601		
Family hardly loses temper* (CG)							0.805			
Family criticizes each other (CG)								0.517		
Family hit each other (CG)								0.798		
Family keeps the peace* (CG)							0.405			
Family tries to outdo each other (CG)								0.625		
Family does not raise voice* (CG)							0.355			
Family fights a lot (Y)					0.723					
Family members rarely angry* (Y)					0.563					
Family throws things when angry (Y)					0.635					
Family hardly loses temper* (Y)					0.663					
Family criticizes each other (Y)					0.541					
Family hit each other (Y)					0.676					
Family keeps the peace* (Y)					0.364					
Family tries to outdo each other (Y)					0.499					
Family does not raise voice* (Y)										
Father alcohol problems (CG)						0.703				
Father drug problems (CG)						0.797				
Mother alcohol and drug problems (CG)						0.747				
Car accident (CG)									0.448	
Another significant accident (CG)									0.416	
Witnessed or caught in fire (CG)									0.524	
Witnessed or caught in natural disaster (CG)									0.597	
Witnessed terrorism, war zone, or community violence (CG)									0.841	
Physically assaulted or threatened to be killed (CG)									0.772	
Witness domestic violence (CG)						0.422			0.378	
Sexual abuse (CG)									0.673	
Sudden unexpected death of loved one (CG)										
Neighborhood safety* (Y)										
Neighborhood safety* (CG)		0.382								
Caregivers know where they are* (Y)										0.480
Caregivers know who they are with* (Y)										0.605
In contact with caregivers when home alone* (Y)										
Discuss plans with caregivers* (Y)										
Eat dinner with caregivers* (Y)										
Neighborhood area deprivation index (O)		0.522								

Measures

- Adult Self Report
- Child Report of Parent Behavior Inventory
- Parent Demographics Survey
- Family Environment Scale
- Family History Inventory
- Diagnostic Interview for Traumatic Events (KSADS)
- Neighborhood Safety/Crime Survey
- Parental Monitoring Survey
- Residential History Derived Scores

* indicates that the variable was reverse-scored. Y = Youth Report; CG = Caregiver Report.

This model identified ELA factors related to 1) caregiver psychopathology, 2) socioeconomic disadvantage and lack of neighborhood safety, 3) secondary caregiver lack of support, 4) primary caregiver lack of support, 5) child report of family conflict, 6) caregiver substance use and separation from biological caregivers, 7) family anger and arguments, 8) family aggression, 9) physical trauma exposure, and 10) caregiver lack of supervision.

Supplementary Analysis. Results (i.e., factor loadings and model fit statistics) were robust and consistent when we systematically ran the EFA removing one site each time. The factor loadings for each subsample are reported in the Supplementary Material (Table S3).

Aim 2: Associations between ELA dimensions and youth behavior

Figure 2 depicts the posterior distributions of the fixed effects estimating the associations between ELA factor scores and child behaviors in the discovery set (see Table S4-S5 for model parameters and Table S6 and Figures S1-S2 for raw correlations). The model accounted for approximately 30% of the variance in internalizing and externalizing problems (R^2_{int} = .30, 95% *CI* = .28-.32; R^2_{ext} = .29, 95% *CI* = .27-.31) and 10% of the variance in cognitive functoning measures ($R^2_{cog\text{-}flexibility}$ = .11, 95% *CI* = .09-.12; $R^2_{inh\text{-}control}$ = .09, 95% *CI* = .08-.11). As shown in Figure 3, the prediction of youth behaviors from the model generated from the discovery set showed medium-to-large correlations between actual and predicted scores in the independent replication set for internalizing problems (r_s = .54, 95% *CI* = .50-.57, $p < .001$), externalizing problems (r_s = .53, 95% *CI* = .49-.56, $p < .001$), cognitive flexibility (r_s = .31, 95% *CI* = .27-.35, $p < .001$), and inhibitory control (r_s = .26, 95% *CI* = .22-.30, $p < .001$). All ELA dimensions contributed to the significant predictions except for child-reported family conflict and caregiver lack of supervision.

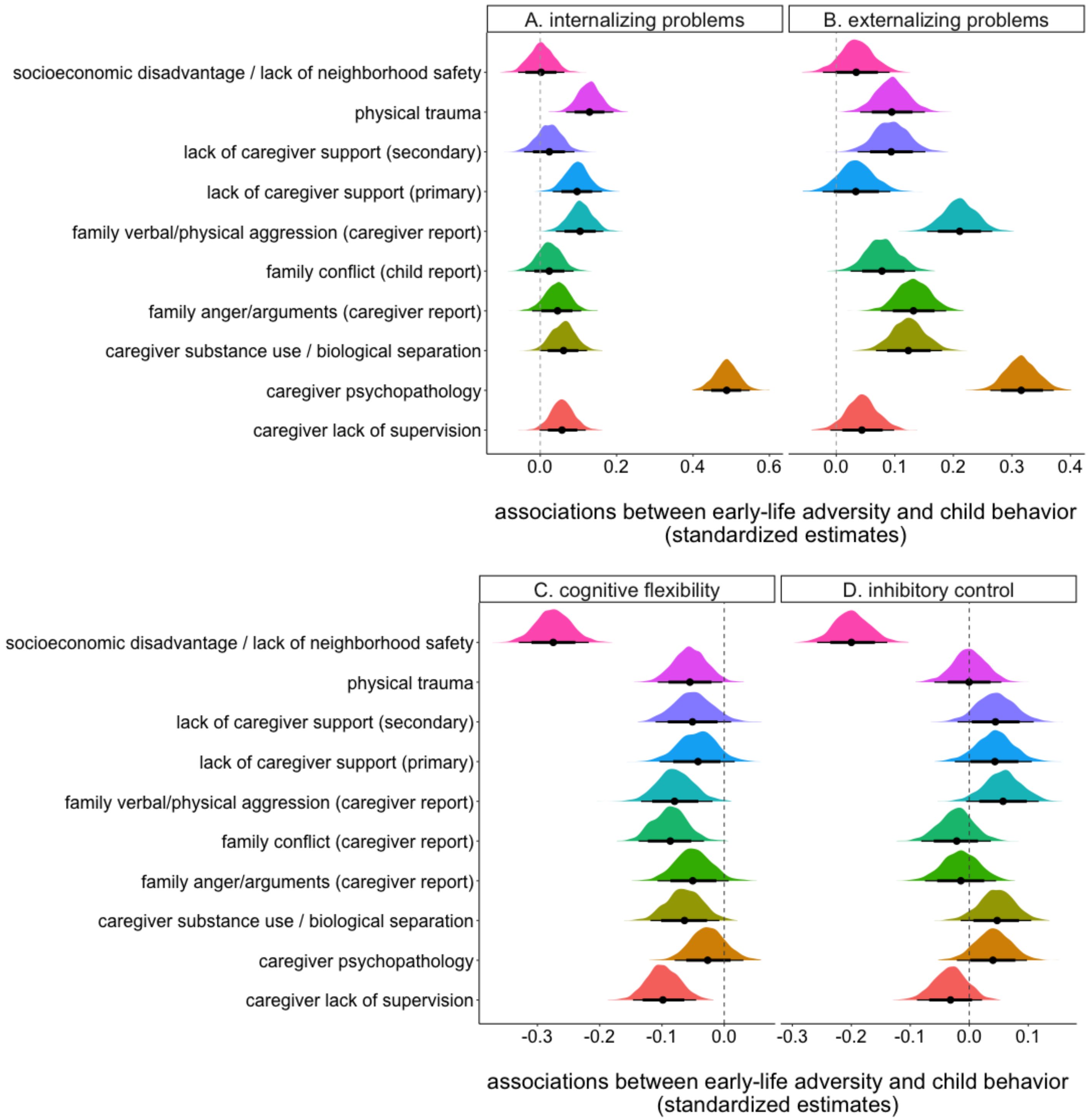

Figure 2. Associations between early-life adversity dimensions and child behaviors were estimated in the discovery set with Bayesian multivariate multilevel models. The x-axis depicts the posterior distributions of the fixed effects estimating the associations between ELA factor scores and child behavior, including A) internalizing problems, B) externalizing problems, C) cognitive flexibility, and D) inhibitory control. The posterior credibility interval suggests that there is a 95% chance of the true value falling between the lower limit and the upper limit given the sample data and a non-informative prior.

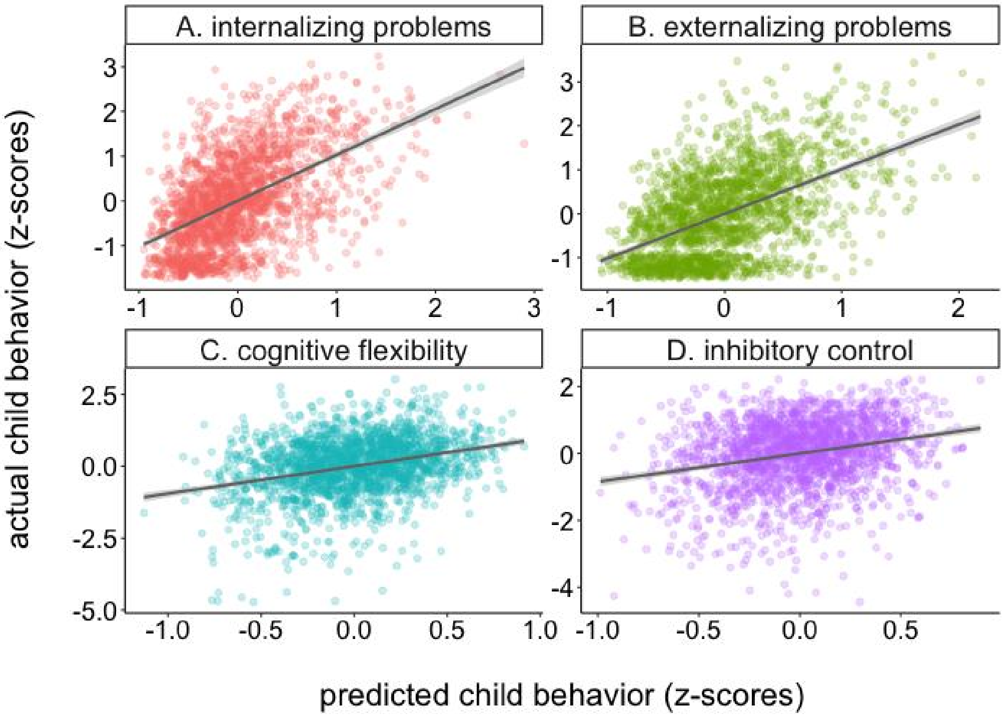

Figure 3. Prediction of youth psychopathology and cognitive performance. Previously unseen youth behavior in the validation set was predicted using only the Bayesian multivariate multilevel models generated in the discovery set. The scatterplots display the Spearman correlations between actual child behavior scores and predicted scores in the independent validation set for A) internalizing problems, B) externalizing problems, C) cognitive flexibility, and D) inhibitory control.

The vast majority of associations between ELA dimensions and youth behavior were consistent across the discovery and replication sets. Higher levels of caregiver psychopathology and physical trauma exposure were associated with higher internalizing *and* externalizing problems, but were not associated with cognitive control measures. Higher levels of socioeconomic disadvantage/lack of neighborhood safety were uniquely associated with lower cognitive flexibility and inhibitory control; there was no association with either internalizing or externalizing problems. Lack of support from a primary caregiver was associated only with more internalizing problems but not other child behaviors, whereas lack of support from a secondary caregiver, family anger/arguments, family verbal/physical aggression, and caregiver substance use / biological caregiver separation were associated only with more externalizing problems (and not other child behaviors). The associations for child-reported family conflict and caregiver lack of supervision observed in the discovery set were not observed in the independent replication set.

Exploratory Aim: Multidimensional ELA Representation

The three-dimension NMDS solution provided a very good fit to the data (stress = .08; Pseudo-R^2 = .99; Figure 4), which was better than the one- and two-dimension solutions (1-D: stress = .28; Pseudo-R^2 = .92; 2-D: stress = .15; Pseudo-R^2 = .98; Figure S3). A four-dimension solution was considered and fit the data very well (stress = .06, Pseudo-R^2 = .99). The three-dimension solution was retained for parsimony given that the four-dimension model only provided a marginal improvement. Results of permutation testing (k = 10,000) indicated that all ELA items contributed to at least one dimension beyond what would be expected due to chance.

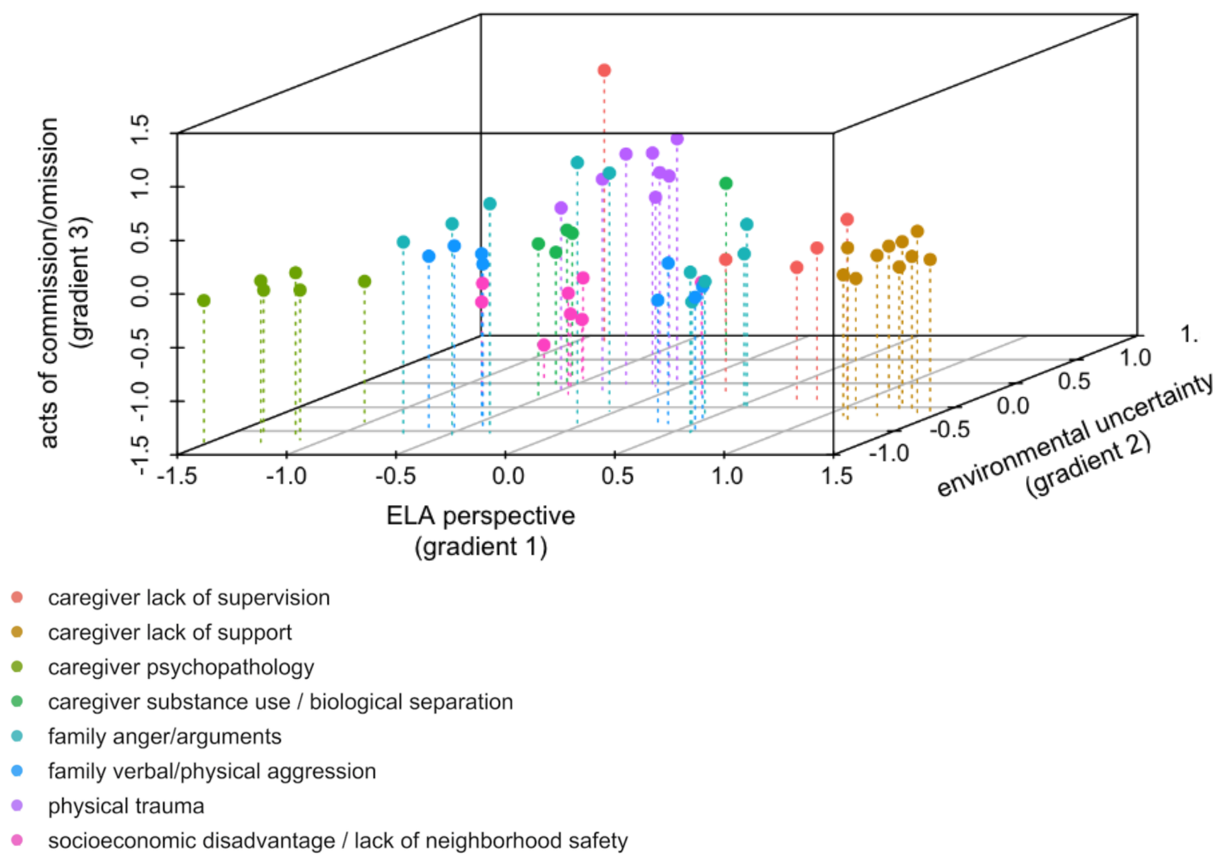

Figure 4. Nonlinear, three-dimensional structure of early-life adversity gradients. The similarities between early-life adversity (ELA) items were derived from non-metric multidimensional scaling (NMDS) in the discovery set, and were projected to a three-dimensional space. Each point depicts an ELA item, and the colors represent eight of the ELA factors. Note: only eight different labels could be used for visualization with the R package, so conceptually similar dimensions were combined under one color label for visualization purposes (e.g., primary and secondary caregiver lack of support factors). When the topography (similarity represented as a distance metric) of ELA items was preserved through NMDS, three supraordinate gradients composed of ELA items spanning ELA factors were identified. The interpretation of the nonlinear ELA gradients should be considered preliminary and tentative.

Figure 5 depicts a tentative, preliminary interpretation of the underlying ELA constructs that the three dimensions may represent.[2] Dimension 1 was characterized as “perspective” because positive values along this dimension consisted of the youth report measures, negative values consisted of the caregiver report measures, and scores near zero were data derived from interviews by trained research personnel. Dimension 2 was characterized as “environmental uncertainty”. Higher, positive values on dimension 2 consisted of physical trauma, socioeconomic disadvantage, lack of neighborhood safety, caregiver lack of supervision, caregiver substance use, and biological caregiver separation. By contrast, negative values on dimension 2 were characterized by more family conflict and caregiver psychopathology. High dimension 2 scores were characterized by unexpected and unpredictable experiences that may be more episodic (e.g., biological caregiver separation, physically traumatic events), whereas low dimension 2 scores were distinguished by volatile environments that may be experienced more consistently (e.g., caregiver psychopathology, family verbal/physical aggression). Finally, dimension 3 was characterized as “acts of commission versus omission”, because higher, positive scores were indicative of physical trauma and family verbal/physical aggression and lower, negative scores were distinguished by socioeconomic disadvantage (e.g., lack of physical resources) and lack of neighborhood safety, caregiver supervision, and caregiver support.

[2] Comparable dimensions were identified when examining the caregiver and child reports separately.

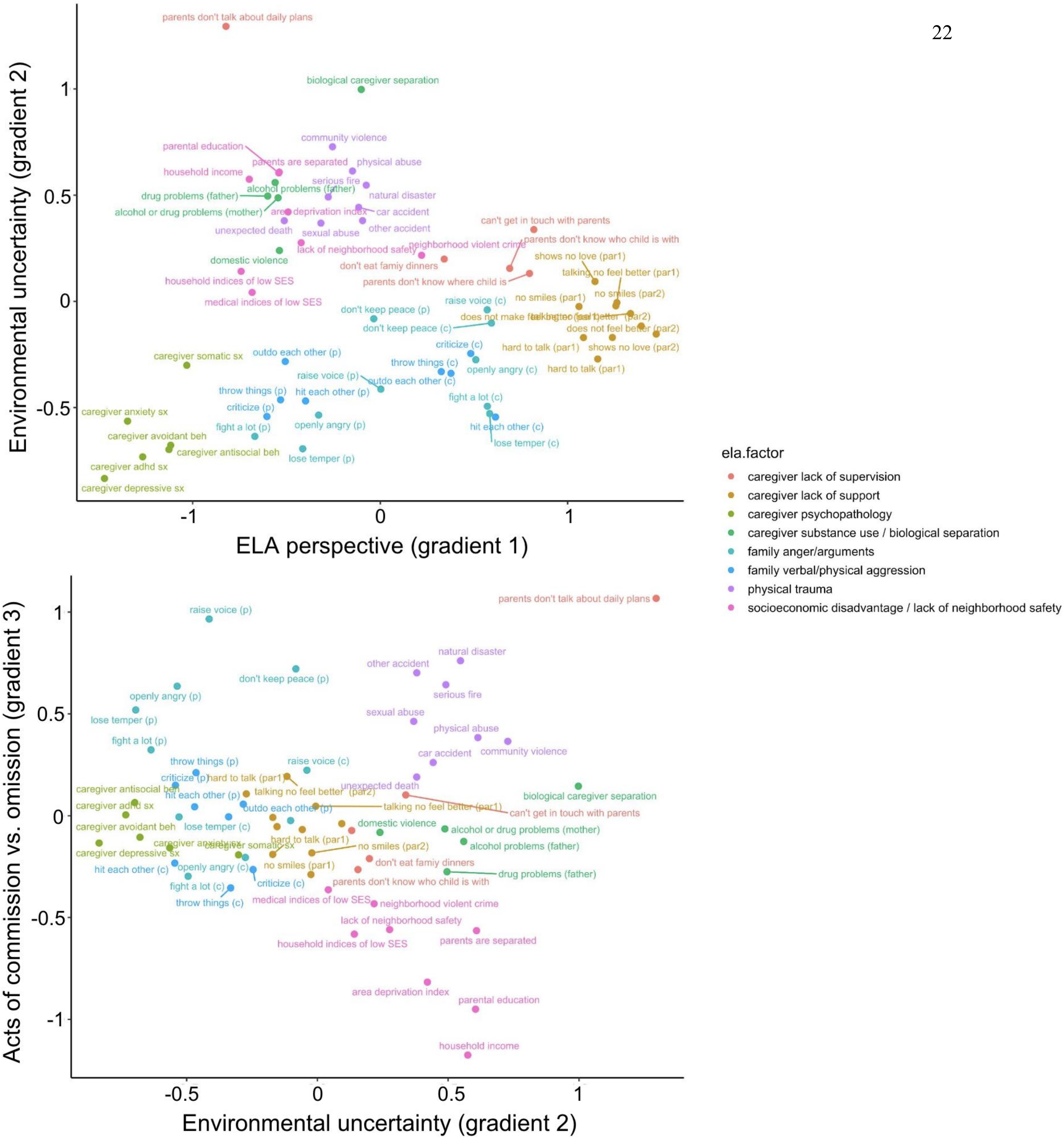

Figure 5. Decomposition of early-life adversity (ELA) gradients. The similarities between ELA items were derived from non-metric multidimensional scaling in the discovery set, and were projected to two-dimensional spaces to facilitate qualitative interpretation. Each point depicts an ELA item and the colors represent ELA dimensions derived from the factor analysis. The interpretation of the nonlinear ELA gradients should be considered preliminary and tentative.

Discussion

We leveraged a data-driven approach with a large, diverse community sample (i.e., not enriched for adversity exposure) of youth to parse heterogeneity in early-life adversity. Using EFA and ESEM approaches, we identified 10 dimensions of adversity co-occurrence pertaining to 1) caregiver psychopathology, 2) socioeconomic disadvantage and lack of neighborhood safety, 3) secondary caregiver lack of support, 4) primary caregiver lack of support, 5) child report of family conflict, 6) caregiver substance use and biological separation, 7) family anger and arguments, 8) family aggression, 9) trauma exposure, and 10) caregiver lack of supervision. These ELA dimensions were associated with distinct behavioral correlates and robustly predicted youth behaviors in an independent replication set, highlighting the utility of these dimensions for characterizing developmental outcomes following ELA exposure. Finally, we also demonstrated that naturally co-occurring patterns of ELA could be represented by more complex nonlinear gradients, rather than linear orthogonal dimensions.

Delineating the vast heterogeneity in adverse early life experiences has historically been challenging, but is a necessary step in understanding neural and psychological development. Small samples, complex data structures, and limited measures of experience have all precluded clear conclusions regarding how ELAs may naturally co-occur, especially in broader community samples that are not enriched for ELA. We capitalized on “big data” from the ABCD Study and data-driven techniques to address some of these limitations and characterize a broad spectrum of ELA dimensions in a normative, community sample. These types of large-scale developmental datasets with wide-ranging variables often require more complex methods. For example, we used ESEM to handle the varied measurement types and skewed distributions inherent to many ELAs in the context of a national sample. Results from these models indicated that a 1-factor solution had poor model fit, supporting the idea that statistical approaches that aggregate all ELAs into one variable may not reflect the actual co-occurrence among ELAs (Brumley et al., 2019). Rather, in this sample, a stable 10-factor solution was identified based on model fit and interpretability of the factors. The number of dimensions we identified was considerably higher than prior work identifying 3-4 dimensions (Ford et al., 2014; Nikolaidis et al., 2022), consistent with evidence that more factors and more complex solutions emerge as wider ranges of ELAs and more items are considered (Mersky et al., 2017).

The identified ELA dimensions shed light on which experiences are likely to co-occur for a child and may facilitate future inquiries into the neurodevelopmental mechanisms through which ELAs relate to child behavior. Nearly all of the ELA dimensions reflect experiences that disrupt caregiver-child relationships or result in the absence of stable and/or safe caregiving, given the many caregiving-related measures that are included in the ABCD Study. One ELA dimension reflected co-occurrence of caregiver substance use and child separation from biological caregivers, perhaps stemming from child custody issues related to caregiver substance use disorders or substance-related arrests (Freisthler & Weiss, 2008). ELA dimensions that indicated the potential presence of caregiver-related emotional maltreatment (i.e., family verbal/physical aggression, family conflict, caregiver lack of support, caregiver substance use / biological caregiver separation) did not load with ELA items related to physical trauma and/or lack of caregiver supervision. These findings are consistent with prior studies identifying caregiver-related emotional maltreatment as a unique dimension that has distinct phenomenology from physical abuse, physical neglect, or supervisory neglect (Lambert et al., 2017; Matsumoto et al., 2020; Nikolaidis et al., 2022). Insufficient caregiver emotional support and supervision also had distinct developmental correlates, with internalizing and externalizing problems being linked only to lack of caregiver support. The reproducibility and out-of-sample predictive value of these associations provide an empirical justification for continued examinations into dimensions of caregiver-related emotional maltreatment.

One ELA dimension did not directly relate to the caregiver-child relationship, which included family socioeconomic factors (income, education, ability to pay for necessities), neighborhood safety, and the Area Deprivation Index (an approximation of neighborhood socioeconomic disadvantage; Kind & Buckingham, 2018). The presence of this dimension suggests that socioeconomic factors across multiple levels of a child's environment may converge, consistent with evidence that family and neighborhood socioeconomic factors are interrelated (Strickhouser & Sutin, 2020). Families living in lower socioeconomic status neighborhoods are also exposed to more harms, such as interpersonal violence (Chong et al., 2015), and are more likely to have concerns about neighborhood safety (Meyer et al., 2014). Consistent with these reports, our results showed that neighborhood socioeconomic disadvantage and neighborhood safety clustered together. Prevailing dimensional theories posit that experiences of physical deprivation linked to poverty (e.g., lack of physical/financial resources) are associated with distinct neural mechanisms and behaviors than community violence exposure (McLaughlin et al., 2014). Our findings suggest that, at least in some samples, it may be challenging to disentangle the developmental sequelae of these experiences given their natural co-occurrence. Of note, higher scores on this dimension were associated with poorer cognitive control and had the largest influence on out-of-sample predictions of cognitive control, but were related to fewer internalizing problems and had no link to externalizing problems. The cognitive control findings may be consistent with observations that smaller cortical volumes and greater cortical thinning are linked to both socioeconomic disadvantage and neighborhood violence

(Butler et al., 2018; Machlin et al., 2019; Miller et al., 2022; Noble, 2015; Whittle et al., 2017). Taken together, these results suggest that future studies seeking to understand social and economic influences on children's cognitive development would benefit from consideration of both family-level and community-level factors, including perceptions of safety and violence.

While the specific dimensions of co-occurrence that were identified align in part with existing theoretical and empirical work, there are also important differences that may be attributed to the goal of dimension reduction, the breadth of the measures used, and the nature of the sample. Namely, a large portion of this theoretical and empirical work has been derived from samples that have been enriched for significant adversity, such as early institutional care or caregiving adversity (McLaughlin et al., 2014; Nikolaidis et al., 2022). The dimensional structure and heterogeneity in experiences may vary in the broader population, as we sought to investigate here with the community sample of youth in the ABCD Study. This area of work will benefit from testing predictions from dimensional models and evaluating heterogeneity in adversity across a wide range of contexts, cultures, and experiences to identify areas of convergence or divergence.

Given the complex relationships between ELA and child development, no single approach is likely to fully capture this complicated and dynamic system. The linear "simple structure" of ELA dimensions derived from factor analysis provides one means of representing experiential heterogeneity. Results further indicated that nonlinear multidimensional representations prioritizing the similarity (pair-wise distances) amongst ELAs (rather than their co-occurrence) may be a useful approach. This representation accounted for more variability in ELA patterns than other data-driven approaches to dimension reduction, and the complex dimensional structure was replicated in an independent sample, suggesting some stability. The three nonlinear and interacting ELA gradients transcended the different ELA measures, revealing underlying constructs tentatively interpreted as 1) ELA perspective (who is observing and reporting on children's experiences); 2) environmental uncertainty (ranging from highly unpredictable, episodic events such as biological caregiver separation to more consistently volatile home environments) (Ellis et al., 2009); and 3) acts of commission (presence of distressing events) versus omission (absence of enriching experiential inputs) (Humphreys & Zeanah, 2015). Overall, the continuous, nonlinear nature of the ELA gradients may align well with an integrative topological conceptualization of ELA as depending on a range of adverse event features, aspects of proximal and distal environments, and contextual factors that dynamically shape children's experiences of their early environments (Cohodes et al., 2021; Pollak & Smith, 2021; Smith & Pollak, 2020).

Although thoughtfully considered, the researcher-imposed, suggested interpretations of the ELA gradients do not preclude other plausible interpretations. The ELA perspective gradient (gradient 1) may in part be driven by shared method variance. However, it is unlikely that this dimension is solely the result of this methodological artifact, as sensitivity analyses estimating the models with parent and child report data separately identified a comparable ELA perspective gradient distinguished by subjective (e.g., child report of family violence) and objective perspectives (e.g., demographic indices of poverty). The role of subjective (vs. objective) perceptions in ELA is an active area of inquiry, with theoretical reasons to expect meaningful variation in child developmental outcomes as a function of who is making the report (Baldwin & Degli Esposti, 2021; Danese & Widom, 2020; Smith & Pollak, 2020). With regard to the environmental uncertainty gradient (gradient 2), higher scores included indicators of SES that could instead be interpreted as more stable or chronic influences (e.g., parental education, household income), rather than unpredictable events in the child's proximal home environment. However, this part of the gradient also included related yet distinct factors such as community violence and caregiver separation. Collectively, we interpreted these factors as possible indicators of uncertainty in physical aspects of the environment that could be construed as discrete, acute events that occur unpredictably. An alternative interpretation is that gradient 2 may capture experiences that are more closely linked to socioeconomic disadvantage (such as community violence, parental substance abuse, physical abuse), ranging to experiences that are equally likely to occur at any point of the socioeconomic stratum (such as verbal emotional abuse or caregiver internalizing and externalizing problems). Future work that seeks to extend this environmental gradient approach with the inclusion of other indices of environmental uncertainty would be valuable.

The results should be interpreted in the context of several limitations. First, while the ABCD Study indexes a range of early experiences, there are nonetheless numerous experiences that are unaccounted for (e.g., caregiving instability, caregiver incarceration, identity-based discrimination) that may have further differentiated ELA dimensions. Relatedly, information on key ELA features such as timing, severity, predictability, and chronicity were not available. Non-human animal models and smaller human samples enriched for ELAs that allow for deeper phenotyping of early life experiences are a crucial complement to large-scale developmental datasets for identifying developmental mechanisms. Second, because of the nature of the measures that are included in the ABCD Study, many of the items clustered together based on the measure that they were part of. Thus, it is possible that the identified dimensions were, in part, artifacts of the measurements used in this particular study rather than "real world" patterns of co-occurrence. We sought to minimize researcher bias in characterizing adversity dimensions by applying a data-driven approach, but findings are nonetheless constrained by the measures that are included in a battery, as well as the concepts of adversity that researchers have in mind when measures are developed. Refined assessment approaches that minimize researcher preconceptions and maximize individuals' lived experiences may further strengthen this area of work. At the same time, we note that not all items clustered simply based on measure; for example, the socioeconomic disadvantage and lack of neighborhood safety factor included items spanning several different measures, including the demographic interview, neighborhood safety questionnaire, and area deprivation index. Additionally, in the associations between the ELA dimensions and youth behavior, we were unable to account for important factors such as heritability of psychopathology and parent reporting styles or biases, which may have also contributed to the observed effects. Furthermore, these were cross-sectional analyses; however, the application of predictive modeling provided an important opportunity to establish the specificity and generalizability of ELA dimension-behavior associations. Future work will be necessary to clarify the temporal associations between ELA dimensions and youth outcomes and to evaluate possible neurobiological mechanisms. Despite these limitations, our results extend and strengthen prior work by incorporating a wide range of variables, multiple informants, and a large diverse community sample of youth. Furthermore, by using a multivariate multi-level model with all ELA dimensions simultaneously, we accounted for the covariation of ELA dimensions. One major challenge for disentangling the complex relations between ELA experiences and child behaviors is the frequent co-occurrence among ELAs. When examining bivariate correlations (not accounting for covariation among ELA dimensions), most dimensions were associated with higher internalizing and externalizing problems as well as poorer cognitive control. However, only certain effects held after accounting for the covariation between ELA dimensions as well as the covaration between child outcomes. This pattern of findings highlights the importance of assessing a broad range of ELA experiences in order to understand more precise associations with neurobehavioral outcomes.

Here, we demonstrate that data-driven ELA dimensions of co-occurrence and more complex nonlinear gradient structures can facilitate characterization of experiential domains and parse the substantial heterogeneity in early experiences. This study is the first to clarify the interrelationships among exposures to early adverse in the ABCD Study sample, a critical step in delineating how, why, when, and which wide-ranging ELAs impact youth development. These findings will directly facilitate planned follow-up analyses linking ELA with neuroimaging metrics of structural and functional brain development in the ABCD Study. Given the breadth of the ABCD Study data, ELA researchers are faced with challenging decisions about how to treat these data and incorporate them into analyses in a comprehensive yet parsimonious way. The results of our analyses suggest 10 different domains of co-occurring adversities that may be important to consider within the ABCD sample at baseline, and in other community samples. By applying the factor scores generated for each of these 10 domains, researchers can further delineate the effects of ELA on neurodevelopmental and behavioral outcomes of interest, thereby increasing standardization and reproducibility of ELA-related research within the ABCD Study.

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