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Regular Article

Cognitive difficulties following adversity are not related to mental health: Findings from the ABCD study

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Abstract

Early life adversity is associated with differences in cognition and mental health that can impact on daily functioning. This study uses a hybrid machine-learning approach that combines random forest classification with hierarchical clustering to clarify whether there are cognitive differences between individuals who have experienced moderate-to-severe adversity relative to those have not experienced adversity, to explore whether different forms of adversity are associated with distinct cognitive alterations and whether these such alterations are related to mental health using data from the ABCD study ($n = 5{,}955$). Cognitive measures spanning language, reasoning, memory, risk-taking, affective control, and reward processing predicted whether a child had a history of adversity with reasonable accuracy (67%), and with good specificity and sensitivity (>70%). Two subgroups were identified within the adversity group and two within the no-adversity group that were distinguished by cognitive ability (low vs high). There was no evidence for specific associations between the type of adverse exposure and cognitive profile. Worse cognition predicted lower levels of mental health in unexposed children. However, while children who experience adversity had elevated mental health difficulties, their mental health did not differ as a function of cognitive ability, thus providing novel insight into the heterogeneity of psychiatric risk.

Keywords: adolescent; adversity; childhood; cognition; mental health

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Introduction

Most extant research suggests that early life adversity (ELA) – such as growing up in poverty or experiencing maltreatment – alters cognitive development (Machlin et al., 2019; Rosen et al., 2020; Slopen et al., 2013) and increases the risk of lifelong mental health difficulties (Copeland et al., 2018; Green et al., 2010). Three theoretical approaches guide our current understanding about how adverse childhood experiences affect development. Specificity models assume that different forms of exposure alter development through distinct pathways (e.g., Heim et al., 2013; St Clair et al., 2015); cumulative risk models focus less on the type of exposure and instead on the number of exposures, assuming that all stressors and events have similar effects (Berman et al., 2022; Evans et al., 2013); and dimensional models share elements of both approaches, splitting exposures into broad theoretically-driven categories that are linked to different outcomes (e.g., McLaughlin & Sheridan, 2016). While informative, these frameworks are difficult to reconcile with high rates of co-occurrence across different types of adversity (Kessler et al., 1997) and with high levels of variability among exposures and outcomes (McLaughlin et al., 2021). Each account has also been inspired and supported by particular methodological approaches that are hard to tease apart from the theoretical conclusions they were designed to support (Bignardi et al., 2022).

Data-driven methods are increasingly popular for exploring links between early environmental risks and developmental outcomes (e.g., Bignardi et al., 2022; Carozza et al., 2022; Dalmaijer et al., 2023; Sheridan et al., 2020). These complement experimental approaches and are free from a priori assumptions about the associations that might exist between exposures and outcomes. In the current study we adopt one such approach, hybrid machine learning (Feczko et al., 2018), to explore whether different forms of adversity are associated with shared or distinct alterations in cognitive function among children who have experienced moderate-to-severe adversity (classified as two or more exposures), and whether any such alterations are related to differences in mental health.

Impact of early adversity on cognitive development and mental health

Cognitive abilities are typically reported as lower among children who have experienced ELA relative to those who have not experienced ELA (Sheridan & McLaughlin, 2016; Slopen et al., 2013). For example, physical or emotional abuse and domestic violence have been associated with difficulties in a broad range of cognitive functions including receptive and expressive language skills, cognitive control, IQ, verbal memory, and affective information processing (Dannehl et al., 2017; Delaney-Black et al., 2002; McLaughlin & Lambert, 2017). Children

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growing up in poverty also tend to exhibit greater cognitive difficulties on measures of attention, language, and reasoning skills, possibly due to lower levels of cognitive and psychosocial stimulation (Gur et al., 2019; McLaughlin et al., 2017; Noble et al., 2007; Sheridan & McLaughlin, 2016).

Exposure to neglect, violence or maltreatment are associated with elevated levels of mental health difficulties in childhood and adolescence (Burkholder et al., 2016; LeMoult et al., 2020), and rates of psychiatric disorders in adulthood are higher among those who have experienced ELA (Arnow, 2004; Juruena et al., 2020; Kessler et al., 2010). It has been hypothesized that adversity-related changes in the neural systems involved in impulse control and emotion-regulation disrupt the ability to deal with future stressors, rendering individuals who have experienced ELA more susceptible to mental health difficulties in later life (Teicher & Samson, 2016; Tooley et al., 2021). For instance, stress-induced changes in connectivity between prefrontal and limbic regions may impact on cognitive processes involved in controlling and regulating emotional responses in challenging situations, including risk-taking, processing threat-related information, and reward sensitivity (Gur et al., 2019; Hanson et al., 2017; Herzberg & Gunnar, 2020; McLaughlin & Lambert, 2017; Mehta et al., 2010).

Challenges of understanding the impact of early adversity

It remains unclear whether different forms of adversity – such as chronic poverty or parental maltreatment – alter cognition in distinct ways (Gee et al., 2013; Gur et al., 2019; Tottenham & Sheridan, 2010). This is, in part, a consequence of the different theoretical approaches adopted to capture adverse experiences, and the methods used to test these theories. Specificity models assume that distinct categories of exposure alter development in distinct ways. For example, emotional abuse/neglect has been specifically linked to cognitive performance that increases risk for depression (Gibb et al., 2007; Rose & Abramson, 1992; Spinhoven et al., 2010). While such models attempt to provide mechanistic accounts, they fail to capture high rates of co-occurrence among different types of adversity (Asmussen et al., 2020; Kessler et al., 1997; McLaughlin et al., 2021). These co-occurrences make measuring specific effects in observational data difficult (Bignardi et al., 2022). Cumulative risk models, in contrast, do not differentiate between the type, chronicity, or severity of exposure, under the assumption that all stressors and events act together through accumulating stress (e.g., Berman et al., 2022; Evans et al., 2013). The assumption that all adversities influence development via shared and homogenous pathways fails to account for divergent effects that may be linked to specific types of exposure (e.g., Kuhlman et al., 2017; McLaughlin & Lambert, 2017). Finally, dimensional models split exposures into broad theory-driven categories that are then examined in relation to different outcomes. For example, the threat vs deprivation model advances that threat-related experiences (i.e., trauma or abuse) lead to alterations in cognitive processes involved in stress and threat response and emotion processing, whereas deprivation (i.e., lack of cognitive stimulation or material resources) leads to more general difficulties in cognition (McLaughlin & Lambert, 2017; McLaughlin & Sheridan, 2016). Although dimensional models sit between specificity and cumulative risk models, the tendency to group categories that appear too specific into a smaller number of theory-driven dimensions, before implementing them as predictors of outcomes, fails to accommodate complex relationships that might exist between different forms of adversity and different outcomes (Carozza et al., 2022). Indeed, all three models make *a priori* assumptions about the structure of adverse experiences and their impact on outcomes of interest. As such, their theoretical conclusions are constrained by the classification model used to test them and cannot be disentangled from this methodological choice (see Bignardi et al., 2022 for a discussion).

A further complication is that many studies assume ELA results in negative outcomes, despite evidence that cognitive alterations and mental health difficulties may not align in individuals who have experienced ELA (Teicher & Samson, 2013a, 2013b, 2016). While some adversity-related changes in cognitive control and socio-emotional processing may contribute to an increased risk for mental health difficulties (e.g., LeMoult & Gotlib, 2019; Millan et al., 2012), they may also be adaptive under conditions of high stress or unpredictability (Belsky et al., 2012; Snell-Rood & Snell-Rood, 2020).

Current study

Data-driven methods are an increasingly popular approach for exploring how early adversity impacts on later outcomes. These circumvent the need for *a priori* assumptions about the categorical structure of adversity. Recent studies have used network approaches and canonical correlations in this way (e.g., Bignardi et al., 2022; Carozza et al., 2022; Dalmaijer et al., 2023; Sheridan et al., 2020). Alternative machine-learning methods, such as Random Forest (RF), may be particularly suited to this problem as they are able to capture complex non-linear interactions between variables in the context of a large number of predictors – something that may be missed with traditional parametric statistical approaches and predictive models (Qi, 2012). RF iteratively constructs a series of decision trees to classify individuals on a prespecified question of interest (i.e., whether an individual has experienced adversity) using a set of input features (i.e., cognitive function; Feczko et al., 2018). In this "wisdom of the crowd" method, each tree casts a predicted classification vote based on the input data fed to the model to determine the predictive value of input features (e.g., cognition) for the classification question at hand (e.g., experienced adversity or not; Breiman, 2001).

In this study we adopted a hybrid machine-learning approach that combined supervised RF classification with hierarchical clustering to explore whether differences in cognitive function were related to having experienced moderate-to-severe ELA. This hybrid approach is better suited to identifying cognitive profiles tied to experiences of childhood adversity than traditional clustering methods because the clustering is based on similarities between participants across features of cognition that have already been identified by the RF model as important for classifying whether a person has experienced ELA (for a detailed overview of this method see: Feczko et al., 2018; Feczko & Fair, 2020). Clustering is therefore less likely to be driven by demographic factors such as age or gender, or by cognitive variables that are not linked to adversity.

Using this approach, we tested: (1) whether cognitive ability could accurately classify children as having experienced either moderate-to-severe adversity or no adversity; (2) whether different forms of adversity were associated with shared or distinct cognitive profiles among those who had experienced moderate-to-severe adversity; and (3) how cognitive function was related to mental health in youth without a history of adversity or with a history of moderate-to-severe adversity. We first trained an RF model to predict whether a young person had experienced moderate-to-severe ELA before age 10 based on their cognitive function

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measured across multiple tasks at ages 10–12. Next, we applied hierarchical clustering to the RF model output to identify subgroups of individuals with different cognitive profiles in those with and without a history of ELA, and explored whether these subgroups differed in terms of the type and degree of adversity experienced, and on measures of mental health at age 12.

Method

Data and measures

The data were obtained from the Adolescent Brain Cognitive Development (ABCD) study, held in the NIMH Data Archive. This is a multisite longitudinal study that involves 21 data acquisition sites across the US, designed to recruit over 11,000 children aged 9–10 and follow them over 10 years into early adulthood (for study details see Garavan et al., 2018). Project details can be found at http://acbdstudy.org. Demographics for the ABCD cohort are reported in Supplementary Table S1. This study uses data from the baseline (T1), 1-year follow-up (T2), and two-year follow-up (T3) points, when children were aged 10, 11 and 12 years respectively.

Early life adversity

Twenty-one questions were used to assess whether a child had been exposed to an adverse experience before the age of 10 (Table S2). These were taken from the Demographics Survey; Family History Assessment; Neighborhood Safety/Crime Survey; PTSD Module; and the Family Environment Scale. Responses were provided by caregivers and covered experiences from birth up to the baseline assessment (T1) at age 10 years, except for the material deprivation questions that asked about experiences in the past 12 months.

Each question was coded as belonging to one of six categories based on the Child Trauma Questionnaire and the Adverse Childhood Experiences adversity scales (Berman et al., 2022; Finkelhor et al., 2013): physical abuse; sexual abuse; domestic violence; community violence; material deprivation; and household substance abuse (Table S2). Each of these categories was then coded as belonging to either the threat or the deprivation dimension based on the threat-deprivation model of adversity (McLaughlin & Sheridan, 2016). We defined *threat* as experiences involving violence, physical harm, or threat of harm to the child, including physical and sexual abuse, domestic violence, and community violence. Deprivation was defined as low levels of social or cognitive stimulation, and material or nutritional resources (Berman et al., 2022; McLaughlin & Sheridan, 2016).

The 21 questions were then summed to create several broader composite scores: First, *threat* and a *deprivation composites* were created by summing the total number of questions endorsed within each dimension (Sumner et al., 2019). Next, an *accumulation score* (i.e., cumulative risk) was created by summing the total number of adverse experiences endorsed (max 21; Berman et al., 2022). Finally, a *multiplicity score* was created by summing the number of distinct categories of adversity endorsed to capture the extent of unique exposures (max 6; Teicher & Parigger, 2015). These multiple indices capture the three different ways in which adversity is measured in the literature.

Cognition

Detailed information about the cognitive tasks and scoring are available in the Method Supplement, Section 1.1, and Table S3.

NIH toolbox cognitive battery – The NIH Toolbox Cognitive Battery (NIHTCB; Weintraub et al., 2013) provided seven standardized measures of cognition. These included the Dimensional Change Card Sort Task to measure shifting and cognitive flexibility; the Flanker task to measure inhibition; the List Sorting Working Memory Test to assess working memory; the Pattern Comparison Processing Speed Task to measure visual information processing speed; the Picture Vocabulary Task to measure vocabulary skills; the Picture Sequence Memory Test to measure visual episodic memory; and the Oral Reading Recognition Test to measure the ability to pronounce words or recognize letters. The majority of NIHTCB measures were taken from the third time point (T3) when the children were aged 12, except the Dimensional Change Card Sort and List Sort Working Memory tasks that were only available at Baseline (T1) when the children were aged 10. Age-corrected scores were used.

Rey auditory verbal learning task – The Rey Auditory Verbal Learning Task was used to measure auditory learning, memory, recognition, and delayed recall (Luciana et al., 2018). T3 raw scores were used.

Little man task – The Little Man Task measured visuospatial reasoning (Acker & Acker, 1982). Raw scores and reaction times from T3 were used.

Matrix reasoning task – A computerized version of the Matrix Reasoning subtest from the Weschler Intelligence test for Children-V (WISC-V) was used to measure nonverbal reasoning (Wechsler, 2014). Scaled scores from T1 were used.

Cash choice task – The Cash Choice Task is a single-item question measuring delay gratification (Wulfert et al., 2002). Item response at Baseline (T1) was used.

Delay discounting task – The Delay Discounting Task measures reward processing (Koffarnus & Bickel, 2014). Indifference scores and response times from Time 2 (T2) were used.

Game of dice task – The Game of Dice Task measured participants' aversion/attraction to risky decisions and probabilistic reasoning (Brand et al., 2005). The number of winning vs losing bets, the final account balance, and the proportion of high- vs low-risk choices from Time 3 (T3) were used.

EN-back task – The EN-Back task is an emotional variant of the traditional N-back task which engages working memory, using a block design that adds elements of facial and emotional processing (Barch et al., 2013). Accuracy and reaction times from Time 3 (T3) were used.

Emotional faces stroop task – The Emotional Faces Stroop (EF Stroop) task, a variant of the classic Stroop task, required individuals to attend to less salient stimulus cues while ignoring more salient or automatically processed cues (Stroop, 1935), with an added emotional component. Accuracy and response times from Time 2 (T2) were used.

Mental health

Child behavior checklist – The parent-reported Child Behavior Checklist (CBCL) was used to assess children's mental health over the last six months using 113 items rated on a three-point scale (not true; somewhat or sometimes true; very often or always true; Achenbach, 2011). These items are then summed into 5 subscales. Three of these, Anxious/Depressed; Withdrawn/Depressed; and Somatic Complaints, are summed to form a broader Internalizing measure. The other two, Rule-Breaking and Aggressive Behavior, are summed to form a broad measure of Externalizing symptoms. The Internalizing and Externalizing scales are summed to provide a Total Problem composite score. The six available DSM-oriented scales that align with clinical disorder definitions were also used (Depression Disorder; Anxiety Disorder; Somatic Disorder;

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Attention-Deficit Hyperactivity (ADHD); Oppositional Defiant disorder; Conduct Disorder). CBCL scores for each of the subscales, the broader composites, and the DSM-oriented scales (all normed t-scores) from T3 were used (Supplementary Table S4).

Prodromal psychosis scale – The Prodromal Psychosis Scale-Brief Child Version was used as a measure of psychotic symptoms (Loewy et al., 2011). The original 21-item self-report screening questionnaire for adolescents and adults was modified for use with children aged 9–11 (Karcher et al., 2018). The "Psychosis Severity" score from T3, based on the number of total questions weighted by the level of distress for each endorsed item (range: 0–126), was used.

Participants

All participants were included unless they had more than 15% of missing data on the adversity or cognitive measures. The remaining missing responses on the adversity questions were coded as "0" (i.e., adverse experience not endorsed). These responses were coded as 0 because sensitivity analyses (reported in the Supplement 1.2) revealed that either coding the missing responses as 1 (endorsing adversity) or using imputation resulted in estimates of adversity that were substantially higher than population prevalence estimates (Finkelhor et al., 2005; McLaughlin et al., 2012; Struck et al., 2020), indicating both approaches were heavily biased. Moreover, imputation was not appropriate for the adversity data as it was both non-binary and not missing at random (see Supplement for details). Imputation algorithms are heavily biased towards rare cases with binary data (e.g., exposures to ELA), explaining why it overestimated the prevalence of adversity. Furthermore, imputation would have increased the standard error, which would have increased the likelihood of model overfitting (a common problem with machine-learning methods such as RF). The remaining missing cognitive data were inputted using the "missForest" package in R (Stekhoven & Buhlmann, 2012). It was possible to apply imputation to these data in a straightforward manner as they were normally distributed and missing at random.

Participants were then allocated to a No Adversity (NOA) or Early Life Adversity (ELA) group based on their responses to the 21 adversity questions. Individuals who had experienced an adversity in two or more categories were coded as having experienced moderate-to-severe ELA ("ELA" group). Individuals who endorsed zero adverse experiences were coded as not having experienced adversity ("NOA" group). Participants who endorsed having experienced only a single type of adversity were removed from the analysis (~21% of the sample). This group were removed because the focus of the study was on differences between those who had experienced moderate-to-severe adversity and those who had not experienced adversity. To compare these groups, it was necessary to adopt a case-control design and to choose a cutoff for group allocation with a clear difference between groups on the adversity measures. While this resulted in approximately 20% of the sample being excluded, it was not appropriate to include cases endorsing one adversity in the moderate-to-severe group for scientific reasons, and because it would have resulted in an "ELA" sample greater than population-based estimates (Finkelhor et al., 2005; McLaughlin et al., 2012; Struck et al., 2020). Similarly, combining this group with the no-adversity sample would not have been appropriate as they had experienced one adverse exposure. In other words, the removal of this middle group allowed for direct comparison between individuals with no exposure and individuals with moderate-to-severe levels of exposure.

Table 1. Sample demographics for the adversity and no-adversity group

	No-adversity group	Adversity group	Statistic	p
N	5216	739		
Age mean *(SD)*	9.9 *(0.6)*	9.9 *(0.6)*	$t = -0.681$	0.496
Female	46.7%	46.1%	$X^2 = 0.08$	0.783
Race/Ethnicity				
% White	63.8%	36.9%	$X^2 = 288.22$	<.001
% African American	8.8%	24.4%		
% Hispanic	3.0%	3.2%		
% Asian	2.6%	0.3%		
% Other/ Multi-racial	21.9%	35.2%		
Household characteristics				
% Married caregivers	80.94%	34.75%	$X^2 = 776.92$	<.001 ***
% College-level education	73.58%	27.88%	$X^2 = 620.49$	<.001 ***
Household income			$X^2 = 1051.66$	<.001 ***
< $25k	6.7%	35.5%		
$25k–$49.99k	9.3%	31.3%		
$50k–$74.99k	12.6%	17.8%		
$75k–$99.99k	17.0%	8.4%		
$100k +	54.4%	6.9%		
Dimensions of exposure				
Threat	0	1.16	$X^2 = 4478.11$	<.001 ***
Deprivation	0	2.29	$X^2 = 5515.53$	<.001 ***

Notes. Demographics reported at the baseline assessment. Age reported in years. Threat and deprivation are reported as the mean number of adverse events experienced in each category. Differences between the no-adversity (NOA) and adversity (ELA) group assessed using *t*-test and chi-square. ***$p < .001$.

Demographics for the final ELA and NOA sample used in the analysis are reported in Table 1. Group comparisons showed that the ELA group had significantly lower performance than the NOA group on 36 of the 57 cognitive variables (lower scores, longer response times) (Figure S1, Table S5). They also had significantly greater difficulties across all 21 measures of mental health (Figure S2, Table S6).

Analysis plan

The primary analyses were conducted in three steps (see Figure 1 for a schematic overview). First, a random forest (RF) was trained to predict whether an individual had a history of ELA (ELA or NOA) using measures of cognition as input features. Hierarchical clustering was then used to identify putative subgroups with distinct cognitive profiles within the ELA and NOA groups. These subgroups were then compared to explore whether they differed by type of ELA exposure and by mental health profile. Analyses were

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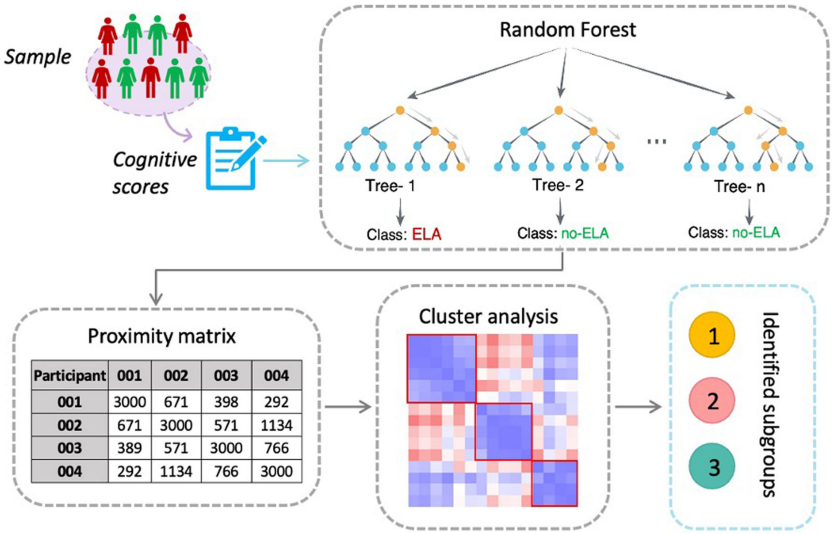

Figure 1. Overview of methodological approach: hybrid machine learning. *Notes*. Simplified schematic for visualization purposes.

conducted in R version 4.0.3 (R Core Team, 2021). Each step of the analysis is summarized below.

Random forest classification

A Random Forest (RF) model was trained to predict whether an individual had a history of ELA (ELA or NOA) using a set of cognitive variables as input. RF is a supervised ensemble learning method that can be used for classification problems. Each tree in the forest is trained using a bootstrapped (randomly selected) subset of the training sample and a randomly selected subset of input features. The random subsampling of input features for each tree allows the model to learn from different features in the data. If a given feature is a strong predictor of the response variable, it will be more frequently selected across multiple trees to maximize classification accuracy. The bootstrap sampling produces an out-of-bag (OOB) error that estimates the error rate for approximately one-third of the observations from the training data that are left out during each bootstrap (Breiman, 2001). The aggregate OOB score across all classification trees provides an overall OOB error rate to validate and tune the RF model. By introducing these two forms of randomness into the model and by averaging results across multiple decision trees, RF is more robust to noise and reduces overfitting (Figure 1).

The RF classification model was made up of 10,000 trees and was implemented using the "randomForest" package in R (Liaw & Wiener, 2022). The number of features to be randomly selected for the splitting decision at each tree node ("mtry") was set to seven based on a built-in package function. The model consisted of 57 cognitive variables as input features (Table S3), while group status (ELA or NOA) served as the outcome variable. 60% of participants formed the training set and 40% formed the testing set. Because of the unbalanced class distribution, with the ELA group representing only 13% of the sample, a stratified sampling approach was used to generate a balanced RF model using the "rfPermute" package in R (Archer, 2022). As described above, the OOB performance was used to tune the model, and a separate test set was used to evaluate its accuracy. As an additional validation, a cumulative binomial distribution was generated to determine whether the predictive accuracy of the RF model was significantly better than chance.

RF provides mean decrease accuracy (MDA) scores to help with model interpretability and to estimate the relative importance and predictive power of each cognitive variable in the model. This is calculated as the loss in prediction accuracy when a given feature is removed from the RF model using the "importance" function in the "randomForest" package in R (Liaw & Wiener, 2022). Due to methodological considerations outlined in the Supplement (see also Lu & Petkova, 2014 for an in-depth discussion), we also report importance metrics derived from elastic net regularization in the Supplementary Materials, Section 1.3 for completeness.

Identifying and characterising subgroups

The RF generates a proximity matrix based on the frequency that any given pair of observations end up in the same terminal node, representing the similarity between participants in terms of their cognitive profile. This proximity matrix can be fed into a clustering algorithm to identify subgroups characterized by similar cognitive profiles based on features identified as important for the original classification. An agglomerative hierarchical clustering approach, an unsupervised method that is commonly used for clustering biological and neurocognitive data, was used to identify subgroups with similar cognitive profiles within each group (ELA and NOA) using the RF proximity matrix (Drysdale et al., 2016; Rihel et al., 2010). The dissimilarity between clusters was measured using Ward's method, which minimizes the within-cluster variance at each iteration (Murtagh & Contreras, 2012). Hierarchical clustering was implemented using the "cluster" package in R (Maechler et al., 2022). Once hierarchical clustering was complete, the optimal number of clusters was chosen using the "elbow" and "silhouette" methods in the "factoextra" package in R (Kassambara & Mundt, 2020) and by examining the structure of the plotted dendrogram. Chi-squared and t-tests were conducted to compare subgroups on multiple indices, including cognitive performance, type of adverse exposure, and mental health.

Results

Random forest classification

Using the cognitive data as input, the RF model successfully classified individuals as having experienced ELA or not with a balanced accuracy of 67%. Comparing the RF model accuracy against a cumulative binomial distribution revealed that the model performed significantly better than chance $p < .001$. Model sensitivity - the ability to correctly identify NOA participants –

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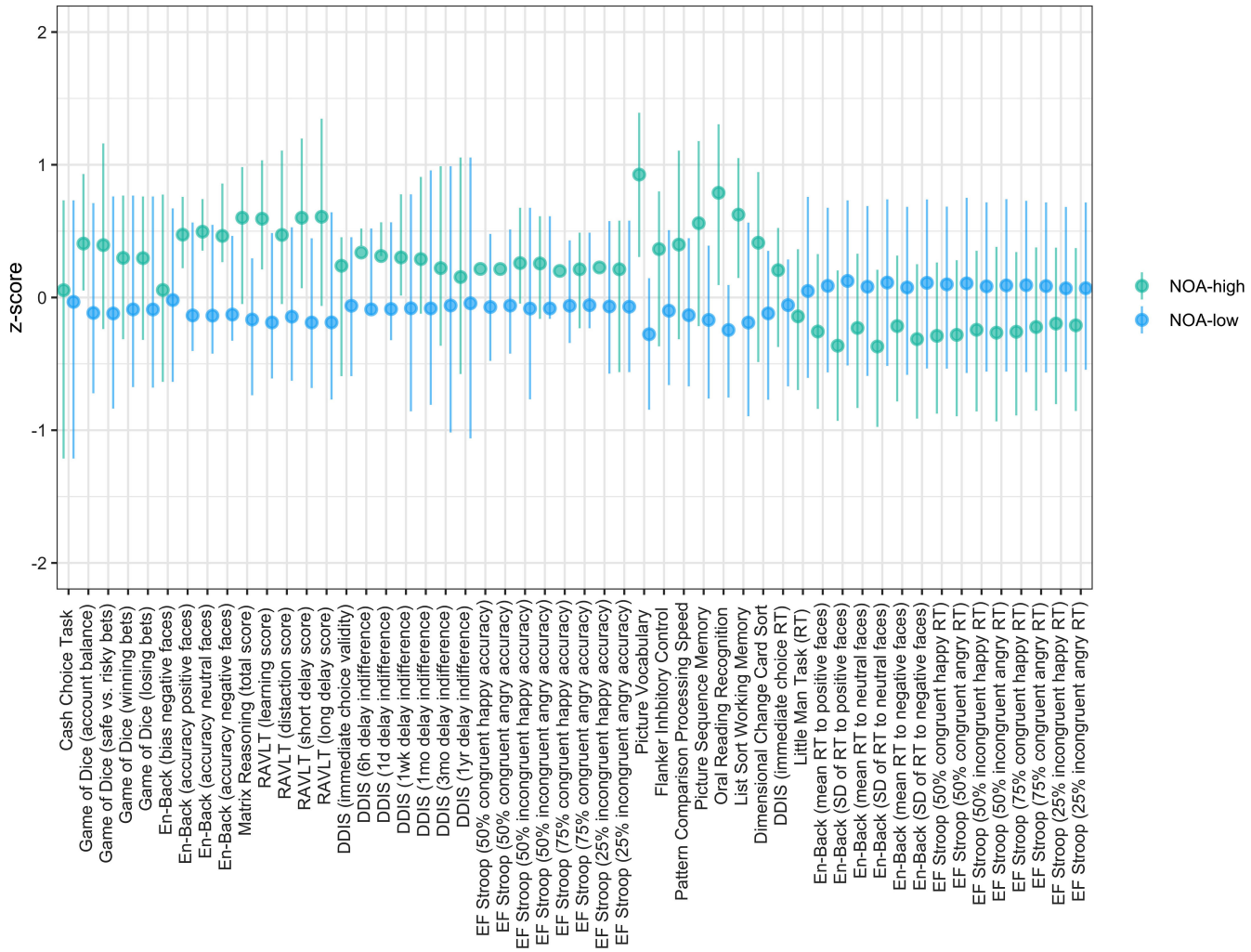

Figure 2. Differences in cognitive function between the NOA-low and NOA-high subgroups. *Notes*. Higher scores indicate greater accuracy and longer response times. Error bars represent the 95% confidence interval for Cohen's d. The original value for Game of Dice (losing bets) was inverted so that higher scores represent better performance as for the other measures in the figure. Only significant differences shown.

was estimated at 61.9%. Model specificity, which represents the ability to identify ELA participants, was 71.7%. Overall, the RF model was successful in using cognitive function to distinguish individuals with a history of ELA from those without.

RF MDA scores were used to identify the relative importance and predictive power of each cognitive variable in the model. Tasks measuring language and vocabulary skills (e.g., Picture Vocabulary and Oral Reading Recognition), nonverbal reasoning (e.g., Little Man Task, Matrix Reasoning), and reward processing (e.g., Delay Discounting) were consistently selected as the most important features driving model classification. RF variable importance is reported in Table S7 by decreasing order of importance.

Identifying subgroups

The agglomerative coefficient (*ac*) for the proximity matrix generated by the RF model showed a strong clustering structure in both groups (*ac* for NOA = 0.995; *ac* for ELA = 0.977). The NOA group had a slightly stronger clustering structure than the ELA group, indicative of greater cognitive homogeneity in the ELA group. Using the cognitive data, hierarchical clustering identified two subgroups within the NOA group, and two subgroups within the ELA group. The two-cluster solution was optimal for minimizing within-cluster and maximizing between-cluster variance within each class (Figures S3–S6). The largest NOA subgroup comprised 3684 participants while the smallest comprised 1532 participants. The largest ELA subgroup comprised 573 participants and the smallest comprised 166 participants. These subgroupings were not driven by demographic differences (see Results Supplement).

Subgroup profiles

Cognition – Independent sample t-tests indicated that there were significant group differences between the two NOA subgroups on 52 of the 57 cognitive variables (FDR-adjusted p's < .01) (Figure 2, Table S8). One subgroup, hereafter referred to as the *NOA-low* group ($n = 1532$) had significantly lower performance on all 52 measures (lower scores, longer response times). They also had significantly worse classification accuracy (50%) than the second group, who are referred to as the *NOA-high* group from hereon (100%), $X^2(1) = 1202.18$, $p < .001$. In other words, the NOA-low group had lower cognitive performance, which was more similar to the mean of the entire ELA group (leading to frequent

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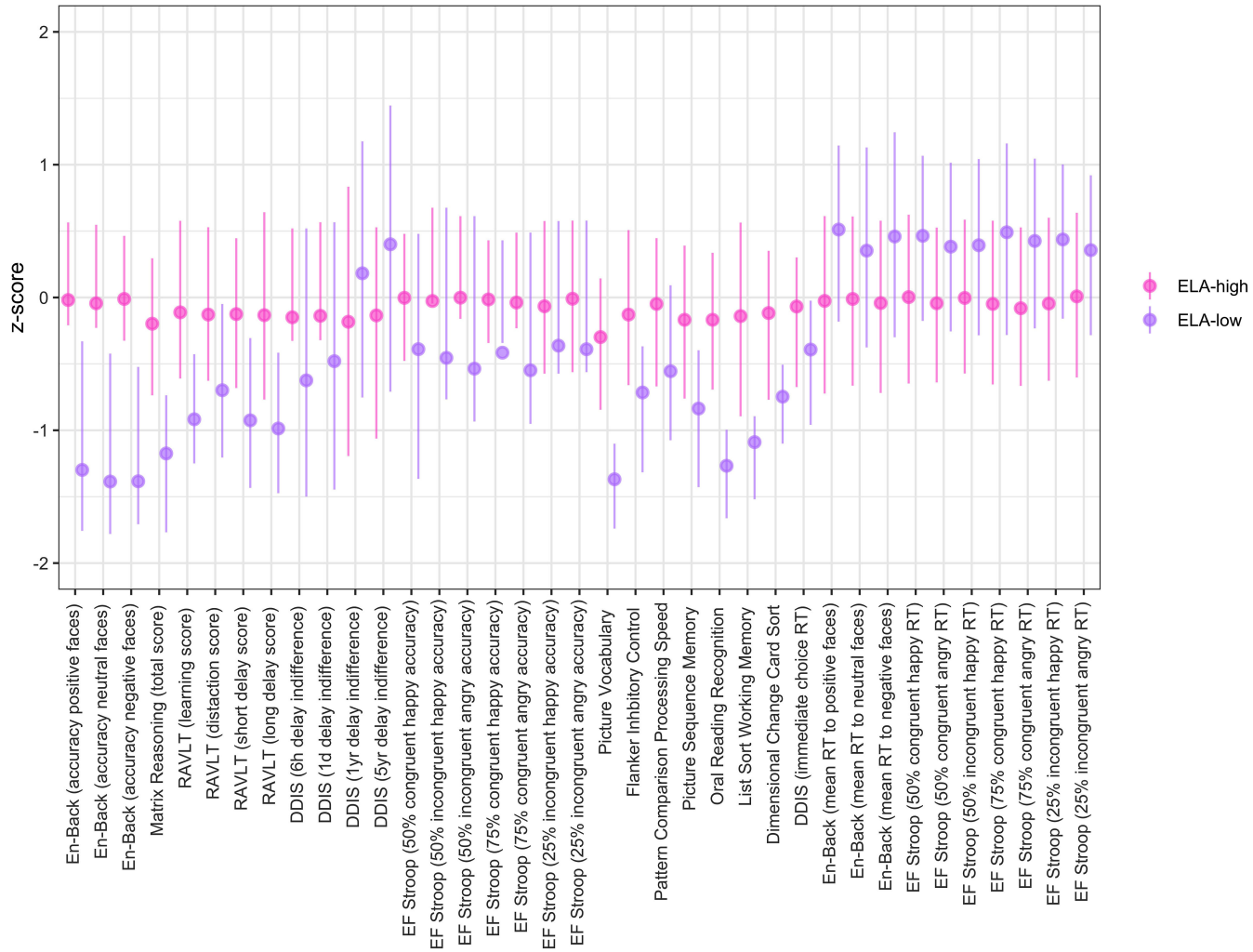

Figure 3. Differences in cognitive function between the ELA-low and ELA-high subgroups. *Notes*. Higher scores indicate greater accuracy or longer response time. Error bars represent the 95% confidence interval for Cohen's d. Only significant differences shown.

misclassification), while the NOA-high group had higher cognitive performance. Subgroup differences were evident across variables from all available cognitive measures, suggesting greater differences across all cognitive domains between the two NOA subgroups.

Independent sample t-tests indicated that there were significant group differences between the two ELA subgroups on 37 of the 57 cognitive variables (FDR-adjusted p's < .01) (Figure 3, Table S9). One group, hereafter referred to as the *ELA-high* group ($n = 166$), had significantly better performance on all 37 measures of cognition (higher scores, faster response times). Their classification accuracy was significantly worse (59%) than the second group, who are referred to as *the ELA-low* group from hereon (100%), $X^2(1) = 100.45$, $p < .001$. In other words, the ELA-high group had higher cognitive function, which was similar to the mean of the entire NOA group (leading to frequent misclassification), whereas the ELA-low group had lower cognitive performance. In contrast to the differences observed between the two NOA subgroups, the ELA subgroups showed fewer cognitive differences, suggesting greater cognitive similarity between the two subgroups. There were no differences in performance on the Cash Choice task, which measures delay of gratification; the Game of Dice Task, which measures aversion/attraction to risky decisions; nor on the Little Man Task, which measures visuospatial reasoning.

Adversity – Using a Bonferroni adjusted alpha level of 0.008 (0.05/6), the ELA-low group experienced greater community violence than ELA-high group, $X^2(1) = 26.079$, $p < .001$, whereas the ELA-high group experienced greater domestic violence than ELA-low group, $X^2(1) = 13{,}013$, $p < .001$. There were no significant subgroup differences in exposure to physical abuse ($X^2(1) = 3.74$, $p = .053$), sexual abuse ($X^2(1) = 2.29$, $p = .13$), material deprivation ($X^2(1) = 6.13$, $p = .013$), nor household substance abuse ($X^2(1) = 3.68$, $p = .055$). There were also no significant differences between subgroups on the accumulation composite ($t(360.71) = 2.06$, $p = .04$), defined as the total number of adverse experiences endorsed, nor on the multiplicity score ($t(290.38) = 0.98$, $p = .328$), which represents the number of distinct categories of adversities endorsed, nor in the degree of exposure to threat, $t(506.5) = 1.44$, $p = .15$, or deprivation, $t(308.49) = 0.99$, $p = .32$.

Mental health – Independent sample t-tests with an FDR-adjusted significance value of .01 indicated that there were significant group differences between the two NOA subgroups on 12 of the 21 measures of mental health (Figure 4, Table S10). The NOA-low group had significantly higher ratings on 12 scales that measure psychotic symptoms, attentional problems, somatic difficulties, and stress-related and externalizing difficulties than the

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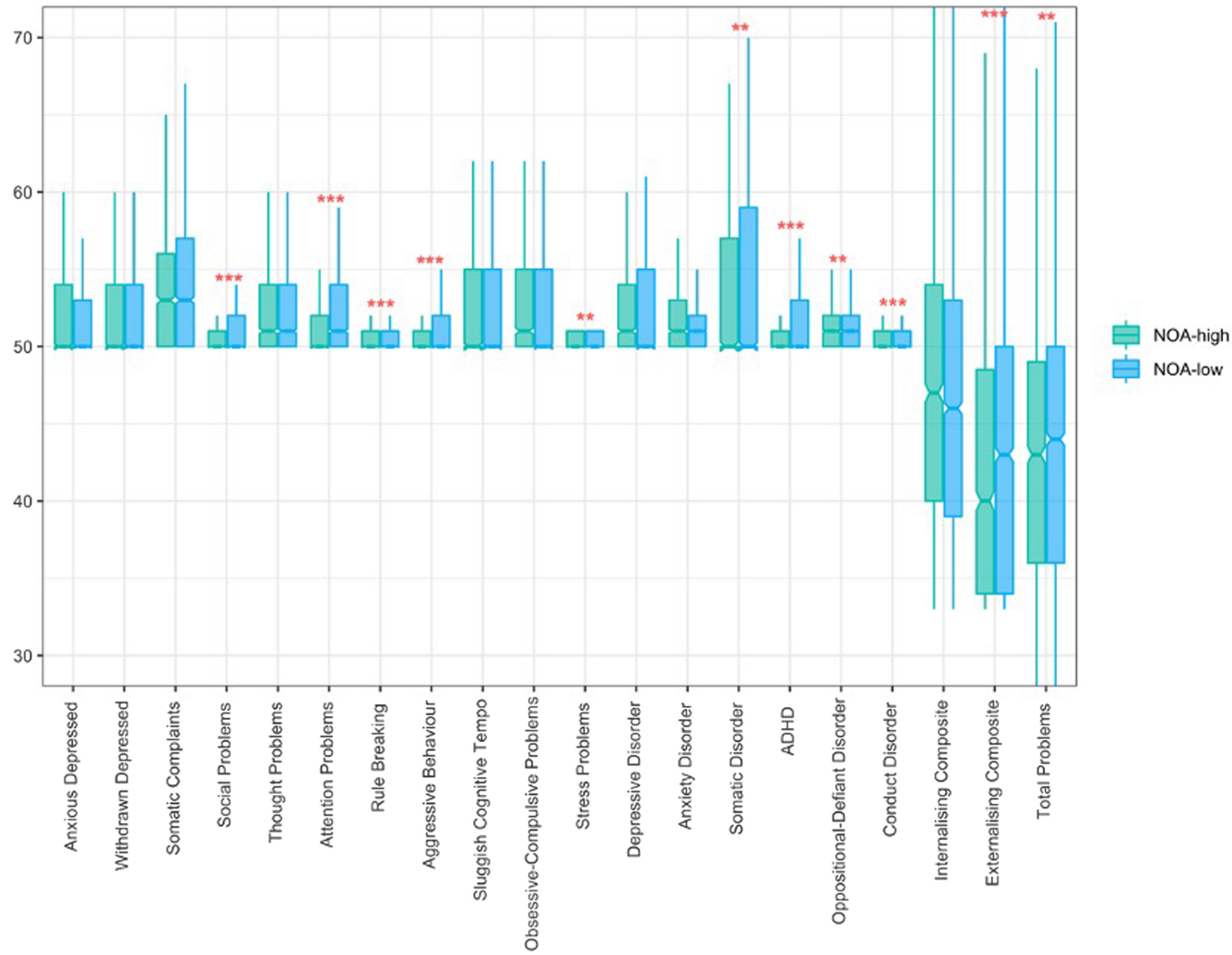

Figure 4. Differences in mental health symptoms between the NOA-low and NOA-high subgroups. *Notes*. Higher scores indicate greater symptoms. Error bars represent the 95% confidence interval for Cohen's d. Prodromal psychosis scale was also significant but not shown in figure due to differences in scale. **FDR-adjusted $p > .01$. ***FDR-adjusted $p > .001$.

NOA-high group. Thus, the NOA-low group had greater overall mental health difficulties compared to NOA-high: lower cognitive performance aligned with elevated mental health difficulties.

Independent sample t-tests with an FDR-adjusted significance value of .01 indicated that there were significant group differences between the two ELA subgroups on only 1 of the 21 measures of mental health (Table S11). The ELA-high group ($M = 56.62$, $SD = 8.22$) had significantly elevated ratings on the CBCL Withdrawal-Depression scale than the ELA-low group ($M = 54.41$, $SD = 6.10$), $t(5214) = -6.741$, $p < .001$, $d = -0.21$. Thus, while the ELA-high group had moderately greater internalizing symptoms on one scale, there were no subgroup differences on the remaining 20 measures of mental health, suggesting that mental health profiles were relatively similar across both ELA subgroups: lower cognitive performance did not align with elevated mental health difficulties.

To test whether differences in mental health outcomes between the high and low cognitive ability groups were specific to those who had not experienced adversity, a MANOVA was run with group (ELA vs NOA) and subgroup (low vs high) entered as factors and mental health ratings as the outcomes. There was a main effect of group (MANOVA: $F = 32.29$, $p < .001$; $Pillai = 0.012$), which revealed the ELA group had significantly higher ratings of mental health difficulties than the NOA. There was also a main effect of subgroup (MANOVA: $F = 6.68$, $p < .001$; $Pillai = 0.026$), revealing there were differences in mental health ratings according to cognitive ability: overall, those with higher cognitive performance had lower ratings of mental health difficulties. Crucially, there was a significant group (ELA vs NOA) by cognitive subgroup (low vs high) interaction for mental health (MANOVA: $F = 3.20$, $p < .001$; $Pillai = 0.013$) suggesting that differences in mental health by cognitive function interacted with, or were different, according to whether a child had experienced adversity: there were significant differences on 12 measures of mental health between the high and low cognitive ability NOA groups, but only 1 significant group difference on a single measure of mental health between children in the high and low ELA groups (see Tables S10 and S11). Post-hoc tests indicated that the interaction was significant for seven of the 21 measures of mental health on scales measuring internalizing, somatic, and conduct difficulties (Table S12). This shows that cognitive function was related to mental health in the NOA group, but not in the ELA group.

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Due to unequal sample sizes across the ELA ($n = 739$) and NOA ($n = 5216$) groups, a supplementary analysis was performed using a randomly sub-sampled NOA group of 739 participants. Broadly similar subgroup differences in mental health emerged between sub-sampled NOA subgroups, suggesting that the primary results are not attributable to greater statistical power in the NOA sample (Table S13).

Discussion

Using a data-driven approach with a large longitudinal population cohort we found that children who had experienced moderate-to-severe early life adversity (referred to as the ELA group from hereon) had lower cognitive performance and elevated levels of mental health difficulties relative to children who had not experienced ELA. However, not all children with moderate-to-severe ELA had low cognitive performance and there was limited evidence for specific associations between the type or degree of adversity experienced and cognitive profile. While children with ELA had elevated mental health difficulties relative to those without ELA, there was no evidence that this was linked to cognitive performance in the ELA group. Mental health was, however, associated with cognitive ability in the children who had not experienced ELA, with those with lower cognitive performance experiencing elevated levels of mental health difficulties. These results will be discussed in turn.

Dominant approaches to understanding how adverse experiences affect development rely on a priori assumptions about how different types of exposure affect different outcomes (e.g., Berman et al., 2022; Evans et al., 2013; McLaughlin & Sheridan, 2016; St Clair et al., 2015), and are hard to reconcile with concomitant adversities (Kessler et al., 1997) and high levels of variability among exposures and outcomes (McLaughlin et al., 2021). By combining supervised machine learning with hierarchical clustering, we were able to explore whether different forms of adversity were associated with shared or distinct alterations in cognitive function among children who had experienced moderate-to-severe adversity, and whether any such alterations were related to differences in mental health, without *a priori* assumptions about how to categorize adversities or the direction of their impact on outcomes.

Overall, a random forest (RF) model was able to predict whether a child had experienced moderate-to-severe adversity based on their cognitive function measured at ages 10–12 with an accuracy that was significantly better than chance (67%), and with good specificity and sensitivity (>70%). Classification accuracy was driven primarily by differences in language ability, nonverbal reasoning, and reward processing across the groups, and was consistent with previous findings showing that those who had experienced ELA had lower cognitive performance than those who had not experienced ELA (e.g., Gur et al., 2019; Sheridan & McLaughlin, 2016; Slopen et al., 2013). When identifying subgroups with different cognitive profiles within those who had, and those who had not experienced ELA, we found that the groups split by overall cognitive ability (i.e., low vs high), rather than by differences in specific domains of function. However, it is notable that the two ELA subgroups did not differ on measures of reward processing and risk aversion, suggesting that alterations in these domains are common across all children exposed to adversity, irrespective of their general cognitive ability. A substantial proportion (23%) of children who had experienced moderate-to-severe adversity had good cognitive performance that was equivalent to that of children who had not experienced adversity, and 29% of children with no reported adversities had cognitive performance that was low and equivalent to children who had experienced moderate-to-severe adversity. These data suggest adversity does not always impact on cognitive development, and that there is no specificity between exposure (i.e., type of adversity) and outcome (i.e., cognition) in children who have experienced moderate-to-severe adversity. If there was, the identified subgroups in those with a history of ELA would not have split simply by severity of cognitive difficulties.

Furthermore, cognitive profiles among those who had experienced moderate-to-severe adversity were not, broadly speaking, associated with distinct forms of adversity. The data revealed that those with lower cognitive ability had experienced higher rates of community violence, while those with higher cognitive ability had experienced higher rates of domestic violence. These patterns indicate that cognitive development is not necessarily impacted following adversity, consistent with the notion that negative outcomes and adversity do not always align (Teicher & Samson, 2013a, 2013b). While it may be the case that early life stress associated with domestic violence is adaptive (e.g., Belsky et al., 2012; Snell-Rood & Snell-Rood, 2020), but that stress associated with community violence is impactful, the absence of other specific associations between cognitive ability and type of adversity suggest variation in exposure does not map onto differences at the level of cognitive function, at least in those who have experienced more than one exposure to adversity. This finding indicates that different forms of adversity likely influence cognition in more shared than distinct ways. Although this contrasts prominent theory-driven models of adversity (e.g., dimensional model of threat/deprivation; Sheridan & McLaughlin, 2016), it does not necessarily negate hypotheses that different features of exposure alter cognition in distinct ways. Instead, our results demonstrate that isolating different dimensions or categories of adversity by recruiting highly selective samples or by implementing strict statistical controls is likely to generate conflicting evidence that lacks real-world validity due to the high levels of co-occurrence between different adversities in the general population (Debowska et al., 2017; Hamby et al., 2010; Herrenkohl & Herrenkohl, 2009; Kessler et al., 1997).

While there was a severity split in cognitive ability among children with a history of moderate-to-severe ELA, this did not map on to the cumulative burden of exposure. There were no significant differences between those with a history of moderate-to-severe ELA and high or low cognitive ability on the accumulation (total number of adverse experiences endorsed) or multiplicity scores (the number of distinct categories of adversities endorsed). This suggests that cumulative risk scores, which sum the number of adverse experiences, do not adequately capture the complex pathways through which ELA modifies development (Herrenkohl & Herrenkohl, 2009; Smith & Pollak, 2020), at least in children who have experienced more than one type of adverse exposure. For instance, there are likely dynamic interactions between the type, timing, subjective severity of exposure, and other individual differences that are not captured by cumulative risk models (Belsky & Pluess, 2009; Gabard-Durnam & McLaughlin, 2019; Khan et al., 2015).

Children with a history of moderate-to-severe ELA had elevated mental health difficulties relative to those with no history of ELA, replicating previous findings (Burkholder et al., 2016; LeMoult et al., 2020). Cognitive ability aligned with mental health in children without a history of adversity: those with lower cognitive performance exhibited greater mental health difficulties on scales measuring psychotic symptoms, attentional problems, somatic

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difficulties, and stress-related and externalizing difficulties relative to those with higher cognitive function. This is consistent with theories showing a strong association between cognitive ability, including language skills, executive control, and reward processing, and mental health. These include the interference hypothesis, which suggests psychological distress disrupts cognitive processing (Donati et al., 2021; Llewellyn et al., 2008; Stawski et al., 2006); the dynamic mutualism hypothesis, which suggests mental health and cognitive function reciprocally interact over time (Fuhrmann et al., 2021); and the cognitive reserve hypothesis, which suggests lower levels of cognitive control impact on the downregulation of negative emotional responses, such as worry, fear or sadness, leading to poor mental health (LeMoult & Gotlib, 2019; Millan et al., 2012).

In contrast, and somewhat unexpectedly, cognitive ability was not linked to mental health in children who had experienced more than one adverse exposure: there were no significant differences in mental health between those with low or high cognitive function, except on the withdrawn-depressed scale. One possibility is that adversity-related alterations in cognition hold adaptive value in environments characterized by high levels of stress and uncertainty, for instance in terms of energy maintenance or stress-reactivity (Ellis & Del Giudice, 2019; Snell-Rood & Snell-Rood, 2020). Another complementary possibility is that because adversity itself is such a strong predictor of mental health, variation in cognitive function does not explain much additional variance in symptom severity (Green et al., 2010). Related to this, adversity might also be a strong predictor of cognitive performance, explaining why it is less variable among children with a history of adversity than those without. If this is the case, and adversity impacts strongly on both mental health and cognition (leading to less variability in both) this might explain why differences in cognition do not appear to drive differences in mental health (i.e., both are driven by adversity). These hypotheses suggest that despite exhibiting elevated mental health symptoms, children with a history of moderate-to-severe adversity may represent a distinct psychiatric phenotype that is less tied to cognitive vulnerability. Such findings provide novel insight into the heterogeneity of psychiatric risk following adversity and may inform the prognosis and tailored treatment of mental disorders based on personal history.

Limitations and future directions

While there are many strengths to this study, several limitations need to be acknowledged. First, although the ABCD is a large nationally representative sample, these findings reflect the US context and may therefore not translate to other populations or ethnic groups. Second, retrospective caregiver reports of adversity were used, which may be subject to some degree of recall bias (Baldwin et al., 2019) and underreporting (Fisher et al., 2011). Although standard practice for this age group (Bartlett, 2020), future studies are needed to validate these results against self-reported measures of childhood adversity as they become available in later waves of ABCD, or to follow parents and children from pregnancy in new or existing datasets (e.g., ALSPAC, Golding et al., 2001). Third, there are likely sensitive periods for exposure to different forms of childhood adversity (Gabard-Durnam & McLaughlin, 2019; Khan et al., 2015), which we were not able to explore in the current study due the absence of data on the timing of exposure in the ABCD dataset. Relatedly, this study was not designed to examine the cumulative and interactive burden of adverse experiences. The exclusion of children who had experienced only a single adversity was necessary to match population prevalence estimates of adversity (Finkelhor et al., 2005; McLaughlin et al., 2012; Struck et al., 2020), and to explore differences between those with moderate-to-severe adversity to those with no adversity, but it means the full range of adversity was not captured. This limits the conclusions we can draw about cumulative risk and links between different forms of adversity and cognition to those who have experienced moderate-to-severe adversity. Future studies adopting dimensional approaches are needed to better capture the cumulative effect of adversity across populations. Fourth, we were limited by the mental health data available at the time of analysis. Adolescence is a period marked by increased risk for the onset of mental health difficulties, with many difficulties emerging after the onset of puberty (Maciejewski et al., 2017). Although we found that at age 12, children with a history of adversity already had significantly elevated mental health difficulties relative to their unexposed peers, it is likely that these differences would become increasingly pronounced in later adolescence. Future longitudinal studies are needed to strengthen directional inferences between cognition and mental health following adversity. Further, the subgrouping was derived using hierarchical clustering. Other clustering approaches, for instance those based on graph theory, may yield different subgroups so it would be worth validating these results using different approaches in future studies. Finally, this study does not allow for directional inference. Although early adversity likely affects cognitive development, preexisting cognitive differences might be related to an increased risk of growing up in an adverse environment (e.g., Tucker-Drob et al., 2013; Turkheimer et al., 2012). Further research, including animal studies where the extent of adversity can be experimentally manipulated (Teicher & Samson, 2016), are needed to determine the extent to which early adversity is a driver of cognitive change.

Summary

This study shows that cognitive function measured at ages 10–12 can be used to predict whether a child has a history of early adversity with reasonable accuracy, and that children who have experienced ELA have both lower cognitive performance and elevated mental health difficulties relative to children who have not experienced ELA. However, it also demonstrates that there is no specificity between the type of exposure and cognitive difficulties, and that cognitive ability is not linked to mental health outcomes in children who have experienced adversity. Lower cognitive performance is, however, associated with elevated mental health difficulties in children who have not experienced ELA. In sum, these outcomes highlight the utility of using data-driven techniques for characterizing the impact of adversity on cognitive and mental health outcomes, and crucially, they demonstrate that cognitive differences in those who have experienced adversity are not linked to an increased risk for poor mental health.

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