Title: Dimensions of early life adversity are differentially associated with patterns of delayed and accelerated brain maturation

Authors: Dani Beck[1,2,3,*], Lucy Whitmore[4], Niamh MacSweeney[1,2,3], Alexis Brieant[5], Valerie Karl[1,2], Ann-Marie G. de Lange[2,6,7], Lars T. Westlye[2,8,9], Kathryn L. Mills[3,4], Christian K. Tamnes[1,2,3]

[1] PROMENTA Research Center, Department of Psychology, University of Oslo, Oslo, Norway
[2] NORMENT, Division of Mental Health and Addiction, Oslo University Hospital & Institute of Clinical Medicine, University of Oslo, Oslo, Norway
[3] Division of Mental Health and Substance Abuse, Diakonhjemmet Hospital, Oslo, Norway
[4] Department of Psychology, University of Oregon, Eugene, OR, USA
[5] Department of Psychological Science, University of Vermont, Vermont, USA
[6] Department of Clinical Neurosciences, CHUV and University of Lausanne, Lausanne, Switzerland
[7] Department of Psychiatry, University of Oxford, Oxford, UK
[8] Department of Psychology, University of Oslo, Oslo, Norway
[9] KG Jebsen Centre for Neurodevelopmental Disorders, University of Oslo, Oslo, Norway

[*] Correspondence: Dani Beck (dani.beck@psykologi.uio.no)

Abstract

Different types of early-life adversity have been associated with children's brain structure and function. However, understanding the disparate influence of distinct adversity exposures on the developing brain remains a major challenge. This study investigates the neural correlates of 10 robust dimensions of early-life adversity identified through exploratory factor analysis in a large community sample of youth from the Adolescent Brain Cognitive Development (ABCD) Study. Brain age models were trained, validated, and tested separately on T1-weighted (T1; N = 9524), diffusion tensor (DTI; N = 8834), and resting-state functional (rs-fMRI; N = 8233) magnetic resonance imaging (MRI) data from two time points (mean age = 10.7 years, SD = 1.2, range = 8.9-13.8 years). Bayesian multilevel modelling supported distinct associations between different types of early-life adversity exposures and younger- and older-looking brains. Dimensions generally related to emotional neglect, such as lack of primary and secondary caregiver support, and lack of caregiver supervision, were associated with lower brain age gaps (BAGs), i.e., younger-looking brains. In contrast, dimensions generally related to caregiver psychopathology, trauma exposure, family aggression, substance use and separation from biological parent, and socio-economic disadvantage and neighbourhood safety were associated with higher BAGs, i.e., older-looking brains. The findings suggest that dimensions of early-life adversity are differentially associated with distinct neurodevelopmental patterns, indicative of dimension-specific delayed and accelerated brain maturation.

Keywords: ABCD Study, Adolescence, Brain age, Development, Early-life Adversity

1. Introduction

Early-life adversity (ELA) such as exposure to abuse, violence, neglect, separation from caregivers, and chronic poverty, among others, can have widespread effects on youth neurodevelopment (McLaughlin et al., 2016) and increase risk for mental disorders (Kessler et al., 2010; Wade et al., 2022). Previous studies investigating how ELA influences neural development have adopted varied theoretical frameworks, reflecting the complex and multifaceted nature of the field (Ellis et al., 2022; Smith & Pollak, 2021). Traditionally, research has focused on a single type of adversity; for example, reporting associations between heightened amygdala activation and early exposure to violence (White et al., 2019), and lower volumes of gray matter and low income (Hanson et al., 2013) and exposure to institutionalisation (Sheridan et al., 2012). A critical limitation of this approach however, is the fact that most children are exposed to numerous types of adversities (McLaughlin et al., 2012). This has led to the employment of a cumulative risk approach, aggregating different forms of adversity into a singular risk factor. For example, Chad-Friedman et al. (2021) found that early cumulative risk was prospectively associated with lower total gray matter volume, cortex volume, and right superior parietal and inferior parietal cortical thickness. While the cumulative risk approach is useful for identifying children at greatest risk for intervention and can thus serve as a vital public health tool, aggregating varying risk factors fails to account for the type, severity, and chronicity of the adverse experiences (Evans et al., 2013). This may obscure potentially diverging effects of different adverse experiences on the developing brain.

More nuanced perspectives that have emerged differentiate between adverse experiences related to threat versus deprivation (Sheridan & McLaughlin, 2014), drawing support for the neural basis of this distinction from studies on fear learning and sensory deprivation. For children exposed to threat, structural magnetic resonance imaging (sMRI) studies have reported lower cortical thickness, surface area, volume of the amygdala and hippocampus (Colich et al., 2020; Gold et al., 2016; Lim et al., 2014), in addition to lower volume of the ventro-medial prefrontal cortex (vmPFC) (De Brito et al., 2013; Hanson et al., 2010). Resting-state and task-based functional connectivity studies have reported associations between threat and reduced resting-state amygdala–vmPFC connectivity (Herringa et al., 2013), reduced hippocampal activity during learning and memory tasks (Carrión et al., 2010), and elevated amygdala reactivity to threatening stimuli (McCrory et al., 2011, 2013). On the other hand, for children exposed to deprivation, such as institutional rearing, lack of social and cognitive stimulation, and other forms of parental absence, research has revealed altered

structure and function in the frontoparietal network, amygdala-hippocampal-PFC connectivity (Sheridan & McLaughlin, 2014; Silvers et al., 2016), and reductions in cortical gray matter and total brain volume, in addition to widespread cortical thinning (McLaughlin et al., 2014; Mehta et al., 2009; Sheridan et al., 2012).

The observed effects may be indicative of accelerated maturation and are consistent with life history and evolutionary-biology theories proposing accelerated development as an adaptation to harsh or stressful environments (Belsky, 2012; Ellis et al., 2022; Frankenhuis & de Weerth, 2013; McEwen & Gianaros, 2010). Similarly, another conceptual model, the stress acceleration hypothesis, argues that adversity may expedite neural development as a means of compensating for species-expectant maternal buffering of emotional reactivity (Callaghan & Tottenham, 2016). That said, it is important to note that regarding threat versus deprivation, a systematic review of 109 studies found strongest support for an association between exposures related to threat and accelerated maturation, but that such a pattern was less consistent for exposures related to deprivation (McLaughlin et al., 2019). In terms of delayed maturation, electroencephalogram (EEG) studies have shown associations between spectral profiles indicative of delayed patterns of functional and cortical maturation and neglect (McLaughlin et al., 2010), poverty (Pietto et al., 2017), and parental stress (Pierce et al., 2019). Delayed maturation has also been found in girls after experiences of abuse (Keding et al., 2021).

Be it a single factor, cumulative risk, or dimensional approaches, research has revealed instances of both accelerated and delayed maturation, as well as cases where no apparent effect is observed. These findings have contributed to a more comprehensive understanding of how different features of ELA are associated with unique brain outcomes (McLaughlin et al., 2021). However, real-world occurrences of adversity are multifaceted and often co-occur in a complex manner, making it a considerable challenge to precisely account for the heterogeneity in ELA. To address this issue, several data-driven methods have been applied (Cohen-Cline et al., 2019; Mersky et al., 2017; Nikolaidis et al., 2022; van Zyl et al., 2023; Zinn et al., 2020). Yet, much of the work has relied on small or homogenous samples that are often enriched for adversity exposure, making them less generalisable to the broader population. Recent research by Brieant et al. (2023) capitalised on big data from the Adolescent Brain Cognitive Development (ABCD) Study and identified 10 dimensions of adversity co-occurrence pertaining to conceptual domains such as caregiver substance use and biological caregiver separation, caregiver psychopathology, caregiver lack of support, and socioeconomic disadvantage/neighbourhood lack of safety. These dimensions exhibited

distinct behavioural correlates and predicted youth behaviours in an independent replication sample. In particular, higher levels of caregiver psychopathology and physical trauma exposure were associated with higher internalising and externalising problems. Additionally, higher levels of socioeconomic disadvantage/lack of neighbourhood safety were uniquely associated with lower cognitive flexibility and inhibitory control. Yet, to date, the neural correlates of these dimensions of ELA have not been investigated.

Brain age prediction offers a framework that can combine multiple imaging features, alleviating the need for selection of specific metrics or regions, and yields an individualised surrogate marker of brain maturation (Cole & Franke, 2017). Brain age involves estimation of biological age based on brain MRI characteristics, which may differ from an individual's chronological age (Franke et al., 2010). This difference, termed the brain age gap (BAG), could reflect deviation from typical neurodevelopmental patterns, and has been validated in several neurodevelopmental studies (Drobinin et al., 2022; Franke et al., 2012; Holm et al., 2023; Whitmore et al., 2023). In the context of ELA, where different dimensions of adversity may be associated with unique brain outcomes (Alnæs et al., 2020; Ellis et al., 2022; Holz et al., 2023; Jeong et al., 2021; Malave et al., 2022; McLaughlin et al., 2021; Modabbernia et al., 2021), brain age can probe individualised markers of delayed or accelerated maturation by means of younger- or older-looking brains. To date, two small-scale cross-sectional studies have utilised brain age prediction and assessed adversity relations. Drobinin et al. (2022) examined a cumulative measure of adverse environmental exposures and reported positive associations with BAG (older-looking brain) among 150 adolescents aged 9-19. In a sample of 234 females aged 8-18 years, Keding et al. (2021) reported childhood abuse relations with lower BAG and physical neglect relations with higher BAG. In light of the existing theoretical models and current empirical evidence, the field would benefit from better understanding the neural correlates of wider-ranging and co-occurring adversities in a large-scale longitudinal developmental dataset.

To this end, using ABCD data, our primary aim was to test for associations between MRI-based estimates of brain maturation and 10 previously characterised dimensions of ELA co-occurrence decomposed from 60 youth and parent report variables (Brieant et al. (2023). These 10 dimensions conceptually reflect 1) caregiver psychopathology, 2) socioeconomic disadvantage and lack of neighbourhood 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 parent separation, 7) family anger and arguments, 8) family aggression, 9) trauma exposure, and 10) caregiver lack of supervision. To obtain MRI measures of

complementary aspects of structural and functional brain maturation at baseline and two-year-follow-up assessment, we trained three brain age models on T1-weighted (T1), diffusion tensor imaging (DTI), and resting-state functional MRI (rs-fMRI) data, respectively.

Based on theoretical accounts and the empirical studies reviewed above, we hypothesised ELA dimensions of 1) caregiver psychopathology, 2) socioeconomic disadvantage and lack of neighbourhood safety, 5) child report of family conflict, 6) caregiver substance use and biological parent separation, 7) family anger and arguments, 8) family aggression, and 9) trauma to be associated with older-looking brains and accelerated maturation between the two time points. We hypothesised ELA exposures of 3) secondary caregiver lack of support, 4) primary caregiver lack of support, and 10) caregiver lack of supervision to be associated with younger-looking brains and delayed maturation over time.

2. Methods

2.1. Sample and ethical approval

The Adolescent Brain Cognitive Development (ABCD) Study (Casey et al., 2018) comprises a community sample of children and adolescents part of an ongoing longitudinal study, including a baseline cohort of ~11,800 nine- and ten-year-olds to be followed for the course of ten years. Interested caregivers underwent a telephone screening to determine whether their children were eligible to participate in the study. Children were excluded using the ABCD Study exclusion criteria, which included non-English proficiency, general MRI contraindications, a history of a major neurological disorder, traumatic brain injury, extreme premature birth (<28 weeks gestational age), a diagnosis of schizophrenia, intellectual disability, moderate to severe autism spectrum disorder, or substance abuse disorder (Karcher et al., 2018). Data used in the present study were drawn from the ABCD curated annual release 5.0, containing data from baseline up until the second-year visit (https://data-archive.nimh.nih.gov/abcd). All ABCD Study data is stored in the NIMH Data Archive Collection #2573, which is available for registered and authorised users (Request #7474, PI: Westlye). The 5.0 release will be permanently available as a persistent dataset defined in the NDA Study 1299 and has been assigned the DOI 10.15154/8873-zj65. The Institutional Review Board (IRB) at the University of California, San Diego, approved all aspects of the ABCD Study (Auchter et al., 2018). Parents or guardians provided written consent, while the child provided written assent. The current study was conducted in line with the Declaration of Helsinki and was approved by the Norwegian Regional Committee for Medical and Health Research Ethics (REK 2019/943).

2.2. Demographic information and data quality assurance

The initial sample consisted of ~11,800 participants (52% male) at mean age 10.75 (SD = 1.18, range 8.92-13.83) years, with baseline and two-year follow-up observations (obs) of T1 (obs = 19,048), DTI (obs = 17,672), and rs-fMRI (obs = 16,495) data. Quality control procedures followed a standard protocol described in Hagler et al. (2019). Briefly, participants with excessive head motion or poor data quality were excluded from the curated data release by the ABCD Study team. Additional quality assurance was carried out following extraction of data using the recommendations for data cleaning provided by the ABCD Study team (using data structure abcd_imgincl01). Here, recommendation criteria for include/exclude is marked by 1/0, respectively, and removal of data marked 0 was carried out for T1, DTI, and rs-fMRI data. Following quality assurance, the final sample included T1 obs of 19,047, DTI obs of 17,668, and rs-fMRI obs of 16,466 used for the current study. Demographic information for each brain MRI modality-specific sample can be found in SI Table 1, while the T1 sample is illustrated in Figure 1.

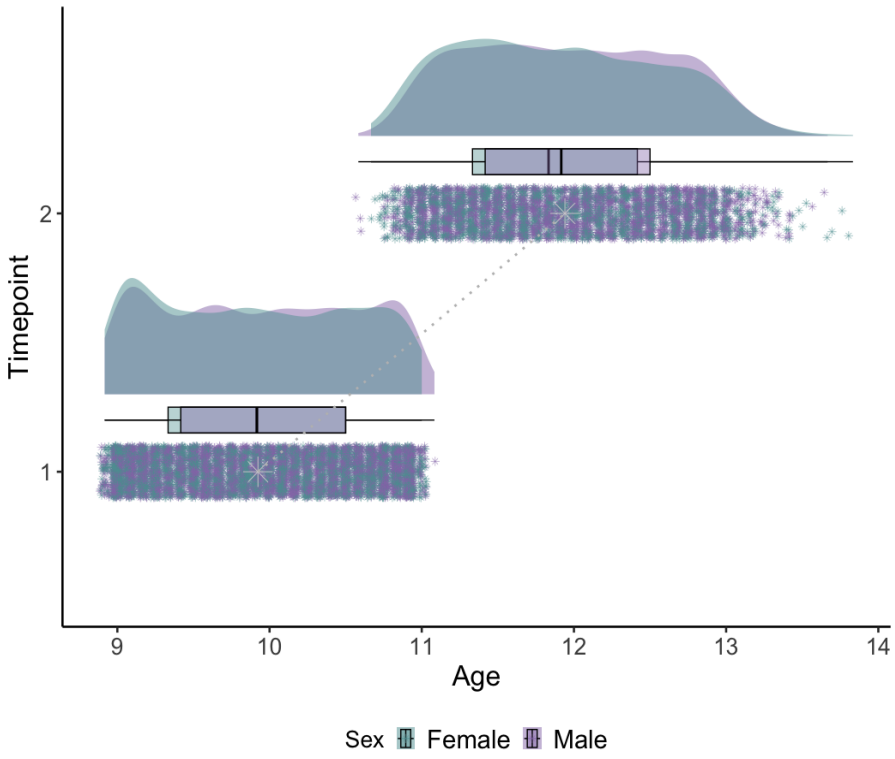

Figure 1. Age distribution split by sex and time point. Time point (1 and 2) represent baseline and two-year-follow-up data from the ABCD Study cohort. Female data in teal blue; male in lavender. Dotted gray line is drawn between mean age at time point 1 and 2.

2.3. MRI acquisition and processing

Neuroimaging data were acquired at 21 different sites (using 31 scanners) and processed by the ABCD Study team. A 3-T Siemens Prisma, General Electric 750 or Phillips scanner was used for data acquisition. Protocols used for data acquisition and processing are described in detail elsewhere (Casey et al., 2018; Hagler et al., 2019). Briefly, for T1-weighted MRI acquisitions on Siemens and Philips 3T scanners, a matrix of 256 × 256, 176 slices (Siemens) and 225 slices (Philips) with a field of view (FOV) of 256 × 256, echo time (TE)/repetition time (TR) (ms) of 2.88/2500 (Siemens) and 2.9/6.31 (Philips), flip angle of 8°. On GE scanners, the same matrix and FOV were used with TE/TR (ms) of 2/2500 and a flip angle of 8°. The spatial resolution was consistent at 1.0 × 1.0 × 1.0 mm across all three platforms. The dMRI acquisition (1.7 mm isotropic) uses multiband EPI with slice acceleration factor 3 and includes 96 diffusion directions, seven b = 0 frames, and four b-values (6 directions with b = 500 s/mm^2, 15 directions with b = 1000 s/mm^2, 15 directions with b = 2000 s/mm^2, and 60 directions with b = 3000 s/mm^2). For rs-fMRI acquisition, the following scanning parameters were used: matrix of 90 × 90, 60 slices, FOV = 216 × 216, TE/TR = 800/30, flip angle = 52° and resolution = 2.4 × 2.4 × 2.4 mm. The fMRI acquisitions (2.4 mm isotropic, TR = 800 ms) used multiband EPI with slice acceleration factor 6 and were split into 2-4 5-minute scanning sessions, in which participants were instructed to keep their eyes open and fixate on a crosshair.

2.4. Brain segmentation

Three modalities of brain structural and functional measures were used in the present study: structural grey matter measures (T1), diffusion white matter microstructural measures (DTI), and resting-state functional connectivity measures (rs-fMRI) (Hagler et al., 2019). Cortical surface reconstruction and subcortical segmentation was performed with FreeSurfer v7.1.1 (Dale et al., 1999; Fischl et al., 2002). White matter microstructural measures were generated using AtlasTrack, a probabilistic atlas-based method for automated segmentation of white matter fibre tracts (Hagler et al., 2009). Measures of functional connectivity were computed using a seed-based, correlational approach (Van Dijk et al., 2010), where average time courses were calculated for cortical surface-based ROIs using a functionally-defined parcellation based on resting-state functional connectivity patterns (Gordon et al., 2016) and subcortical ROIs (Fischl et al., 2002).

For T1, we extracted tabulated total and regional measures of cortical surface area, thickness, volume, sulcal depth, intensity-gray-white contrast, and subcortical volume (401 measures). For DTI, full and inner (multi) shell tissue properties including functional anisotropy (FA) and mean (MD), longitudinal (or axial, AD), and transverse (or radial, RD) diffusivity were extracted for total and regional features (576 measures). For rs-fMRI, functional connectivity within and between parcellations from Gordon network, including subcortical data (Gordon et al., 2016) were extracted (416 measures). Following procedures of quality assurance (Section 2.2), harmonisation of multi-scanner effects was carried out using *longCombat* (Beer et al., 2020) (see SI Section 1 and SI Figures 1-3).

2.5. Brain age prediction

Brain age prediction was carried out using the eXtreme Gradient Boosting (XGBoost) regression model (Chen & Guestrin, 2016). Parameters were tuned using ten-fold cross-validation, stratified by age. The models were fitted using the best estimators and optimised models were applied to the (hold-out) test sample. R2, RMSE, and MAE were calculated to evaluate prediction accuracy in the test set. For each brain modality (T1, DTI, rs-fMRI), 50% of the data was used as the hold-out test sample and 50% was used for model training and validation. Here, data was split ensuring an equal distribution of cross-sectional and longitudinal data across training and testing samples, whereby no two datapoints from the same individual (longitudinal) were separated. To further reduce potential differences and bias between the training and test samples, a t-test was carried out comparing the age distributions and means, with a non-significant effect providing evidence of no difference between the samples. Consistent with a recent brain age paper using the ABCD Study sample (Dehestani et al., 2023), confounding effects from complex family-related factors were minimised using a group shuffle split with family ID as the group indicator to ensure that no siblings were split across training and test sets. A detailed overview of T1, DTI, and rs-fMRI training and test samples, including demographic information are provided in SI Section 2, SI Table 1, and SI Figures 4-6.

To adjust for commonly observed age-bias (overestimated predictions for younger participants and underestimated predictions for older participants) (Liang et al., 2019), we applied a statistical correction as previously described in (de Lange & Cole, 2020); we first fitted $Y = \alpha \times \Omega + \beta$ to the training data, where Y is the modelled predicted age as a function of chronological age (Ω), and α and β represent the slope and intercept. Next, we used the derived values of α and β to correct predicted age with corrected predicted age = predicted

age + [Ω - (α x Ω x β)] in the test set. BAG was calculated using (corrected predicted age - chronological age) for each of the models, providing T1, DTI, and rs-fMRI-based BAG values for all participants.

2.6. Early life adversity

The current study utilised 10 previously obtained factor scores from 60 measures of early-life adversity (ELA) as detailed in Brieant et al. (2023). Briefly, Brieant and colleagues identified 139 potential ELA items from the ABCD Study baseline measures, which encompass a spectrum of ELA constructs including caregiving disruption, caregiver psychopathology, maltreatment, neighbourhood safety/violence, among others. These variables were sourced from child and parent reports, as well as researcher assessments, and originated from modified versions of validated scales. Variables with significant data gaps were excluded and highly intercorrelated items were merged to form six composite scores, thus reducing statistical bias while preserving essential ELA constructs. The resulting 60 ELA variables, which were binary, polytomous, and continuous in nature, were coded to ensure that higher scores indicated greater adversity. To identify dimensions, the 60 ELA variables were entered into an exploratory factor analysis (EFA) conducted in Mplus version 8.7 (Muthén & Muthén, 1998), resulting in 10 dimensions (F1 to F10; see Table 2 below and SI Figure 7 for correlation matrix). To obtain factor scores, an exploratory structural equation model was carried out specifying the number of factors identified in the EFA. ELA items were considered meaningful for interpretation when factor loadings were greater than 0.35. Further details of the variable selection process, identification of ELA dimensions, and calculation of factor loadings can be found in Brieant et al. (2023).

Table 2. Factor loadings for the ten early-life adversity dimensions. Adapted from Brieant et al. (2023), with permission from the author.

Early-Life Adversity Variables	Factor 1 Caregiver Psycho-pathology	Factor 2 Socio-economic disadvantage and neighbour-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)	0.72									
Caregiver antisocial symptoms (CG)	0.551									
Caregiver anxiety symtpoms (CG)	0.728									
Caregiver avoidant symptoms (CG)	0.704									
Caregiver depression symptoms (CG)	0.91									
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)				0.65						
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)		0.6								
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)							0.5			
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*										0.48
Caregivers know who they are with*										0.605
In contact with caregivers when home alone*										
Discuss plans with caregivers*										
Eat dinner with caregivers*										
Neighborhood area deprivation index		0.522								

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

Measures

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

2.7. Statistical analysis

All analyses were carried out using R version 4.2.1 (R Core Team, 2022). To investigate the association between each ELA dimension (F1:F10) and deviation from expected age patterns (i.e., BAG), Bayesian multilevel models were carried out in *Stan* (Stan Development Team, 2023) using the *brms* (Bürkner, 2017, 2018) R-package, where multivariate models are fitted in familiar syntax to comparable frequentist approaches such as a linear mixed effects model using the *lme4* (Bates et al., 2015). We assessed the relationship between each ELA dimension at baseline and residualised (age-bias corrected) BAG, where modality-specific BAG (T1, DTI, rs-fMRI) was first entered as the dependent variable, each ELA dimension (F1:F10) and interaction term between timepoint (TP) and ELA dimensions (F1:F10) were separately entered as independent fixed effects variables with sex entered as a covariate, and with subject ID as the random effect.

To prevent false positives and to regularise the estimated associations, we defined a standard prior around zero with a standard deviation of 0.1 for all regression coefficients, reflecting a baseline expectation of effects being small but allowing for sufficient flexibility in estimation. All variables bar sex were standardised before running the analyses. Each model was run with 8000 iterations, including 4000 warmup iterations, across four chains. This setup was chosen to ensure robust convergence and adequate sampling from the posterior distributions. For each coefficient of interest, we report the mean estimated value of the posterior distribution (b) and its 95% credible interval (the range of values that with 95% confidence contains the true value of the association), and calculated the Bayes Factor (BF) – provided as evidence ratios in the presented figures – using the Savage-Dickey method (Wagenmakers et al., 2010). Briefly, BF can be interpreted as a measure of the strength of evidence (*extreme, very strong, strong, moderate, anecdotal, none*) in favour of the null or alternative hypothesis. For a pragmatic guide on BF interpretation, see SI Table 2.

3. Results

3.1. Descriptive statistics

Descriptive statistics can be found in SI Table 1. Table 3 summarises descriptive and model validation statistics pertaining to each brain age prediction model, following age-correction. Figure 2 shows predicted age as a function of chronological age for each age prediction model. SI Figure 8 shows a correlation matrix including each modality-specific predicted brain age and BAG.

Table 3. Average R^2, root mean square error (RMSE), mean absolute error (MAE), and Pearson's correlations between predicted and chronological age (*r*) for each brain age prediction model, with 95% confidence intervals.

	T1	**DTI**	**rs-fMRI**
r	0.59 [0.57-0.60]	0.66 [0.65-0.67]	0.41 [0.39-0.43]
R^2	0.34	0.43	0.17
RMSE	0.96	0.89	1.08
MAE	0.79	0.71	0.89

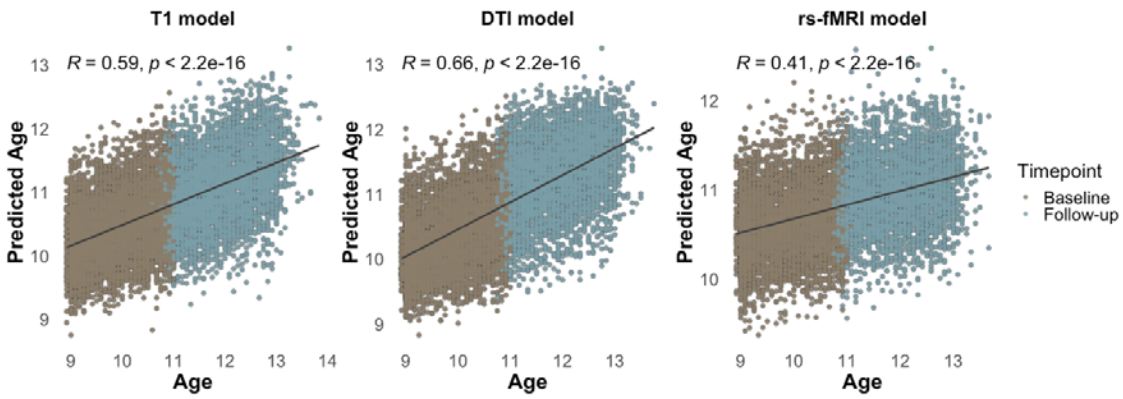

Figure 2. Predicted age as a function of age. Scatter plots demonstrating the correlation between chronological and predicted ages for three brain imaging modalities: T1, DTI, and rs-fMRI. Each plot illustrates the Pearson correlation coefficient (r) and statistical significance (*p*-value), with data points representing individual samples at baseline and follow-up time points. The plots reveal varying degrees of performance accuracy across modalities, with T1 and DTI models showing higher correlations compared to rs-fMRI.

3.2. Bayesian multilevel modelling

Bayesian multilevel modelling tested the association between each ELA dimension and modality-specific BAG. The full results are available in SI Tables 3-5. For estimated credible intervals, see SI Figures 9 and 10.

3.2.1. T1 BAG relations

For T1 BAG, the test revealed evidence of a positive association between ELA dimension F2 (socioeconomic disadvantage and neighbourhood safety) and T1 BAG (BF < 0.01, $\beta = 0.13$), indicating that this dimension was associated with older-looking brains. Further, the tests revealed evidence of negative associations between ELA dimensions F3 (secondary caregiver

lack of support) (BF = 0.9, β = -0.05) and F4 (primary caregiver lack of support) (BF = 0.17, β = -0.08) and T1 BAG, indicating that dimensions related to caregiver emotional neglect are associated with younger-looking brains. In terms of interaction effects of time point, we found a negative association between F10 (lack of supervision) and T1 BAG (BF = 0.08, β = -0.09), indicating that unsupervised youth diverge more from normative age patterns throughout the course of the study period.

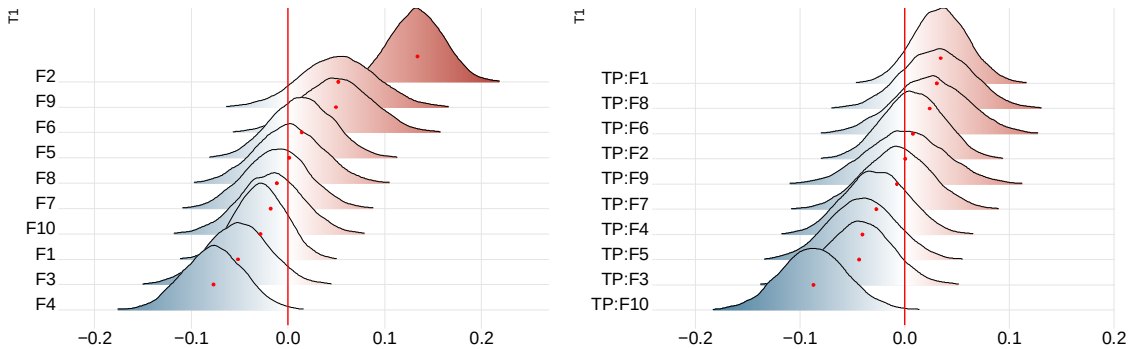

Figure 4. Associations between ELA dimensions and T1 BAG. The figure shows posterior distributions of the estimates of the standardised coefficient. Estimates for each ELA dimension on T1 BAG (main effect) on the left, and ELA dimension interaction effect of time point (TP:ELA) on T1 BAG on the right. Colour scale follows directionality of evidence, with positive (red) values indicating evidence in favour of positive associations (greater adversity linked to older-looking brains) and negative (blue) values indicating evidence in favour of negative associations (greater adversity linked to younger-looking brains) for each ELA dimension. The width of the distributions represent the uncertainty of the parameter estimates. Table 2 presents a list of what each dimension (F1:F10) represents.

3.2.2. DTI BAG relations

For DTI, the tests revealed evidence of a positive association between F2 and DTI BAG (BF = 0.27, β = 0.06), aligning with the T1 BAG findings, and indicating that those living in more disadvantaged and less safe environments may have older-looking brains. In terms of interaction effects of time point, the tests revealed evidence supporting a positive association between ELA dimension F1 (caregiver psychopathology) and DTI BAG (BF = 0.09, β = 0.07), indicating that the brain ages of these youth will diverge more (accelerate) from normative age patterns over time.

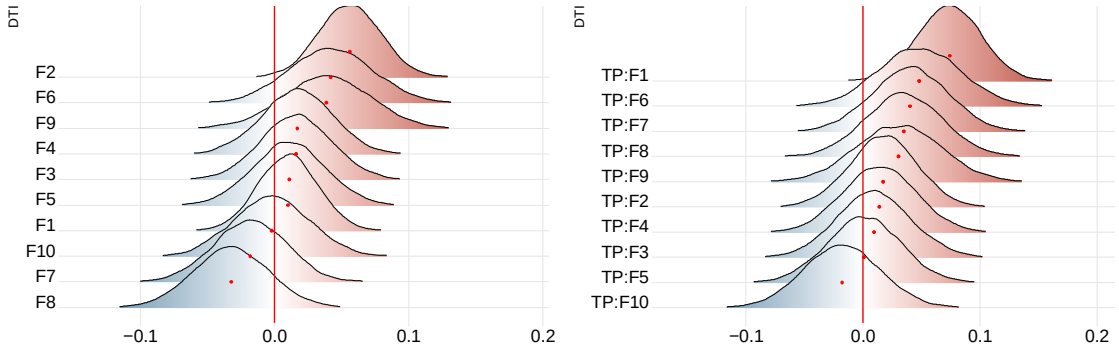

Figure 5. Associations between ELA dimensions and DTI BAG. The figure shows posterior distributions of the estimates of the standardised coefficient. Estimates for each ELA dimension on DTI BAG (main effect) on the left, and ELA dimension interaction effect of time point (TP:ELA) on DTI BAG on the right.

3.2.3. fMRI BAG relations

For fMRI, the tests revealed evidence of a positive association between F2 and fMRI BAG (BF < 0.01, β = 0.18), aligning with findings from DTI and T1 BAG. The tests also revealed positive associations between F1 (BF = 0.63, β = 0.07), F6 (caregiver substance abuse and separation from biological parents) (BF = 0.03, β = 0.15), F8 (family aggression) (BF = 0.66, β = 0.08), and F9 (trauma exposure) (BF = 0.07, β = 0.15) and fMRI BAG. These positive associations largely indicate that dimensions linked to a threatening environment relate to older-looking brains. Further, the tests revealed a negative association between F4 and fMRI BAG (BF = 0.27, β = -0.10), in line with findings from T1 BAG. In terms of interaction effects of time point, we found evidence supporting negative associations between both F3 (BF = 0.62, β = -0.08) and F5 (family conflict) (BF = 0.58, β = -0.08) and fMRI BAG, and a positive association between F6 (BF = 0.51, β = 0.09) and fMRI BAG.

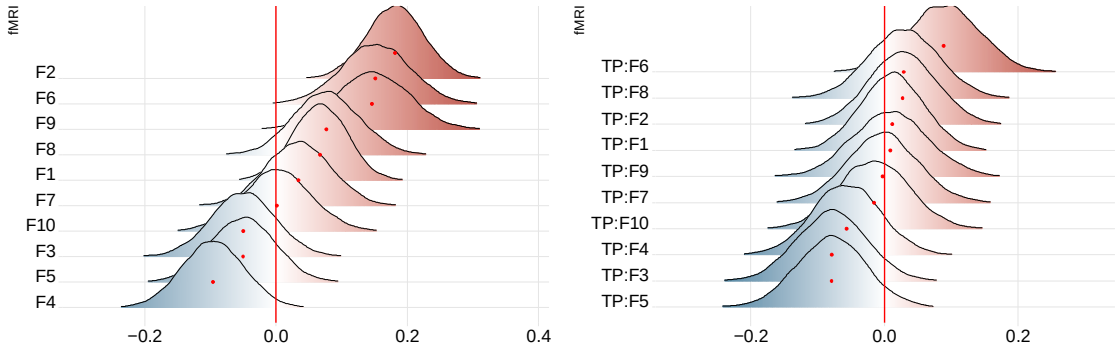

Figure 6. Associations between ELA dimensions and rs-fMRI BAG. The figure shows posterior distributions of the estimates of the standardised coefficient. Estimates for each ELA dimension on rs-fMRI BAG (main effect) on the left, and ELA dimension interaction effect of time point (TP:ELA) on rs-fMRI BAG on the right.

4. Discussion

Research indicates that approximately half of all children will experience at least one form of adversity by the time they reach adulthood (Green et al., 2010; Kessler et al., 2010). Different forms of early-life adversity co-occur and may uniquely impact child brain structure and function. This work sought to delineate the potentially unique brain outcomes of 10 co-occurring dimensions of early-life adversity in a longitudinal sample of 9–14-year-old youth. Our main findings indicate that ELA dimensions of caregiver lack of support and supervision are associated with younger-looking brains and that ELA dimensions of caregiver psychopathology, socioeconomic disadvantage and neighbourhood safety, caregiver substance abuse and separation from biological parents, family aggression, and trauma exposure are associated with older-looking brains. Our findings largely align with and extend the current literature on the differential impact of different co-occurring patterns of environmental exposures and adversity on brain development (Alnæs et al., 2020; Modabbernia et al., 2021).

4.1. Links to accelerated brain maturation

Families living in lower socioeconomic status neighbourhoods are exposed to more harms, such as interpersonal violence (Chong et al., 2015), and are more likely to have concerns about neighbourhood safety (Meyer et al., 2014). Positive associations between the dimension representing socioeconomic disadvantage and neighbourhood safety (F2) and BAG were found with all three brain age models, and are consistent with research showing socioeconomic disadvantage and neighbourhood violence linked to smaller cortical volumes and greater cortical thinning (Alnæs et al., 2020; Butler et al., 2018; Noble et al., 2015; Whittle et al., 2017). Positive associations between exposure to trauma (F9) and BAG is also consistent with previous research showing that children exposed to trauma are more likely to be misclassified as adults by means of older DNA methylation age compared to chronological age, and earlier pubertal maturation (Mendle et al., 2011; Sumner et al., 2019; Wolf et al., 2018).

For caregiver psychopathology (F1), we found both positive BAG associations as main effects and as interaction effects of time, suggesting that parent psychopathology-related deviations from expected age-patterns accelerate over time. Our findings are challenging to interpret in the context of mixed results from previous research. ABCD Study findings have revealed smaller volume in the right putamen (Pagliaccio et al., 2020), left

hippocampus (Chen et al., 2010), and bilateral hippocampi (Rao et al., 2010), aligning with our results. However, studies using other datasets have found that parental history of depression is associated with larger volume in the bilateral amygdala (Lupien et al., 2011), and others have reported no effects (Mattoni et al., 2023). ELA dimensions that indicated the potential presence of household hostility including family aggression (e.g., throwing things, hitting) (F8) revealed a positive main effect for fMRI BAG, but no effects for family arguments (e.g., expressing anger, fighting, raising voices) (F7), with the latter finding going against our hypothesis.

Co-occurrence of caregiver substance abuse and separation from biological parents in one dimension (F6) might reflect child custody issues related to caregiver substance use disorders or arrests (Brieant et al., 2023; Freisthler & Weiss, 2008). Moreover, this dimension also has factor loadings from domestic violence. Our results revealed positive fMRI BAG associations both as a main effect and an interaction effect of time. Drawing from concepts of stress acceleration, parental deprivation accelerates the functional development of the mPFC in children, such that amygdala–mPFC interactions are more adultlike following deprivation experiences (Callaghan & Tottenham, 2016). Children in this group may have accelerated maturation as a means of adapting from a state of parent-regulated to self-regulated emotional processing due to absent or inconsistent parental care (Callaghan & Tottenham, 2016; Ellis et al., 2022; Frankenhuis & de Weerth, 2013; McEwen & Gianaros, 2010). Although speculative, this is also in line with life history evolutionary theories positing that an organism under stress may allocate energy to growth and reproduction rather than maintenance (Belsky et al., 1991; Ellis et al., 2009). Further research is needed to understand the underlying mechanisms at play. In summary, dimensions of ELA co-occurrence related to older-looking brains support research reporting accelerated brain maturation in children exposed to potentially more hostile or dangerous environments. The strength of the effects indicated by the beta estimates and Bayes factor values suggest stronger effects were present for socioeconomic disadvantage and neighbourhood safety, caregiver substance abuse and separation from biological parents, and exposure to trauma, compared to caregiver psychopathology and family aggression.

4.2. Links to delayed brain maturation

Neurobiological studies of brain development have long assumed a deficit model in which lack of input to the development of a child will result in delay of certain skills (Glaser, 2000). In the child brain, this may be reflected by delay in pruning and thus larger brain volumes and

younger-looking brains. Our results support this, with lack of primary (F4) and secondary (F3) caregiver support as well as lack of caregiver supervision (F10) all revealing negative associations with T1 and fMRI BAG, with main effects for F3 and F4, and interaction effects for F3 and F10. Importantly, these factors each share elements of emotional neglect.

Previous research investigating more severe forms of neglect (physical and emotional) have found that children reared in institutions demonstrate EEG patterns suggestive of a delay in cortical maturation in frontal, temporal, and occipital regions (McLaughlin et al., 2010). However, a wealth of studies also report conflicting results indicative of advanced maturation in similar samples. Sheridan et al. (2012) found that children with a history of institutional rearing had significantly smaller cortical gray matter volume than never-institutionalised children. This is consistent with other work (Mehta et al., 2009), though after correcting for difference in brain volume, the institutionalised group had larger left amygdala volume. Keding et al. (2021) reported accelerated brain maturity in association with physical neglect, though this study was primarily designed to test the impact of abuse, with more girls in their sample having no exposure to physical neglect than having experienced physical neglect. For this reason, the study does not provide strong insight into the impact of neglect in the absence of abuse, or even for individuals who might experience high levels of both abuse and neglect (Stenson & Jovanovic, 2021). The limitation of Keding and colleagues may be indicative of the reported effects from previous studies, whereby the research carried out on neglect focuses on current or previously institutionalised children in environments enriched for several co-occurring ELAs, making it difficult to rely on the stability of the neglect scores while considering other stressors. Importantly, our results specifically capture emotional forms of neglect in terms of lack of household emotional support in a community with relatively lower levels of risk, which may explain divergence from prior studies on extreme physical neglect or institutionalisation.

Lastly, a negative interaction effect of time for fMRI BAG and family conflict (F5) was also found, indicating that youth exposed to family conflict diverge more from normative age patterns (i.e., delayed maturation) over time. Previous research also utilising the ABCD Study cohort has reported high family conflict associations with smaller cortical surface areas of the orbitofrontal cortex, anterior cingulate cortex, and middle temporal gyrus (Gong et al., 2021), in line with our results. In summary, ELA dimensions related to emotional neglect were associated with younger-looking brains and delayed maturation. The beta estimate and Bayes values indicated stronger effects present for lack of supervision (change over time) compared to moderate effects observed in lack of primary and secondary caregiver support.

4.3. Strengths and limitations

Our study adds new insight into the neural correlates of co-occurring ELA dimensions in a large-scale longitudinal community sample. Using a community sample not enriched for adversity exposure has the added value of demonstrating that even (on average) less severe ELA exposure is associated with changes in the developing brain, facilitating broader generalisation. However, there is trade-off in that our findings cannot necessarily be generalised to interpret neural correlates of children exposed to more severe forms of adversity, as these groups may not be well-represented in the ABCD Study. Future research is required to address this without losing adequate power. There remain also additional challenges such as accounting for differences in chronicity of adversity events, interindividual differences in resilience, and overlap in adversity types. The current study did not investigate potential sex differences or focus on delineating genes and environments in this complex context. We recommend future research to address these challenges.

Building on data driven methods applied in Brieant et al. (2023), the current study benefitted from ELA dimensions accounting for more variability in ELA patterns and a dimensional structure replicated in an independent sample, suggesting some stability. Brain age prediction has the advantage of reducing complex multidimensional brain data into an individualised summary score. With the BAG, an indirect measure of deviation from normative developmental patterns can be calculated and potentially reveal information regarding delayed or accelerated maturation. The current study utilised three estimates of brain age based on different MRI modalities in an attempt to capture potentially tissue-specific effects of ELA dimensions. While the multimodal approach is a strength that potentially shows modality-specific associations, state-of-the-art deep learning methods applied on T1-weighted MRI data have shown greater accuracy in recent years (Holm et al., 2023; Leonardsen et al., 2022). Moreover, while the MAE and RSME indicate good model performance, r values for age versus predicted age were relatively low for the rs-fMRI model relative to the structural models, although this is also observed in other studies (de Lange et al., 2020). A strength of the brain age models is the inclusion of longitudinal data.

Another strength of our analyses involves the use of a Bayesian statistical framework that allows for the discussion of the probability that an alternative hypothesis is true given the available data and prior information (Lecoutre & Poitevineau, 2022), and allows future studies to incorporate current results in their model priors. Lastly, a note of caution must be made for interpreting the results. While several of the reported Bayes factors reflect values

suggesting strong evidence of associations between the ELA dimensions and BAG, the beta estimates are relatively small. It must also be noted that not everyone that experiences early-life adversity will have an older or younger brain, and that BAG values can change over time, and may also be influenced by genetic, prenatal, or other early-life factors (Leonardsen et al., 2023; Vidal-Pineiro et al., 2021).

4.4. Conclusion

The current study supports notions that brain MRI outcomes related to early-life adversity are differentially associated with accelerated and delayed brain maturation. Neurodevelopmental processes influenced by experiences of trauma, parental psychopathology, socio-economic disadvantage and neighbourhood safety, caregiver substance abuse and separation from biological parents, and family aggression, are at least partially distinct from those influenced by experiences of emotional neglect, with brain age deviations indicating differential maturational patterns.

5. Funding

This work was supported by the Research Council of Norway (#223273, #288083, #323951, #276082, #249795, #248238, #298646, #300767), the South-Eastern Norway Regional Health Authority (#2019069, #2021070, #500189, #2014097, #2015073, #2016083, #2018076, #2019101), KG Jebsen Stiftelsen, the European Union-funded Horizon Europe project 'environMENTAL' (101057429); and the UK Research and Innovation (UKRI) under the UK government's Horizon Europe (10041392 and 10038599), the Swiss National Science Foundation (#PZ00P3_193658), and the European Research Council under the European Union's Horizon 2020 Research and Innovation program (ERC StG, #802998 and RIA #847776). The work was performed on the Service for Sensitive Data (TSD) platform, owned by the University of Oslo, operated, and developed by the TSD service group at the University of Oslo IT-Department (USIT). Computations were performed on resources provided by Sigma2 - the National Infrastructure for High Performance Computing and Data Storage in Norway.

6. Acknowledgments

Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive DevelopmentSM (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000

children aged 9-10 and follow them over 10 years into early adulthood. The ABCD Study® is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041048, U01DA050989, U01DA051016, U01DA041022, U01DA051018, U01DA051037, U01DA050987, U01DA041174, U01DA041106, U01DA041117, U01DA041028, U01DA041134, U01DA050988, U01DA051039, U01DA041156, U01DA041025, U01DA041120, U01DA051038, U01DA041148, U01DA041093, U01DA041089, U24DA041123, U24DA041147. A full list of supporters is available at https://abcdstudy.org/federal-partners.html. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/consortium_members/. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in the analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. We thank the co-authors of Brieant et al. (2023) for their contributions to the development of the factor scores used in this paper (Anna Vannucci, Hajer Nakua, Jenny Harris, Jack Lovell, Divya Brundavanam, Nim Tottenham, and Dylan Gee).

7. References

Alnæs, D., Kaufmann, T., Marquand, A. F., Smith, S. M., & Westlye, L. T. (2020). Patterns of sociocognitive stratification and perinatal risk in the child brain. *Proceedings of the National Academy of Sciences*, *117*(22), 12419–12427. https://doi.org/10.1073/pnas.2001517117

Auchter, A. M., Hernandez Mejia, M., Heyser, C. J., Shilling, P. D., Jernigan, T. L., Brown, S. A., Tapert, S. F., & Dowling, G. J. (2018). A description of the ABCD organizational structure and communication framework. *Developmental Cognitive Neuroscience*, *32*, 8–15. https://doi.org/10.1016/j.dcn.2018.04.003

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using **lme4**. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Beer, J. C., Tustison, N. J., Cook, P. A., Davatzikos, C., Sheline, Y. I., Shinohara, R. T., & Linn, K. A. (2020). Longitudinal ComBat: A method for harmonizing longitudinal multi-scanner imaging data. *NeuroImage*, *220*, 117129. https://doi.org/10.1016/j.neuroimage.2020.117129

Belsky, J. (2012). The Development of Human Reproductive Strategies: Progress and Prospects. *Current Directions in Psychological Science*, *21*(5), 310–316. https://doi.org/10.1177/0963721412453588

Belsky, J., Steinberg, L., & Draper, P. (1991). Childhood Experience, Interpersonal Development, and Reproductive Strategy: An Evolutionary Theory of Socialization. *Child Development*, *62*(4), 647–670. Scopus. https://doi.org/10.1111/j.1467-8624.1991.tb01558.x

Brieant, A., Vannucci, A., Nakua, H., Harris, J., Lovell, J., Brundavanam, D., Tottenham, N., & Gee, D. G. (2023). Characterizing the dimensional structure of early-life adversity in the Adolescent Brain Cognitive Development (ABCD) Study. *Developmental Cognitive Neuroscience*, *61*, 101256. https://doi.org/10.1016/j.dcn.2023.101256

Bürkner, P.-C. (2017). **brms**: An *R* Package for Bayesian Multilevel Models Using *Stan*. *Journal of Statistical Software*, *80*(1). https://doi.org/10.18637/jss.v080.i01

Bürkner, P.-C. (2018). Advanced Bayesian Multilevel Modeling with the R Package brms. *The R Journal*, *10*(1), 395. https://doi.org/10.32614/RJ-2018-017

Butler, O., Yang, X., Laube, C., Kühn, S., & Immordino Yang, M. H. (2018). Community violence exposure correlates with smaller gray matter volume and lower IQ in urban adolescents. *Human Brain Mapping*, *39*(5), 2088–2097. https://doi.org/10.1002/hbm.23988

Callaghan, B. L., & Tottenham, N. (2016). The Stress Acceleration Hypothesis: Effects of early-life adversity on emotion circuits and behavior. *Current Opinion in Behavioral Sciences*, *7*, 76–81. https://doi.org/10.1016/j.cobeha.2015.11.018

Carrión, V. G., Haas, B. W., Garrett, A., Song, S., & Reiss, A. L. (2010). Reduced Hippocampal Activity in Youth with Posttraumatic Stress Symptoms: An fMRI Study. *Journal of Pediatric Psychology*, *35*(5), 559–569. https://doi.org/10.1093/jpepsy/jsp112

Casey, B. J., Cannonier, T., Conley, M. I., Cohen, A. O., Barch, D. M., Heitzeg, M. M., Soules, M. E., Teslovich, T., Dellarco, D. V., Garavan, H., Orr, C. A., Wager, T. D., Banich, M. T., Speer, N. K., Sutherland, M. T., Riedel, M. C., Dick, A. S., Bjork, J. M., Thomas, K. M., … Dale, A. M. (2018). The Adolescent Brain Cognitive Development (ABCD) study: Imaging acquisition across 21 sites. *Developmental Cognitive Neuroscience*, *32*, 43–54. https://doi.org/10.1016/j.dcn.2018.03.001

Chad-Friedman, E., Botdorf, M., Riggins, T., & Dougherty, L. R. (2021). Early childhood cumulative risk is associated with decreased global brain measures, cortical thickness, and cognitive functioning in school-age children. *Developmental Psychobiology*, *63*(2), 192–205. https://doi.org/10.1002/dev.21956

Chen, M. C., Hamilton, J. P., & Gotlib, I. H. (2010). Decreased Hippocampal Volume in Healthy Girls at Risk of Depression. *Archives of General Psychiatry*, *67*(3), 270–276. https://doi.org/10.1001/archgenpsychiatry.2009.202

Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785

Chong, V. E., Lee, W. S., & Victorino, G. P. (2015). Neighborhood socioeconomic status is associated with violent reinjury. *The Journal of Surgical Research*, *199*(1), 177–182. https://doi.org/10.1016/j.jss.2015.03.086

Cohen-Cline, H., Jones, K. G., Kulkarni-Rajasekhara, S., Polonsky, H. M., & Vartanian, K. B. (2019). Identifying underlying constructs of childhood adversity in a low-income population. *Child Abuse & Neglect*, *91*, 1–11. https://doi.org/10.1016/j.chiabu.2019.02.005

Cole, & Franke, K. (2017). Predicting Age Using Neuroimaging: Innovative Brain Ageing Biomarkers. *Trends in Neurosciences*, *40*(12), 681–690. https://doi.org/10.1016/j.tins.2017.10.001

Colich, N. L., Platt, J. M., Keyes, K. M., Sumner, J. A., Allen, N. B., & McLaughlin, K. A. (2020). Earlier age at menarche as a transdiagnostic mechanism linking childhood trauma with multiple forms of psychopathology in adolescent girls. *Psychological Medicine*, *50*(7), 1090–1098. https://doi.org/10.1017/S0033291719000953

Dale, A. M., Fischl, B., & Sereno, M. I. (1999). *Cortical Surface-Based Analysis*. 16.

De Brito, S. A., Viding, E., Sebastian, C. L., Kelly, P. A., Mechelli, A., Maris, H., & McCrory, E. J. (2013). Reduced orbitofrontal and temporal grey matter in a community sample of maltreated children. *Journal of Child Psychology and Psychiatry*, *54*(1), 105–112. https://doi.org/10.1111/j.1469-7610.2012.02597.x

de Lange, A.-M. G., Anatürk, M., Suri, S., Kaufmann, T., Cole, J. H., Griffanti, L., Zsoldos, E., Jensen, D. E. A., Filippini, N., Singh-Manoux, A., Kivimäki, M., Westlye, L. T., & Ebmeier, K. P. (2020). Multimodal brain-age prediction and cardiovascular risk: The Whitehall II MRI sub-study. *NeuroImage*, *222*, 117292. https://doi.org/10.1016/j.neuroimage.2020.117292

de Lange, & Cole. (2020). Commentary: Correction procedures in brain-age prediction. *NeuroImage: Clinical*, *26*, 102229. https://doi.org/10.1016/j.nicl.2020.102229

Dehestani, N., Whittle, S., Vijayakumar, N., & Silk, T. J. (2023). Developmental brain changes during puberty and associations with mental health problems. *Developmental Cognitive Neuroscience*, *60*, 101227. https://doi.org/10.1016/j.dcn.2023.101227

Drobinin, V., Van Gestel, H., Helmick, C. A., Schmidt, M. H., Bowen, C. V., & Uher, R. (2022). The Developmental Brain Age Is Associated With Adversity, Depression, and Functional Outcomes Among Adolescents. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *7*(4), 406–414. https://doi.org/10.1016/j.bpsc.2021.09.004

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature (Hawthorne, N.Y.)*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Ellis, B. J., Sheridan, M. A., Belsky, J., & McLaughlin, K. A. (2022). Why and how does early adversity influence development? Toward an integrated model of dimensions of environmental experience. *Development and Psychopathology*, *34*(2), 447–471. https://doi.org/10.1017/S0954579421001838

Evans, G. W., Li, D., & Whipple, S. S. (2013). Cumulative risk and child development. *Psychological Bulletin*, *139*(6), 1342–1396. https://doi.org/10.1037/a0031808

Fischl, B., Salat, D. H., Busa, E., Albert, M., Dieterich, M., Haselgrove, C., van der Kouwe, A., Killiany, R., Kennedy, D., Klaveness, S., Montillo, A., Makris, N., Rosen, B., & Dale, A. M. (2002). Whole Brain Segmentation. *Neuron*, *33*(3), 341–355. https://doi.org/10.1016/S0896-6273(02)00569-X

Franke, K., Luders, E., May, A., Wilke, M., & Gaser, C. (2012). Brain maturation: Predicting individual BrainAGE in children and adolescents using structural MRI. *NeuroImage*, *63*(3), 1305–1312. https://doi.org/10.1016/j.neuroimage.2012.08.001

Franke, K., Ziegler, G., Klöppel, S., & Gaser, C. (2010). Estimating the age of healthy subjects from T1-weighted MRI scans using kernel methods: Exploring the influence of various parameters. *NeuroImage*, *50*(3), 883–892. https://doi.org/10.1016/j.neuroimage.2010.01.005

Frankenhuis, W. E., & de Weerth, C. (2013). Does Early-Life Exposure to Stress Shape or Impair Cognition? *Current Directions in Psychological Science*, *22*(5), 407–412. https://doi.org/10.1177/0963721413484324

Freisthler, B., & Weiss, R. E. (2008). Using Bayesian Space-Time Models to Understand the Substance Use Environment and Risk for Being Referred to Child Protective Services. *Substance Use & Misuse*, *43*(2), 239–251. https://doi.org/10.1080/10826080701690649

Glaser, D. (2000). Child Abuse and Neglect and the Brain—A Review. *Journal of Child Psychology and Psychiatry*, *41*(1), 97–116. https://doi.org/10.1017/S0021963099004990

Gold, A. L., Sheridan, M. A., Peverill, M., Busso, D. S., Lambert, H. K., Alves, S., Pine, D. S., & McLaughlin, K. A. (2016). Childhood abuse and reduced cortical thickness in brain regions involved in emotional processing. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *57*(10), 1154–1164. https://doi.org/10.1111/jcpp.12630

Gong, W., Rolls, E. T., Du, J., Feng, J., & Cheng, W. (2021). Brain structure is linked to the association between family environment and behavioral problems in children in the

ABCD study. *Nature Communications*, *12*(1), Article 1. https://doi.org/10.1038/s41467-021-23994-0

Gordon, E. M., Laumann, T. O., Adeyemo, B., Huckins, J. F., Kelley, W. M., & Petersen, S. E. (2016). Generation and Evaluation of a Cortical Area Parcellation from Resting-State Correlations. *Cerebral Cortex (New York, NY)*, *26*(1), 288–303. https://doi.org/10.1093/cercor/bhu239

Green, J. G., McLaughlin, K. A., Berglund, P. A., Gruber, M. J., Sampson, N. A., Zaslavsky, A. M., & Kessler, R. C. (2010). Childhood adversities and adult psychiatric disorders in the national comorbidity survey replication I: Associations with first onset of DSM-IV disorders. *Archives of General Psychiatry*, *67*(2), 113–123. https://doi.org/10.1001/archgenpsychiatry.2009.186

Hagler, D. J., Hatton, SeanN., Cornejo, M. D., Makowski, C., Fair, D. A., Dick, A. S., Sutherland, M. T., Casey, B. J., Barch, D. M., Harms, M. P., Watts, R., Bjork, J. M., Garavan, H. P., Hilmer, L., Pung, C. J., Sicat, C. S., Kuperman, J., Bartsch, H., Xue, F., … Dale, A. M. (2019). Image processing and analysis methods for the Adolescent Brain Cognitive Development Study. *NeuroImage*, *202*, 116091. https://doi.org/10.1016/j.neuroimage.2019.116091

Hagler Jr., D. J., Ahmadi, M. E., Kuperman, J., Holland, D., McDonald, C. R., Halgren, E., & Dale, A. M. (2009). Automated white-matter tractography using a probabilistic diffusion tensor atlas: Application to temporal lobe epilepsy. *Human Brain Mapping*, *30*(5), 1535–1547. https://doi.org/10.1002/hbm.20619

Hanson, J. L., Chung, M. K., Avants, B. B., Shirtcliff, E. A., Gee, J. C., Davidson, R. J., & Pollak, S. D. (2010). Early stress is associated with alterations in the orbitofrontal cortex: A tensor-based morphometry investigation of brain structure and behavioral

risk. *Journal of Neuroscience*, *30*(22), 7466–7472. Scopus. https://doi.org/10.1523/JNEUROSCI.0859-10.2010

Hanson, J. L., Hair, N., Shen, D. G., Shi, F., Gilmore, J. H., Wolfe, B. L., & Pollak, S. D. (2013). Family Poverty Affects the Rate of Human Infant Brain Growth. *PLOS ONE*, *8*(12), e80954. https://doi.org/10.1371/journal.pone.0080954

Herringa, R. J., Birn, R. M., Ruttle, P. L., Burghy, C. A., Stodola, D. E., Davidson, R. J., & Essex, M. J. (2013). Childhood maltreatment is associated with altered fear circuitry and increased internalizing symptoms by late adolescence. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(47), 19119–19124. https://doi.org/10.1073/pnas.1310766110

Holm, M. C., Leonardsen, E. H., Beck, D., Dahl, A., Kjelkenes, R., de Lange, A.-M. G., & Westlye, L. T. (2023). Linking brain maturation and puberty during early adolescence using longitudinal brain age prediction in the ABCD cohort. *Developmental Cognitive Neuroscience*, *60*, 101220. https://doi.org/10.1016/j.dcn.2023.101220

Holz, N. E., Zabihi, M., Kia, S. M., Monninger, M., Aggensteiner, P.-M., Siehl, S., Floris, D. L., Bokde, A. L. W., Desrivières, S., Flor, H., Grigis, A., Garavan, H., Gowland, P., Heinz, A., Brühl, R., Martinot, J.-L., Martinot, M.-L. P., Orfanos, D. P., Paus, T., … Marquand, A. F. (2023). A stable and replicable neural signature of lifespan adversity in the adult brain. *Nature Neuroscience*, *26*(9), 1603–1612. https://doi.org/10.1038/s41593-023-01410-8

Jeong, H. J., Durham, E. L., Moore, T. M., Dupont, R. M., McDowell, M., Cardenas-Iniguez, C., Micciche, E. T., Berman, M. G., Lahey, B. B., & Kaczkurkin, A. N. (2021). The association between latent trauma and brain structure in children. *Translational Psychiatry*, *11*(1), Article 1. https://doi.org/10.1038/s41398-021-01357-z

Karcher, N. R., Barch, D. M., Avenevoli, S., Savill, M., Huber, R. S., Simon, T. J., Leckliter, I. N., Sher, K. J., & Loewy, R. L. (2018). Assessment of the Prodromal Questionnaire–Brief Child Version for Measurement of Self-reported Psychoticlike Experiences in Childhood. *JAMA Psychiatry*, *75*(8), 853–861. https://doi.org/10.1001/jamapsychiatry.2018.1334

Keding, T. J., Heyn, S. A., Russell, J. D., Zhu, X., Cisler, J., McLaughlin, K. A., & Herringa, R. J. (2021). Differential Patterns of Delayed Emotion Circuit Maturation in Abused Girls With and Without Internalizing Psychopathology. *American Journal of Psychiatry*, *178*(11), 1026–1036. https://doi.org/10.1176/appi.ajp.2021.20081192

Kessler, R. C., McLaughlin, K. A., Green, J. G., Gruber, M. J., Sampson, N. A., Zaslavsky, A. M., Aguilar-Gaxiola, S., Alhamzawi, A. O., Alonso, J., Angermeyer, M., Benjet, C., Bromet, E., Chatterji, S., Girolamo, G. de, Demyttenaere, K., Fayyad, J., Florescu, S., Gal, G., Gureje, O., … Williams, D. R. (2010). Childhood adversities and adult psychopathology in the WHO World Mental Health Surveys. *The British Journal of Psychiatry*, *197*(5), 378–385. https://doi.org/10.1192/bjp.bp.110.080499

Lecoutre, B., & Poitevineau, J. (2022). The Significance Test Controversy Revisited. In B. Lecoutre & J. Poitevineau (Eds.), *The Significance Test Controversy Revisited: The Fiducial Bayesian Alternative* (pp. 41–54). Springer. https://doi.org/10.1007/978-3-662-65705-8_5

Leonardsen, E. H., Peng, H., Kaufmann, T., Agartz, I., Andreassen, O. A., Celius, E. G., Espeseth, T., Harbo, H. F., Høgestøl, E. A., Lange, A.-M. de, Marquand, A. F., Vidal-Piñeiro, D., Roe, J. M., Selbæk, G., Sørensen, Ø., Smith, S. M., Westlye, L. T., Wolfers, T., & Wang, Y. (2022). Deep neural networks learn general and clinically relevant representations of the ageing brain. *NeuroImage*, *256*, 119210. https://doi.org/10.1016/j.neuroimage.2022.119210

Leonardsen, E. H., Vidal-Piñeiro, D., Roe, J. M., Frei, O., Shadrin, A. A., Iakunchykova, O., de Lange, A.-M. G., Kaufmann, T., Taschler, B., Smith, S. M., Andreassen, O. A., Wolfers, T., Westlye, L. T., & Wang, Y. (2023). Genetic architecture of brain age and its causal relations with brain and mental disorders. *Molecular Psychiatry*, *28*(7), Article 7. https://doi.org/10.1038/s41380-023-02087-y

Liang, H., Zhang, F., & Niu, X. (2019). Investigating systematic bias in brain age estimation with application to post traumatic stress disorders. *Human Brain Mapping*, hbm.24588. https://doi.org/10.1002/hbm.24588

Lim, L., Radua, J., & Rubia, K. (2014). Gray Matter Abnormalities in Childhood Maltreatment: A Voxel-Wise Meta-Analysis. *American Journal of Psychiatry*, *171*(8), 854–863. https://doi.org/10.1176/appi.ajp.2014.13101427

Lupien, S. J., Parent, S., Evans, A. C., Tremblay, R. E., Zelazo, P. D., Corbo, V., Pruessner, J. C., & Séguin, J. R. (2011). Larger amygdala but no change in hippocampal volume in 10-year-old children exposed to maternal depressive symptomatology since birth. *Proceedings of the National Academy of Sciences*, *108*(34), 14324–14329. https://doi.org/10.1073/pnas.1105371108

Malave, L., van Dijk, M. T., & Anacker, C. (2022). Early life adversity shapes neural circuit function during sensitive postnatal developmental periods. *Translational Psychiatry*, *12*(1), Article 1. https://doi.org/10.1038/s41398-022-02092-9

Mattoni, M., Hopman, H. J., Dadematthews, A., Chan, S. S. M., & Olino, T. M. (2023). Specificity of associations between parental psychopathology and offspring brain structure. *Psychiatry Research: Neuroimaging*, *334*, 111684. https://doi.org/10.1016/j.pscychresns.2023.111684

McCrory, E. J., De Brito, S. A., Kelly, P. A., Bird, G., Sebastian, C. L., Mechelli, A., Samuel, S., & Viding, E. (2013). Amygdala activation in maltreated children during pre-

attentive emotional processing. *The British Journal of Psychiatry: The Journal of Mental Science*, *202*(4), 269–276. https://doi.org/10.1192/bjp.bp.112.116624

McCrory, E. J., De Brito, S. A., Sebastian, C. L., Mechelli, A., Bird, G., Kelly, P. A., & Viding, E. (2011). Heightened neural reactivity to threat in child victims of family violence. *Current Biology*, *21*(23), R947–R948. https://doi.org/10.1016/j.cub.2011.10.015

McEwen, B. S., & Gianaros, P. J. (2010). Central role of the brain in stress and adaptation: Links to socioeconomic status, health, and disease. *Annals of the New York Academy of Sciences*, *1186*(1), 190–222. https://doi.org/10.1111/j.1749-6632.2009.05331.x

McLaughlin, K. A., Fox, N. A., Zeanah, C. H., Sheridan, M. A., Marshall, P., & Nelson, C. A. (2010). Delayed Maturation in Brain Electrical Activity Partially Explains the Association Between Early Environmental Deprivation and Symptoms of Attention-Deficit/Hyperactivity Disorder. *Biological Psychiatry*, *68*(4), 329–336. https://doi.org/10.1016/j.biopsych.2010.04.005

McLaughlin, K. A., Green, J. G., Gruber, M. J., Sampson, N. A., Zaslavsky, A. M., & Kessler, R. C. (2012). Childhood adversities and first onset of psychiatric disorders in a national sample of adolescents. *Archives of General Psychiatry*, *69*(11), 1151–1160. https://doi.org/10.1001/archgenpsychiatry.2011.2277

McLaughlin, K. A., Sheridan, M. A., Gold, A. L., Duys, A., Lambert, H. K., Peverill, M., Heleniak, C., Shechner, T., Wojcieszak, Z., & Pine, D. S. (2016). Maltreatment Exposure, Brain Structure, and Fear Conditioning in Children and Adolescents. *Neuropsychopharmacology*, *41*(8), Article 8. https://doi.org/10.1038/npp.2015.365

McLaughlin, K. A., Sheridan, M. A., Humphreys, K. L., Belsky, J., & Ellis, B. J. (2021). The Value of Dimensional Models of Early Experience: Thinking Clearly About Concepts

and Categories. *Perspectives on Psychological Science*, *16*(6), 1463–1472. https://doi.org/10.1177/1745691621992346

McLaughlin, K. A., Sheridan, M. A., Winter, W., Fox, N. A., Zeanah, C. H., & Nelson, C. A. (2014). Widespread Reductions in Cortical Thickness Following Severe Early-Life Deprivation: A Neurodevelopmental Pathway to Attention-Deficit/Hyperactivity Disorder. *Biological Psychiatry*, *76*(8), 629–638. https://doi.org/10.1016/j.biopsych.2013.08.016

McLaughlin, K. A., Weissman, D., & Bitrán, D. (2019). *Childhood Adversity and Neural Development: A Systematic Review* (SSRN Scholarly Paper 3515831). https://doi.org/10.1146/annurev-devpsych-121318-084950

Mehta, M. A., Golembo, N. I., Nosarti, C., Colvert, E., Mota, A., Williams, S. C. R., Rutter, M., & Sonuga-Barke, E. J. S. (2009). Amygdala, hippocampal and corpus callosum size following severe early institutional deprivation: The English and Romanian Adoptees Study Pilot. *Journal of Child Psychology and Psychiatry*, *50*(8), 943–951. https://doi.org/10.1111/j.1469-7610.2009.02084.x

Mendle, J., Leve, L. D., Van Ryzin, M., Natsuaki, M. N., & Ge, X. (2011). Associations Between Early Life Stress, Child Maltreatment, and Pubertal Development Among Girls in Foster Care. *Journal of Research on Adolescence : The Official Journal of the Society for Research on Adolescence*, *21*(4), 871–880. https://doi.org/10.1111/j.1532-7795.2011.00746.x

Mersky, J. P., Janczewski, C. E., & Topitzes, J. (2017). Rethinking the Measurement of Adversity: Moving Toward Second-Generation Research on Adverse Childhood Experiences. *Child Maltreatment*, *22*(1), 58–68. https://doi.org/10.1177/1077559516679513

Meyer, O. L., Castro-Schilo, L., & Aguilar-Gaxiola, S. (2014). Determinants of Mental Health and Self-Rated Health: A Model of Socioeconomic Status, Neighborhood Safety, and Physical Activity. *American Journal of Public Health*, *104*(9), 1734–1741. https://doi.org/10.2105/AJPH.2014.302003

Modabbernia, A., Reichenberg, A., Ing, A., Moser, D. A., Doucet, G. E., Artiges, E., Banaschewski, T., Barker, G. J., Becker, A., Bokde, A. L. W., Quinlan, E. B., Desrivières, S., Flor, H., Fröhner, J. H., Garavan, H., Gowland, P., Grigis, A., Grimmer, Y., Heinz, A., … Frangou, S. (2021). Linked patterns of biological and environmental covariation with brain structure in adolescence: A population-based longitudinal study. *Molecular Psychiatry*, *26*(9), Article 9. https://doi.org/10.1038/s41380-020-0757-x

Muthén, L., & Muthén, B. (1998). *Mplus User Guide*. https://www.statmodel.com/HTML_UG/introV8.htm

Nikolaidis, A., Heleniak, C., Fields, A., Bloom, P. A., VanTieghem, M., Vannucci, A., Camacho, N. L., Choy, T., Gibson, L., Harmon, C., Hadis, S. S., Douglas, I. J., Milham, M. P., & Tottenham, N. (2022). Heterogeneity in caregiving-related early adversity: Creating stable dimensions and subtypes. *Development and Psychopathology*, *34*(2), 621–634. https://doi.org/10.1017/S0954579421001668

Noble, K. G., Houston, S. M., Brito, N. H., Bartsch, H., Kan, E., Kuperman, J. M., Akshoomoff, N., Amaral, D. G., Bloss, C. S., Libiger, O., Schork, N. J., Murray, S. S., Casey, B. J., Chang, L., Ernst, T. M., Frazier, J. A., Gruen, J. R., Kennedy, D. N., Van Zijl, P., … Sowell, E. R. (2015). Family income, parental education and brain structure in children and adolescents. *Nature Neuroscience*, *18*(5), Article 5. https://doi.org/10.1038/nn.3983

Pagliaccio, D., Alqueza, K. L., Marsh, R., & Auerbach, R. P. (2020). Brain Volume Abnormalities in Youth at High Risk for Depression: Adolescent Brain and Cognitive Development Study. *Journal of the American Academy of Child & Adolescent Psychiatry*, *59*(10), 1178–1188. https://doi.org/10.1016/j.jaac.2019.09.032

Pierce, L. J., Thompson, B. L., Gharib, A., Schlueter, L., Reilly, E., Valdes, V., Roberts, S., Conroy, K., Levitt, P., & Nelson, C. A. (2019). Association of Perceived Maternal Stress During the Perinatal Period With Electroencephalography Patterns in 2-Month-Old Infants. *JAMA Pediatrics*, *173*(6), 561–570. https://doi.org/10.1001/jamapediatrics.2019.0492

Pietto, M. L., Kamienkowski, J. E., & Lipina, S. J. (2017). Electrophysiological Approaches in the Study of the Influence of Childhood Poverty on Cognition. In A. Ibáñez, L. Sedeño, & A. M. García (Eds.), *Neuroscience and Social Science: The Missing Link* (pp. 349–381). Springer International Publishing. https://doi.org/10.1007/978-3-319-68421-5_15

Rao, U., Chen, L.-A., Bidesi, A. S., Shad, M. U., Thomas, M. A., & Hammen, C. L. (2010). Hippocampal Changes Associated with Early-Life Adversity and Vulnerability to Depression. *Biological Psychiatry*, *67*(4), 357–364. https://doi.org/10.1016/j.biopsych.2009.10.017

Sheridan, M. A., Fox, N. A., Zeanah, C. H., McLaughlin, K. A., & Nelson, C. A. (2012). Variation in neural development as a result of exposure to institutionalization early in childhood. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(32), 12927–12932. https://doi.org/10.1073/pnas.1200041109

Sheridan, M. A., & McLaughlin, K. A. (2014). Dimensions of early experience and neural development: Deprivation and threat. *Trends in Cognitive Sciences*, *18*(11), 580–585. https://doi.org/10.1016/j.tics.2014.09.001

Silvers, J. A., Lumian, D. S., Gabard-Durnam, L., Gee, D. G., Goff, B., Fareri, D. S., Caldera, C., Flannery, J., Telzer, E. H., Humphreys, K. L., & Tottenham, N. (2016). Previous Institutionalization Is Followed by Broader Amygdala-Hippocampal-PFC Network Connectivity during Aversive Learning in Human Development. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *36*(24), 6420–6430. https://doi.org/10.1523/JNEUROSCI.0038-16.2016

Smith, K. E., & Pollak, S. D. (2021). Rethinking Concepts and Categories for Understanding the Neurodevelopmental Effects of Childhood Adversity. *Perspectives on Psychological Science*, *16*(1), 67–93. https://doi.org/10.1177/1745691620920725

Stenson, A. F., & Jovanovic, T. (2021). Abuse and Delayed Brain Maturation in Girls: The Cost of Lagging Behind. *American Journal of Psychiatry*, *178*(11), 988–990. https://doi.org/10.1176/appi.ajp.2021.21090910

Sumner, J. A., Colich, N. L., Uddin, M., Armstrong, D., & McLaughlin, K. A. (2019). Early Experiences of Threat, but Not Deprivation, Are Associated With Accelerated Biological Aging in Children and Adolescents. *Biological Psychiatry*, *85*(3), 268–278. https://doi.org/10.1016/j.biopsych.2018.09.008

Van Dijk, K. R. A., Hedden, T., Venkataraman, A., Evans, K. C., Lazar, S. W., & Buckner, R. L. (2010). Intrinsic Functional Connectivity As a Tool For Human Connectomics: Theory, Properties, and Optimization. *Journal of Neurophysiology*, *103*(1), 297–321. https://doi.org/10.1152/jn.00783.2009

van Zyl, T.-L., O'Neill, T., & Rushe, T. (2023). Distinct Psychological Profiles Linking Childhood Adversity and Substance Misuse in High-Risk Young Adults. *Journal of Family Violence*, *38*(4), 633–645. https://doi.org/10.1007/s10896-022-00397-3

Vidal-Pineiro, D., Wang, Y., Krogsrud, S. K., Amlien, I. K., Baaré, W. F., Bartres-Faz, D., Bertram, L., Brandmaier, A. M., Drevon, C. A., Düzel, S., Ebmeier, K., Henson, R.

N., Junqué, C., Kievit, R. A., Kühn, S., Leonardsen, E., Lindenberger, U., Madsen, K. S., Magnussen, F., … Fjell, A. (2021). Individual variations in ‘brain age’ relate to early-life factors more than to longitudinal brain change. *eLife*, *10*, e69995. https://doi.org/10.7554/eLife.69995

Wade, M., Wright, L., & Finegold, K. E. (2022). The effects of early life adversity on children’s mental health and cognitive functioning. *Translational Psychiatry*, *12*(1), Article 1. https://doi.org/10.1038/s41398-022-02001-0

Wagenmakers, E.-J., Lodewyckx, T., Kuriyal, H., & Grasman, R. (2010). Bayesian hypothesis testing for psychologists: A tutorial on the Savage–Dickey method. *Cognitive Psychology*, *60*(3), 158–189. https://doi.org/10.1016/j.cogpsych.2009.12.001

White, S. F., Voss, J. L., Chiang, J. J., Wang, L., McLaughlin, K. A., & Miller, G. E. (2019). Exposure to violence and low family income are associated with heightened amygdala responsiveness to threat among adolescents. *Developmental Cognitive Neuroscience*, *40*, 100709. https://doi.org/10.1016/j.dcn.2019.100709

Whitmore, L. B., Weston, S. J., & Mills, K. L. (2023). BrainAGE as a measure of maturation during early adolescence. *Imaging Neuroscience*, *1*, 1–21. https://doi.org/10.1162/imag_a_00037

Whittle, S., Vijayakumar, N., Simmons, J. G., Dennison, M., Schwartz, O., Pantelis, C., Sheeber, L., Byrne, M. L., & Allen, N. B. (2017). Role of Positive Parenting in the Association Between Neighborhood Social Disadvantage and Brain Development Across Adolescence. *JAMA Psychiatry*, *74*(8), 824–832. https://doi.org/10.1001/jamapsychiatry.2017.1558

Wolf, E. J., Maniates, H., Nugent, N., Maihofer, A. X., Armstrong, D., Ratanatharathorn, A., Ashley-Koch, A. E., Garrett, M., Kimbrel, N. A., Lori, A., Aiello, A. E., Baker, D. G.,

Beckham, J. C., Boks, M. P., Galea, S., Geuze, E., Hauser, M. A., Kessler, R. C., Koenen, K. C., … Logue, M. W. (2018). Traumatic Stress and Accelerated DNA Methylation Age: A Meta-Analysis. *Psychoneuroendocrinology*, *92*, 123–134. https://doi.org/10.1016/j.psyneuen.2017.12.007

Zinn, M. E., Huntley, E. D., & Keating, D. P. (2020). Resilience in adolescence: Prospective Self moderates the association of early life adversity with externalizing problems. *Journal of Adolescence*, *81*(1), 61–72. https://doi.org/10.1016/j.adolescence.2020.04.004