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Executive Network Activation Moderates the Association between Neighborhood Threats and Externalizing Behavior in Youth

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Abstract

Neighborhood threats can increase risk for externalizing problems, including aggressive, oppositional, and delinquent behavior. Yet, there is substantial variability in how youth respond to neighborhood threats. Difficulty with cognitive functioning, particularly in the face of emotional information, may increase risk for externalizing in youth who live in neighborhoods with higher threats. However, little research has examined: 1) associations between neighborhood threats and executive networks involved in cognitive functioning or 2) whether executive networks may amplify risk for externalizing in the context of neighborhood threats. Further, most research on neighborhood threats does not account for youth's experiences in other social contexts. Utilizing the large, sociodemographically diverse cohort of youth (ages 9–10) included in the Adolescent Brain Cognitive Development^{SM} Study, we identified four latent profiles of youth based on threats in their neighborhoods, families, and schools: low threat in all contexts, elevated family threat, elevated neighborhood threat, and elevated threat in all contexts. The elevated neighborhood threat and elevated all threat profiles showed lower behavioral performance on an emotional *n*-back task relative to low threat and elevated family threat profiles. Lower behavioral performance in the elevated neighborhood threat profile specifically was paralleled by lower executive network activity during a cognitive challenge. Moreover, among youth with lower executive network activity, higher probability of membership in the elevated neighborhood threat profile was associated with higher externalizing. Together, these results provide evidence that interactions between threats that are concentrated in youth's neighborhoods and attenuated executive network function may contribute to risk for externalizing problems.

Keywords Neighborhood · Threat · Youth · Cognitive functioning · Executive networks · Externalizing

For youth, neighborhoods function as a backdrop for daily life–a physical context connecting their homes and schools and a social context in which they interact with family, peers, and other community members. As youth navigate their neighborhoods, they may perceive a variety of threats from violence to crimes to indicators of social decay that undermine their personal feelings of safety. These perceptions of threats in the neighborhood can have a profound influence on cognitive (Conley et al., 2022), emotional, and behavioral development (Goldman-Mellor et al., 2016). In particular, researchers document a robust association between living in neighborhoods with higher threats and the expression of externalizing behaviors including aggressive, oppositional, and delinquent behavior (Leventhal & Dupéré, 2019). However, there is substantial variability in how youth respond to neighborhood threats. Therefore, research is needed to identify factors that may interact with living in neighborhoods with higher threats to increase risk for externalizing during development.

Difficulty in cognitive functioning is one well-studied factor that is associated with neighborhood threats. For example, living in neighborhoods with high levels of crime and violence has been associated with lower performance in reading and vocabulary (Sampson et al., 2008; Sharkey, 2010), selective attention (McCoy et al., 2015),

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and executive functioning (Muñoz et al., 2020; Sharkey et al., 2012). Further, a recent study examined relationships between principal components of threats and resources in youth's environments across different social contexts and cognitive functioning (Meredith et al., 2022). This study found that a component capturing youth's neighborhoods, which included variable loadings for neighborhood violence and crime, had stronger associations with general cognitive ability and executive functioning than components capturing their families or schools.

General cognitive abilities and executive functions such as inhibition, shifting, and updating/working memory are supported by large scale executive networks, which are distributed throughout prefrontal cortex and posterior parietal cortex (e.g., Rosenberg et al., 2020; Satterthwaite et al., 2013; Sripada et al., 2020). Research suggests youth's neighborhoods can be related to executive network recruitment. For instance, neighborhood disadvantage, which is strongly correlated with neighborhood violence and crime (Friedson & Sharkey, 2015), has been related to lower behavioral performance and executive network activation during response inhibition (Tomlinson et al., 2020) and working memory (Murtha et al., 2022). Another study showed that a group of youth exposed to violence, who were primarily recruited from high crime neighborhoods, had decreased executive network activity during an emotional working memory task (Jenness et al., 2018). Therefore, living in neighborhoods with higher threats appears associated with difficulty with cognitive functioning broadly and executive network function more specifically, but the direct tests of these associations have yet to be examined.

In addition to the association between neighborhood threats and behavioral and neurobiological correlates of cognitive functioning, externalizing in youth also is related to difficulties with cognitive functions that include executive functions (Ogilvie et al., 2011), particularly in emotional contexts (Zelazo, 2020), and lower executive network recruitment (Shanmugan et al., 2016). Furthermore, there is reason to believe that environmental experiences, such as neighborhood threats, may interact with specific forms of cognitive function in youth to influence development (Jakubovic & Drabick, 2020). Several theoretical susceptibility models propose that biological factors play a role in youth's sensitivity to environmental experiences and may amplify or buffer against the negative effects of certain environments on development (Chong et al., 2022; Ellis et al., 2011; Giudice et al., 2011). Moreover, accumulating research suggests that neurobiological function is one factor that can moderate the extent to which youth's experiences in their neighborhoods are related to developmental outcomes (Guyer, 2020).

For example, one study, not specifically about externalizing, found that neighborhood violence interacted with lower executive network resting-state functional connectivity to predict markers of cardiometabolic risk that are thought to be related to reduced self-regulation (Miller et al., 2018). Another study found that decreased emotion processing-related activation during an introspection task amplified the association between neighborhood threats and externalizing (Weissman et al., 2018). To our knowledge, though, no studies have examined whether task-based activation in executive networks, a correlate of both neighborhood threats and externalizing, may function as a risk factor in moderating their relationship.

The overarching goal of the current study was to investigate associations between neighborhood threats, behavioral and neurobiological correlates of cognitive functioning during an emotional *n*-back task, and externalizing among youth enrolled in the Adolescent Brain Cognitive Development[SM] Study (ABCD Study®). Although our primary focus was on neighborhood threats, it is widely recognized that development occurs in multiple social contexts and there is growing evidence that youth's experiences in different contexts can have distinct influences on cognition (Conley et al., 2022; Meredith et al., 2022) and neurobiological function (Gard et al., 2021; Ip et al., 2022; Saxbe et al., 2018). Therefore, we started by conducting a latent profile analysis (LPA) to identify subgroups of youth based on their levels of neighborhood, school, and family threats. Next, we addressed two separate aims. First, extending from previous work linking neighborhood threats and difficulty in cognitive functioning, we examined associations between latent threat profiles, behavioral performance, and functional magnetic resonance imaging (fMRI) activity during an emotional *n*-back task. We hypothesized that profiles with elevated neighborhood threats would be associated with lower behavioral performance and reduced executive network activity during cognitive processing. Second, given evidence that neurobiological function can moderate associations between youth's neighborhood experiences and emotional and behavioral development (Guyer, 2020; Weissman et al., 2018), we evaluated whether activity in regions that overlapped with executive networks moderated the relationship between neighborhood threats and externalizing. The focus on activity in executive networks as a potential moderator was guided by several developmental susceptibility models suggesting combinations of neurobiology and environmental experiences interact to influence emotional and behavioral development (Chong et al., 2022; Ellis et al., 2011; Giudice et al., 2011; Guyer, 2020). In addition, a recent meta-analysis on behavioral and neuroimaging studies found that the impact of emotional information on executive functioning, specifically working memory, was negligible when assessing behavioral performance, but associated with different patterns of fMRI activation throughout regions of executive networks (Schweizer et al., 2019). We hypothesized that lower activity in regions that overlapped with executive networks during cognitive processing would be associated with higher externalizing among youth living in neighborhoods with higher threats.

Method

Participants

Participants were youth included in ABCD Study Data Release 3.0 (https://doi.org/10.15154/1519007). The ABCD Study is a longitudinal study following youth from 21 research sites across the United States (Volkow et al., 2018). Participants were primarily recruited through schools using a stratified probability sampling method (Garavan et al., 2018). Here, we analyzed behavioral and fMRI data from the baseline assessment when youth were ages 9–10. Sample demographics and exclusionary criteria are detailed below.

Procedure

ABCD Study data collection includes annual assessments of physical and mental health, neurocognition, biospecimens, substance use, culture and environment, and a biennial neuroimaging battery (Casey et al., 2018). Study procedures were approved by the centralized University of California, San Diego and site-specific institutional review boards (for details about ABCD Study organizational structure and biomedical ethics see: Auchter et al., 2018 and Clark et al., 2017). Prior to assessment, all caregivers provided written informed consent and youth provided written assent for participation in the study.

Multicontextual Threats

We evaluated threats across youth's neighborhoods, schools, and families using measures from the ABCD Study Culture and Environment battery (Zucker et al., 2018). Measures of internal consistency within the ABCD Study sample are detailed below. Neighborhood threats were measured using the ABCD Neighborhood Safety/Crime, which assesses perceived safety and crime in participants' neighborhoods. Because the youth assessment included only one item asking youth whether they strongly agreed or strongly disagreed with the statement: *My neighborhood is safe from crime*, neighborhood threats were measured as the mean of all youth- and caregiver-report items. The caregiver survey included the exact item administered to the youth with two additional items asking caregivers whether they strongly agreed or strongly disagreed with the statements: *I feel safe walking in my neighborhood, day or* night and *Violence is not a problem in my neighborhood.* All youth- and caregiver-report items were reverse-scored such that higher scores indicated *more* neighborhood threats (range = 1–5; α = 0.87).

School threats were measured as the sum of all School Environment subscale items from the youth-report School Risk and Protective Factor (SRPF) survey, which assesses youth's perceptions of school safety and support. The SRPF School Environment subscale included six items evaluating youth's perceptions of the school climate related to safety and support (e.g., *I feel safe at my school; My teacher(s) notices when I am doing a good job and lets me know about it*). For each item, youth indicated whether a statement was definitely true or definitely not true. All items were summed and reverse scored with higher scores indicating a *less* safe/supportive school environment (range = 1–19; α = 0.60).

Family threats were measured with the youth-report ABCD Family Environment Scale-Family Conflict Subscale (FES-FCS), which assesses the amount of conflict and anger expressed among family members. The FES-FCS included nine items assessing the amount of conflict expressed by family members (e.g., *we fight a lot in our family; family members often criticize each other; family members sometimes hit each other*.) For each item, youth indicated whether each statement was true or false for most members of their family. All items were summed and scored with higher scores indicating *more* family conflict (range = 0–9; α = 0.68).

Emotional n-back (EN-back) Task

The EN-back task includes two ~5-minute fMRI runs, each with eight task blocks and four 15s fixation blocks (Casey et al., 2018). The eight task blocks included four 0-back (low cognitive load) and four 2-back (high cognitive load) blocks with happy, fear, or neutral face or place stimuli (two blocks for each stimulus type) presented across 10 trials. For each trial, the stimulus was presented for 2s and followed by a 500ms fixation cross. For 0-back blocks, participants were instructed to press "match" when the stimulus was identical to the target presented at the beginning of the block, and "no match" if not. For 2-back blocks, participants were instructed to press "match" when the stimulus was identical to the stimulus presented two trials back, and "no match" if not.

Externalizing

Externalizing was measured using the t-scores from the externalizing subscale from the Achenbach System of Empirically Based Assessment Child Behavior Checklist, a caregiver-report assessment of youth behavioral and emotional problems validated for use in school aged youth ages 6–18 (α = 0.78–0.97; Achenbach, 2009). Supplemental analyses were conducted using the internalizing subscale for comparison.

Neuroimaging Data Acquisition and Preprocessing

Data were collected on Siemens Prisma, Phillips and GE 750 3 T scanners using a 32-channel head coil (Casey et al., 2018). Functional images were collected with a multiband gradient echo-planar imaging sequence and the following parameters: TR = 800 ms, TE = 30 ms, flip angle = 52°, 60 slices acquired in the axial plane, voxel size = 2.4mm^3, multiband slice acceleration factor = 6.

All fMRI data were preprocessed by the ABCD Study Data Analysis, Informatics & Resource Center (DAIRC) detailed elsewhere (Hagler et al., 2019). Preprocessing included correcting for 1) head motion using AFNI's 3dvolvreg, 2) B_0-distortion using a reversing polarity method, 3) gradient nonlinearity distortion, and 4) between-scan motion by resampling each scan with cubic interpolation into alignment with a mid-session reference scan. Automated registration between the spin-echo, B_0 calibration scans, and T1-weighted structural images was performed using mutual information, and functional images were aligned to T1-weighted images with rigid-body transformation.

Analytic Approach

Trial-level behavioral data were extracted for the number of hits, misses, false alarms, and correct rejections across each EN-back condition and stimulus type using processing scripts in MATLAB R2016a (https://github.com/ABCD-STUDY/abcd_extract_eprime). Profile, task performance, and moderation analyses were performed in R version 4.0.3 (R Core Team, 2022) and grayordinate-wise fMRI activation analyses were conducted using FSL's PALM software (Winkler et al., 2014).

Latent Profile Analysis

Profiles of multicontextual threats were identified with latent profile analysis (LPA), which utilizes the maximum likelihood estimator via the expectation–maximization algorithm. LPA was performed on all participants with complete neighborhood, school, and family threat data (n = 11,806; Table 2). Each threat variable was z-scored prior to LPA.

The optimal profile solution was identified by comparing fit indices across six latent profile models (1–6 class models) and interpretability. Comparative fit was assessed using the Bayesian Information Criterion (BIC) and sample size-adjusted BIC (SABIC) (lower values indicating better fit), entropy (values > 0.80 indicating acceptable classification certainty and discrimination), and bootstrapped likelihood ratio tests (BLRT) where a model k was preferred relative to a model $k-1$ when indicated with a significant p-value (Weller et al., 2020). Finally, participants were assigned to the profile for which their probability of membership was the largest and probabilities were retained for use in fMRI activation analyses (see Supplement for alternative clustering analysis).

EN-back Performance

Associations between profiles and EN-back performance were examined in all participants with complete LPA and demographic (i.e., sex assigned at birth, interview age) data, whose behavioral and fMRI EN-back data were recommended for inclusion by the DAIRC (n = 7,847; see Supplement for analyses with a restricted sample of participants included in the fMRI analyses). EN-back performance was measured with sensitivity (d'), calculated as: $d' = z$(hits)-z(false alarms), and adjusted for extreme values (Makowski, 2018).

To examine the effects of condition (2- vs. 0-back), profile, and the interactions between condition and profile on performance (d'), we utilized mixed effect models. Analyses examining d' by stimulus type (happy, fear, or neutral faces and places) are provided in the Supplement. For each model, age and sex were included as fixed-effect covariates[1] and family nested within site was included as a random intercept. All covariates were standardized. Given a significant interaction, post hoc models examined the effect of profile within each condition. Finally, differences in the magnitude of pairs of associations between d' and profiles were evaluated with post hoc pairwise comparisons. All analyses were Bonferroni corrected for multiple comparisons. Supplemental analyses were conducted to evaluate the specificity of results to higher order cognitive functions (i.e., working memory; cognitive control) that are recruited during the EN-back task (Casey et al., 2018; Sripada et al., 2020) (see Supplement).

fMRI Activation Analyses

Following preprocessing, EN-back activation estimates were calculated for each participant using general linear models with fixation, 0-back and 2-back condition, and happy, fearful, and neutral face and place stimuli included as predictors (Hagler et al., 2019). Here, we evaluated relationships between profiles and fMRI activity during cognitive processing, indexed with the linear contrast of 2- vs. 0-back

[1] Although adjusting for other demographic covariates (i.e., household income, caregiver education) is common within the broader literature, there is controversy about the causal structure of relationships between these variables and our independent variables. Therefore, given that misspecifying covariates can produce biased and/or inaccurate estimates (Wysocki et al., 2022), we omitted household income and caregiver education from our primary analyses. We provide further details and supplemental results from models including these variables as covariates in the Supplement.

Table 1 Model fit of the latent profile analysis

Classes	Log-Likelihood	AIC	BIC	SABIC	Entropy	BLRT	BLRT p
1	-50,254.46	100,520.93	100,565.19	100,546.12	1.00	NA	NA
2	-48,894.71	97,809.41	97,883.17	97,851.40	0.81	2719.14	0.01
3	-48,454.38	96,936.75	97,040.02	96,995.53	0.79	881.07	0.01
4	***-48,023.38***	***96,082.77***	***96,215.54***	***96,158.34***	***0.80***	***862.16***	***0.01***
5	-48,023.35	96,090.69	96,252.97	96,183.06	0.55	240.18	0.01
6	-47,901.82	95,855.65	96,047.43	95,964.81	0.62	558.95	0.01

The selected class solution (4-class) is italicized and bolded

AIC Akaike information criterion, *BIC* Bayesian information criterion, *SABIC* Sample size-adjusted Bayesian information criterion, *BLRT* bootstrapped likelihood ratio test

task blocks. Analyses examining fMRI activity during emotion processing were conducted for comparison (see Supplement). Participants with autism or epilepsy diagnoses, low quality structural scans, fewer than 550 degrees of freedom in preprocessed, concatenated time series data, or whose task contrasts had greater than 260 missing grayordinate values (e.g., missing values exceeding the medial wall), and extreme values (> 3SDs from the group mean) for the mean or SD of beta-weights across all grayordinates were excluded. Finally, to account for the presence of twins and siblings, only one youth per family was included in the fMRI analyses ($n = 2{,}873$). We followed this conservative approach implemented by Rosenberg et al. (2020) rather than attempting to statistically adjust for family structure with multilevel block permutation (Winkler et al., 2015) given the range and complexity of familial relationships (e.g., monozygotic and dizygotic twins, triplets, full siblings, half siblings, etc.) within the ABCD Study sample.

For each profile, participant-specific beta weights were entered into a multiple regression model with the probability of membership in the profile of interest as a predictor and age, sex, scanner serial number,[2] and mean frame-to-frame head motion as covariates. Probabilities were utilized to preserve some of the variance associated with youth's experiences in different contexts and reduce the impact of unbalanced sample sizes across latent profiles.[3] For each model, 1,000 permutations were run and the tail of the permutation distribution was fit to a generalized Pareto distribution, from which p-values were computed (Winkler et al., 2016). Regression coefficients were considered significant at family-wise error-corrected, two-tailed $p < 0.05$.

Finally, we performed a region of interest (ROI) analysis based on our a priori hypothesis of executive network activation moderating the relationship between neighborhood threats and externalizing. Following recommendations to avoid introducing bias with selective analyses (Kriegeskorte et al., 2009), the ROI analysis was conducted using the average beta weights for the 2- vs. 0-back contrast (i.e., averaged across runs) from independently processed task data mapped to cortical surface ROIs using a canonical anatomically-defined parcellation (Destrieux et al., 2010; Hagler et al., 2019). Because the anatomically-defined parcellation does not perfectly contour executive networks, we used a partially data-driven approach and selected ROIs that visually overlapped with executive networks (Yeo et al., 2011) and significant vertices in the grayordinate analysis described above. We then used mixed effect models to examine the main effects of average fMRI activation (i.e., averaged across ROIs), probability of membership in the neighborhood threat profile, and their interaction to predict externalizing in hierarchical models with age, sex, and mean frame-to-frame head motion[4] as fixed effect covariates and scanner serial number as a random intercept. Johnson-Neyman analysis was used to examine the region of significance for the interaction term.

Results

Latent Profiles of Multicontextual Threats

Across models with 1–6 latent classes (Table 1), BLRT indicated that models with 2–6 classes showed improved fit relative to those with one fewer class. The five- and six-class solutions were rejected because of low entropy values (0.55 and 0.62, respectively). The four-class solution was selected as the best fitting model indicated by lower BIC (96,215.54)

[2] Some ABCD Study sites have more than one MRI scanner. Following recommendations for imaging analyses with ABCD Study data (Hagler et al., 2019), scanner serial number was included as a random intercept to account for between-scanner variance.

[3] Supplemental analyses were conducted to evaluate whether the behavioral analyses described above replicated in mixed-effect models utilizing the probability of membership in each profile as independent variables.

[4] Sensitivity analyses were conducted to examine the impact of head motion as a covariate.

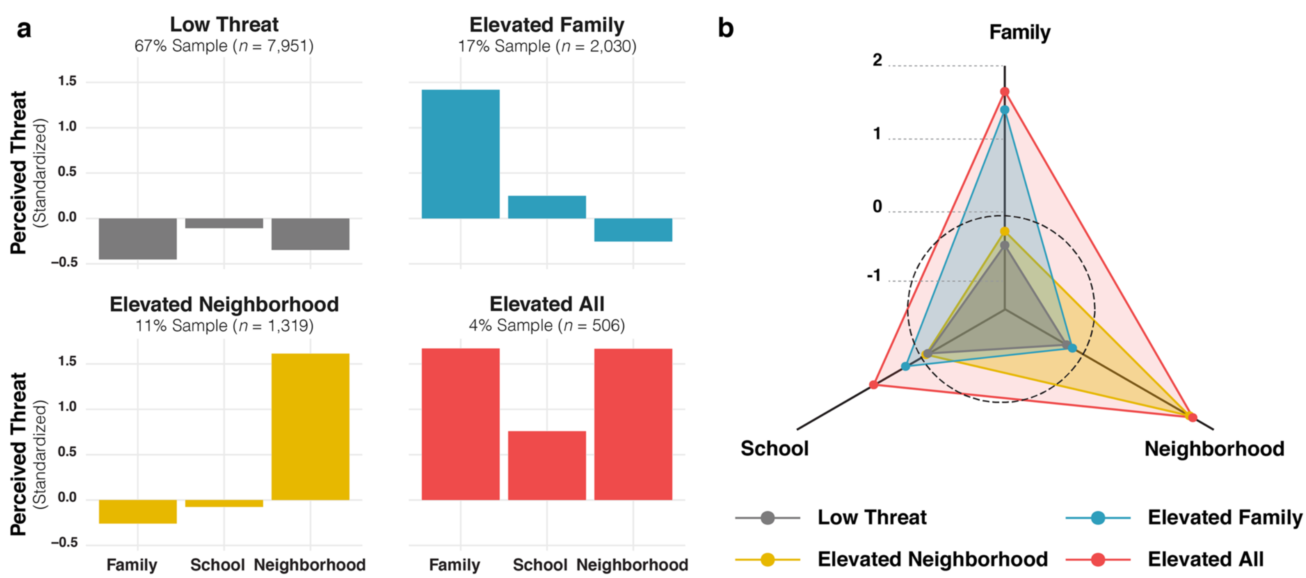

Fig. 1 Four-class model results from the Latent Profile Analysis showing **a** box plots for standardized perceived threat in the family, school, and neighborhood contexts for each profile and **b** the spatial distribution of each latent threat profile. The dashed circle represents the 0-line

and SABIC (96,158.34) values than the two- and three-class solutions and acceptable entropy (0.80).

The largest profile, Low Threat, was characterized by low neighborhood threat, low school threat, and low family threat (Fig. 1; Table 2). The next largest profile, Elevated Family, was characterized by elevated family threat, low neighborhood threat, and low school threat. The third largest profile, Elevated Neighborhood, was characterized by elevated neighborhood threat, low family threat, and low school threat. The smallest profile, Elevated All, was characterized by elevated neighborhood threat, elevated school threat, and elevated family threat.

Profiles Characterized by Elevated Neighborhood Threats Show Diminished EN-back Performance

We examined EN-back performance (*d'*) as a function of the interactive effects of profile and condition (2-back vs 0-back). There was a main effect of condition [$F(1) = 710.85$, $p < 0.001$] such that *d'* was significantly lower for 2-back versus 0-back blocks [B(SE) = -0.55 (0.01), $\beta = -0.63$, $p < 0.001$]. There was a main effect of profile [$F(3) = 26.08$, $p < 0.001$], indicating that all profiles with elevated threat showed lower *d'* relative to the Low Threat profile (Fig. 2). Because a significant interaction of condition by profile was revealed [$F(3) = 2.93$, $p = 0.03$], effects were examined for associations between profiles and overall (total), high (2-back), and low (0-back) cognitive load performance (*d'*) with the Low Threat profile as the reference group.

Consistent with our hypotheses, profiles characterized by elevated neighborhood threats (Elevated Neighborhood and Elevated All) showed diminished overall, high, and low cognitive load performance[5] relative to the Low Threat and Elevated Family profiles[6] (Table 3). The Elevated Family threat profile showed poorer overall and low cognitive load performance relative to the Low Threat profile. There were no significant differences in performance between the Elevated Neighborhood and Elevated All profiles. Supplemental analyses showed no interaction between stimulus type and profile on EN-back performance (see Supplement).

Neighborhood Threats are Associated with Decreased Executive Network Activity during Cognitive Processing

We examined associations between the probability of membership in each profile and fMRI activation during cognitive processing, indexed with the linear contrast of 2-back versus 0-back. Probability of membership in the Elevated Neighborhood profile was significantly related to activation

[5] Behavioral results were consistent in analyses with the probability of membership in each profile as independent variables. Probability of membership in the Elevated Neighborhood and Elevated All profiles was significantly associated with lower overall, 0-back, and 2-back performance. Conversely, probability of membership in the Low Threat profile was significantly associated with higher overall, 0-back, and 2-back performance. The probability of membership in the Elevated Family profile was not significantly associated with EN-back performance.

[6] Sensitivity analyses demonstrated that associations between the threat profiles and EN-back performance remained when adjusting for fluid intelligence measured with WISC-V matrix reasoning.

Table 2 Demographics across latent profiles

	Low Threat	Elevated Family	Elevated Neighborhood	Elevated All	*p*
n	7,951	2,030	1,319	506	
Female[a] (%)	3,849 (48.4)	902 (44.5)	682 (51.8)	220 (43.5)	< 0.001
Race/Ethnicity (%)					< 0.001
Hispanic or Latinx	1,506 (19.0)	369 (18.2)	403 (30.8)	111 (22.2)	
White	4,580 (57.8)	1,134 (56.1)	310 (23.7)	125 (25.0)	
Black	868 (11.0)	265 (13.1)	426 (32.5)	209 (41.8)	
Asian	195 (2.5)	32 (1.6)	24 (1.8)	3 (0.6)	
AIAN[b]	25 (0.3)	5 (0.2)	6 (0.5)	3 (0.6)	
NHPI[c]	8 (0.1)	2 (0.1)	2 (0.2)	0 (0.0)	
Other[d]	33 (0.4)	14 (0.7)	17 (1.3)	2 (0.4)	
Mixed	708 (8.9)	201 (9.9)	121 (9.2)	47 (9.4)	
Caregiver Education (%)					< 0.001
< HS Diploma	285 (3.6)	84 (4.2)	169 (12.8)	49 (9.7)	
HS Diploma/GED	563 (7.1)	195 (9.6)	254 (19.3)	107 (21.2)	
Some College	1,801 (22.7)	522 (25.8)	505 (38.3)	228 (45.1)	
Bachelor	2,194 (27.6)	538 (26.6)	187 (14.2)	81 (16.0)	
Post Graduate Degree	3,099 (39.0)	683 (33.8)	203 (15.4)	40 (7.9)	
Family Income (%)					< 0.001
< $50 K	1,649 (22.4)	521 (28.2)	702 (61.7)	319 (72.2)	
> $50 K – < $100 K	2,122 (28.8)	575 (31.1)	283 (24.9)	77 (17.4)	
> $100 K	3,598 (48.8)	751 (40.7)	152 (13.4)	46 (10.4)	
Threat (mean(SD))					
Neighborhood	1.79 (0.55)	1.85 (0.57)	3.60 (0.51)	3.59 (0.55)	< 0.001
School	4.81 (2.61)	5.62 (2.95)	4.81 (2.88)	7.50 (3.83)	< 0.001
Family	1.14 (1.06)	5.01 (1.16)	1.59 (1.18)	5.50 (1.30)	< 0.001

Group differences were evaluated using one-way ANOVA for continuous variables and χ^2 tests for categorical variables

[a]Sex assigned at birth

[b]*AIAN* American Indian and Alaska Natives

[c]*NHPI* Native Hawaiian and Pacific Islander

[d]Reflects youth whose caregivers selected "Other race" as an indication that the provided groups did not apply to them

in frontal and parietal cortex including bilateral dorsal premotor cortex, precuneus, and right angular gyrus (Fig. 3c). Specifically, youth with higher probabilities of membership in the Elevated Neighborhood profile showed decreased activity in areas that overlap with executive networks.[7] Conversely, probability of membership in the Low Threat profile was significantly related to increased activation in regions of the dorsal attention network (left dorsal premotor cortex [Fig. 3a]). Probability of membership in the Elevated All (Fig. 3d) and Elevated Family (Fig. 3b) profiles was not significantly related to fMRI activity during cognitive processing. Emotion processing fMRI activation was not related to the profiles (see Supplement).

[7] Sensitivity analyses demonstrated that associations between probability of membership in the Elevated Neighborhood and Low Threat profiles and executive network activation remained when adjusting for fluid intelligence measured with WISC-V matrix reasoning (Supplemental Fig. 2).

Decreased Executive Network Activity during Cognitive Processing Amplified the Association between Neighborhood Threats and Externalizing

We conducted a ROI-based analysis to examine whether executive network activity during cognitive processing moderated the relationship between the Elevated Neighborhood threat profile and externalizing. Mean ROI-based executive network activity was calculated across bilateral precuneus, superior frontal sulcus, and angular gyrus using beta weights for the 2-back vs. 0-back contrast from independently processed task data mapped to cortical surface ROIs using a

Table 3 Mixed effect models and post-hoc comparisons for associations between latent profiles and behavioral performance on the EN-back task

Total *d'*					
Profiles	Estimate (SE)	95% CI	β (SE)	*p*	Post-hoc comparisons (Cohen's *d*)
Low Threat	1.78 (0.02)	1.73, 1.83	0.06 (0.04)	**< 0.001**	LT vs EF (0.07) LT vs EN (0.18) LT vs EA (0.22) EF vs EN (0.11) EF vs EA (0.15)
Elevated Family	-0.07 (0.02)	-0.11, -0.03	-0.10 (0.03)	**< 0.001**	
Elevated Neighborhood	-0.18 (0.02)	-0.23, -0.13	-0.27 (0.04)	**< 0.001**	
Elevated All	-0.23 (0.04)	-0.31, -0.14	-0.34 (0.06)	**< 0.001**	
0-back *d'*					
Profiles	Estimate (SE)	95% CI	β (SE)	*p*	Post-hoc comparisons (Cohen's *d*)
Low Threat	2.10 (0.03)	2.04, 2.15	0.05 (0.03)	**< 0.001**	LT vs EF (0.12) LT vs EN (0.27) LT vs EA (0.35) EF vs EN (0.15) EF vs EA (0.23)
Elevated Family	-0.10 (0.03)	-0.15, -0.05	-0.11 (0.03)	**< 0.001**	
Elevated Neighborhood	-0.22 (0.03)	-0.29, -0.15	-0.24 (0.04)	**< 0.001**	
Elevated All	-0.28 (0.06)	-0.40, -0.17	-0.31 (0.06)	**< 0.001**	
2-back *d'*					
Profiles	Estimate (SE)	95% CI	β (SE)	*p*	Post-hoc comparisons (Cohen's *d*)
Low Threat	1.55 (0.03)	1.50, 1.61	0.05 (0.04)	**< 0.001**	LT vs EN (0.24) LT vs EA (0.26) EF vs EN (0.15) EF vs EA (0.17)
Elevated Family	-0.06 (0.02)	-0.10, -0.01	-0.08 (0.03)	0.010	
Elevated Neighborhood	-0.15 (0.03)	-0.21, -0.10	-0.21 (0.04)	**< 0.001**	
Elevated All	-0.16 (0.05)	-0.25, -0.07	-0.22 (0.06)	**< 0.001**	

All models include sex and age as covariates and a random intercept for family nested within site. Bold p-values indicate significance following Bonferroni correction for $n = 12$ comparisons (4 profiles × 3 outcomes). Listed pairwise comparisons indicate significant differences ($p < 0.05$) between profiles

LT Low Threat, *EF* Elevated Family, *EN* Elevated Neighborhood, *EA* Elevated All

canonical, anatomically-defined parcellation (Destrieux et al., 2010; Hagler et al., 2019; Supplemental Fig. 3). The omnibus model test was significant [$\chi^2(1) = 5.26$, $p = 0.02$] indicating that the interaction between probability of membership in the Elevated Neighborhood profile and ROI-based executive network activity improved model fit. The main effect of probability of membership in the Elevated Neighborhood profile was significant [B(SE) = 0.72 (0.18), β = 0.07, $p < 0.001$], but the main effect of ROI-based executive network activity was not [B(SE) = -0.26 (0.18), β = -0.03, $p = 0.15$]. The interaction between ROI-based executive network activity and probability of membership in the Elevated Neighborhood profile[8] was significantly related to externalizing[9] [B(SE) = -0.43 (0.19), β = -0.04, $p = 0.02$][10] such that at lower levels of ROI-based executive network activity, higher probability of membership in the Elevated Neighborhood profile was associated with higher externalizing (Fig. 4).

Discussion

Neighborhood threats are associated with difficulty in cognitive functioning (Jakubovic & Drabick, 2020; McCoy et al., 2015; Muñoz et al., 2020; Sampson et al., 2008; Sharkey, 2010; Sharkey et al., 2012) and externalizing (Goldman-Mellor et al., 2016). Moreover, susceptibility models suggest that some youth may be more vulnerable to negative environmental experiences during development as a function

[8] Only the interaction between cognitive processing-related fMRI activity and the Elevated Neighborhood profile was significant in an additional ROI-based moderation analysis using profile membership as an independent variable.

[9] Analyses demonstrated that cognitive processing-related fMRI activity did not moderate the association between probability of membership in the Elevated Neighborhood profile and internalizing [(SE) = -0.21 (0.20), $p = 0.30$].

[10] Sensitivity analyses demonstrated that mean activity across ROIs moderated the relationship between probability of membership in the Elevated Neighborhood profile and externalizing with the inclusion of fluid intelligence (WISC-V matrix reasoning) as a covariate [B(SE) = -0.40 (0.19), β = -0.04, $p = 0.03$] and with the exclusion of head motion as a covariate [B(SE) = -0.43 (0.19), β = -0.04, $p = 0.02$].

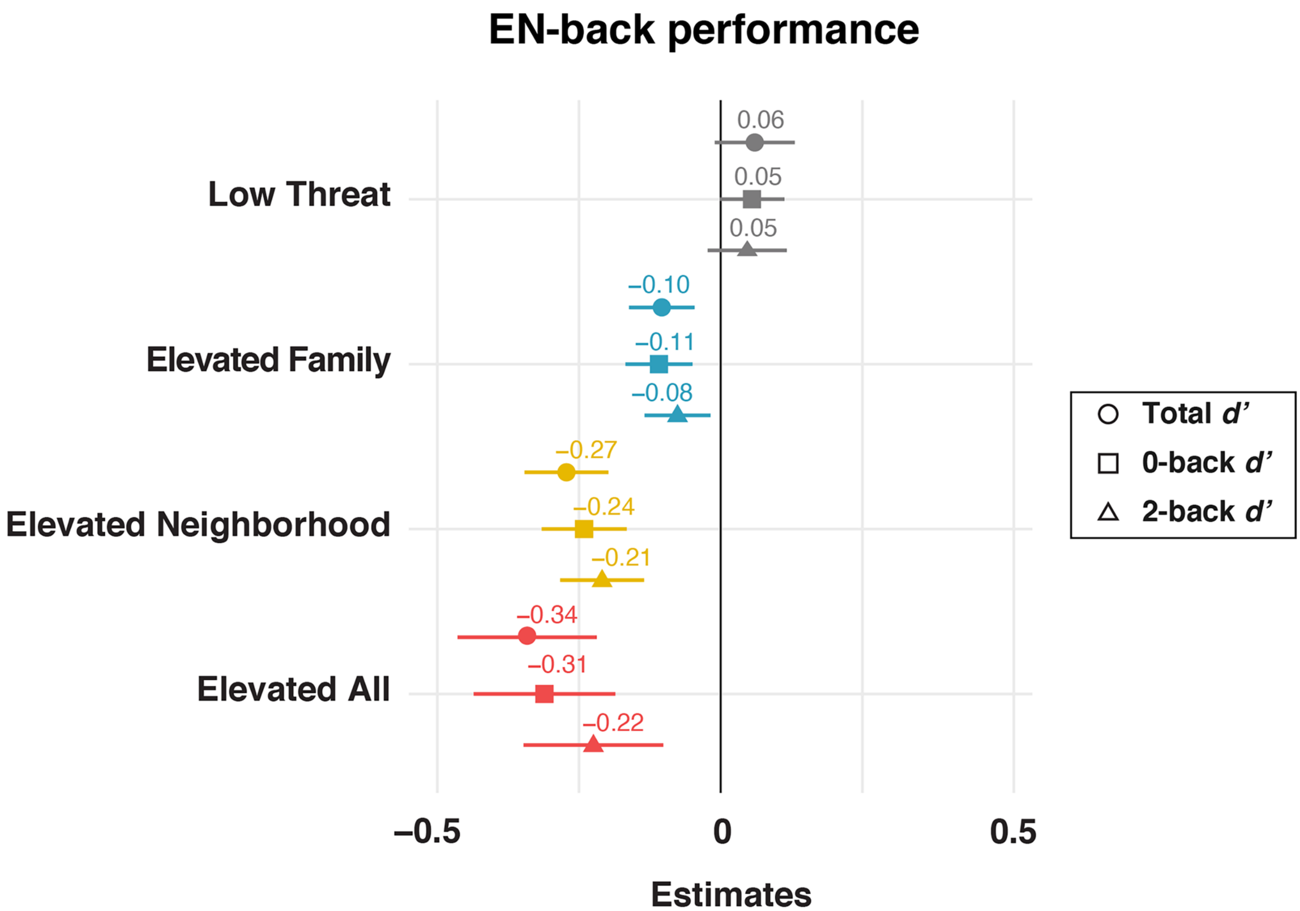

Fig. 2 Dot-and-whisker plot showing task performance (*d'*) as a function of latent threat profile (a between-subjects factor). Standardized estimates are depicted for visualization purposes

of certain neurobiological factors. The current study sought to test the association between neighborhood threats and behavioral and neurobiological correlates of cognitive functioning and whether executive network activation, specifically, acts as a moderator of the relationship between neighborhood threats and externalizing.

Using a large, sociodemographically diverse cohort of US youth, the current study found unique associations between profiles of multicontextual threats and cognitive functioning during an emotional *n*-back task. Consistent with previous work (Conley et al., 2022), we identified four profiles of youth based on their levels of neighborhood, school, and family threats. While the Elevated Neighborhood and Elevated All profiles displayed diminished behavioral performance, only the Elevated Neighborhood profile showed decreased executive network activity during cognitive processing. Moreover, among youth with lower executive network activity, higher probability of membership in the Elevated Neighborhood profile was significantly related to higher externalizing (see also Jakubovic & Drabick, 2020). These findings add to a growing body of research that suggests associations between neighborhood threats and difficulty with cognitive functioning can be detected across multiple levels of analysis (i.e., behavioral and neurobiological; Jenness et al., 2018; Murtha et al., 2022; Tomlinson et al., 2020) and identify executive network function as a potential neurobiological marker of risk for externalizing in youth who reside in neighborhoods with higher threats.

So, why might executive network activation be a relevant neurobiological factor that confers risk for externalizing in youth who live in neighborhoods with higher threats? Executive network activation has been related to threat reappraisal (Wessing et al., 2013) and inhibition (Turner et al., 2018). As such, decreased executive network activation may reflect a neurobiological sensitivity that aids youth in appraising and being prepared to respond to potential threats in their

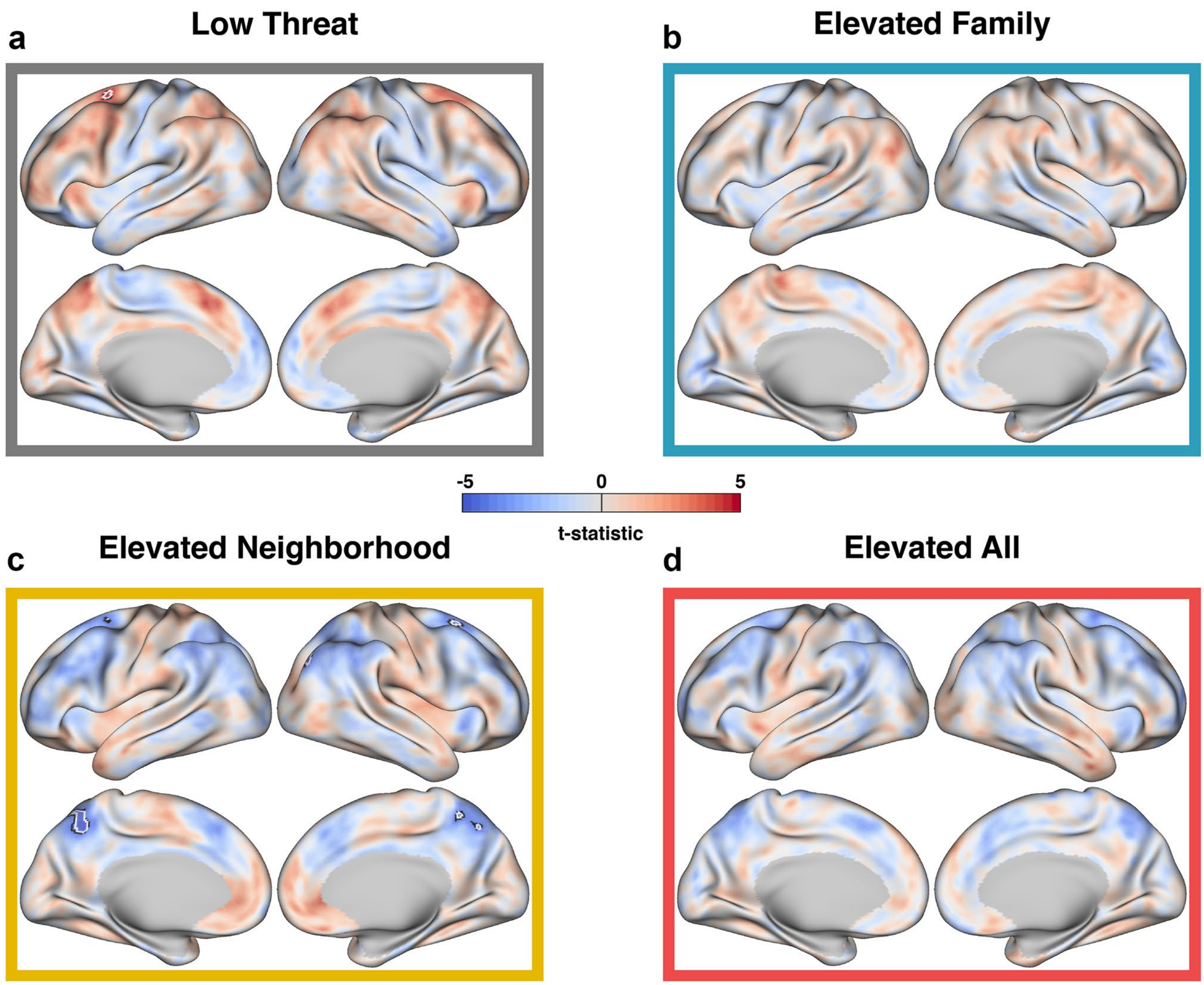

Fig. 3 Relationships between cognitive processing-related (2-back vs. 0-back) fMRI activity and probability of membership in the profiles. Analyses included age, sex, scanner, and mean frame-to-frame head motion during the EN-back as covariates. Unthresholded *t*-statistic maps are visualized on the inflated cortical surface. White (family-wise error-corrected, two-tailed $p < 0.05$) and black outlines (family-wise error-corrected, one-tailed $p < 0.05$) indicate significant vertices. For *t*-statistic maps in color, please see the web version of this article

neighborhoods at the expense of other aspects of cognitive functioning. Prior research also shows that executive networks are involved in suppressing intrusive thoughts and memories and regulating subsequent affective responses (Gagnepain et al., 2017). Therefore, difficulty recruiting executive networks may interact with neighborhood threats to influence externalizing by interfering with youth's ability to suppress goal-irrelevant information and downregulate distracting thoughts and affective responses, especially in non-threatening contexts. For instance, difficulty suppressing reminders about neighborhood violence and subsequent affective responses could lead youth to appear "hot-headed" in the context of a safe block, resulting in behavior that is risky or aggressive. Together, executive network activation may represent a potential neurobiological marker of responsiveness to neighborhood threats that supports youth in navigating their neighborhoods while simultaneously interfering with other aspects of cognitive and affective functioning.

Results from the current study add to our understanding of relationships between neighborhood threats, cognitive functioning, and externalizing. Across behavioral and neurobiological levels of analysis, a consistent association

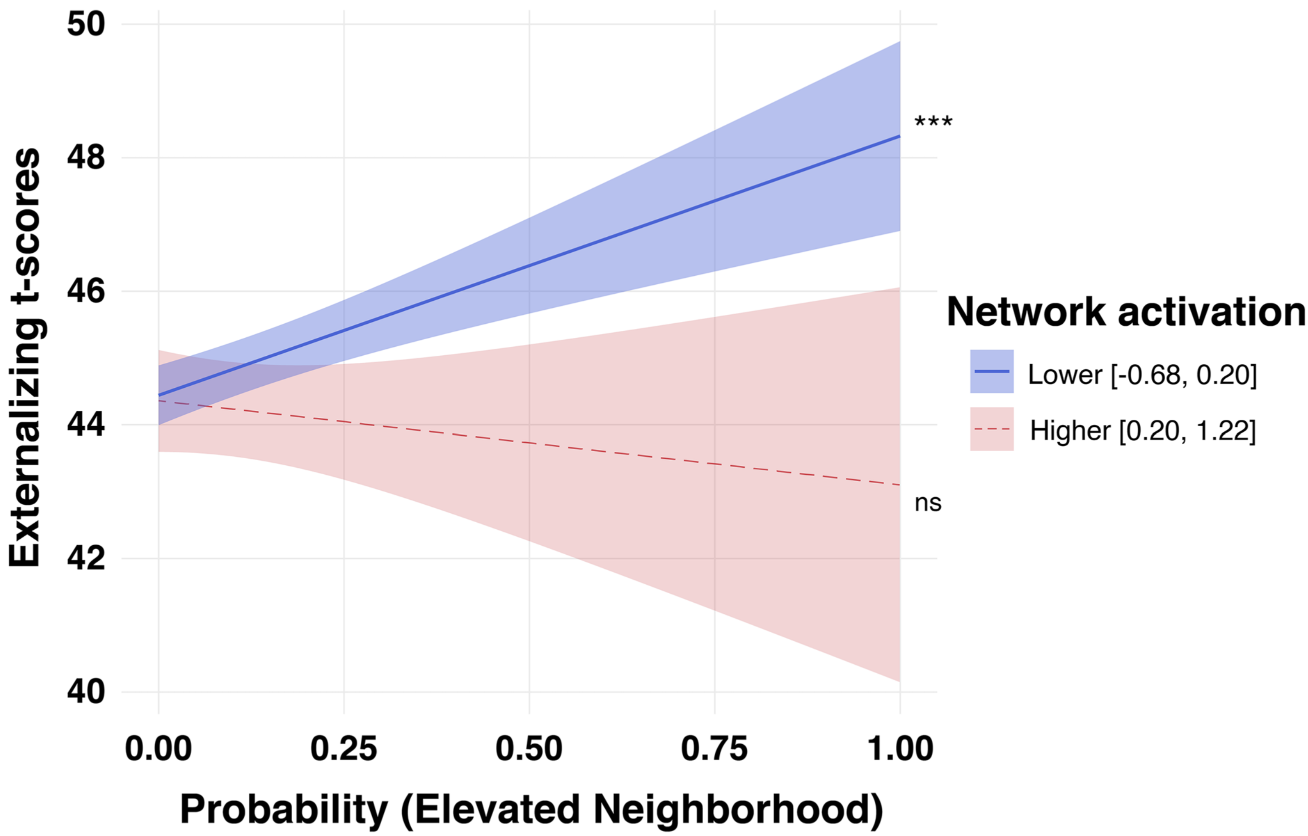

Fig. 4 Cognitive processing-related executive network activity moderated the association between probability of membership in the Elevated Neighborhood threat profile and externalizing. Johnson-Neyman analysis demonstrated that the interaction term was only significant for executive network activation beta values outside the interval (0.22, 2.62) [range of observed executive network beta values = (-0.68, 1.22), mean (SD) = 0.10 (0.19)]

between neighborhood threats and lower cognitive functioning was evident. However, while all three elevated threat profiles showed poorer behavioral performance relative to the Low Threat profile, membership in the Elevated Family and Elevated All profiles was not significantly associated with cognitive processing-related fMRI activation. It is theorized that emotionally or motivationally significant information can impact cognitive performance due to competition for processing resources (Pessoa, 2009). Thus, it is possible that the lower behavioral performance associated with the Elevated Family and Elevated All profiles may be related to other processes that were not captured in the 2-back vs 0-back contrast. For instance, family threats have been associated with heightened attention to angry faces (Pollak et al., 2000) and cumulative threat exposure has been related to interrupted automatic emotion regulation, which may interfere with cognitive functioning in emotionally salient contexts (Lambert et al., 2017). In the current study, angry faces were not included, and the EN-back task was not designed to manipulate automatic emotion regulation. Therefore, future research examining different aspects of processing may be useful for elucidating other neurobiological factors that may be related to decreased behavioral performance across the distinct threat profiles.

Before concluding, several limitations warrant discussion. First, the EN-back task is thought to recruit several cognitive functions including working memory, sustained attention, and emotion processing (Casey et al., 2018). In addition, executive network activation, including a variety of specific ROIs (see ROI-based moderation analysis), during 2-back vs. 0-back task blocks is a robust predictor of general cognitive ability (Sripada et al., 2020). Therefore, while the current study cannot speak to the specificity of associations between neighborhood threats and different cognitive functions, some results may provide preliminary clues. For example, all elevated threat profiles performed worse than the Low Threat profile on sustained attention (0-back) task blocks (Kardan et al., 2021), however, supplemental analyses revealed specific associations between profiles characterized by neighborhood threats and indices of higher-order cognitive processing (i.e., performance on 2-back task blocks adjusting for 0-back, the list sorting working memory test, and principal components of executive functioning and learning/memory; see Supplement). These results raise the possibility that threats in youth's neighborhoods, in particular, are related to higher-order cognitive functions. This conceptualization is consistent with the grayordinate-wise results showing a unique relationship between the Elevated Neighborhood profile and 2-back vs. 0-back activation in executive networks, which is considered a neurobiological signature of higher-order cognitive processing (Rosenberg et al., 2020). Nevertheless, more research is needed to evaluate the specificity of relationships between neighborhood threats and different cognitive functions.

Second, the neighborhood, school, and family threats measures included in the LPA were not equivalent in every respect due, in part, to the relative trade-off between breadth and depth across ABCD Study measures (e.g., parent- and youth-perceptions of neighborhood crime and violence versus youth-perceptions of school safety and support). While perceptions of school safety are negatively correlated with experiences of school threats (e.g., physical and emotional violence) (Cornell et al., 2021), future studies may benefit from using direct measures of school threats and focusing only on youth-report measures of neighborhood threats.

Third, while the ABCD sample approximates the diversity of the US on sex, race and ethnicity, and socioeconomic status, the sample may not generalize to all US youth (Compton et al., 2019) or capture the full range of youth who face neighborhood threats. While the Elevated Neighborhood and Elevated All profiles indicated higher neighborhood threats relative to the other profiles, most youth did not endorse maximal threat, and more research is needed to examine relationships between cognitive functioning and externalizing in youth indicating more severe neighborhood threats. Furthermore, the Elevated Neighborhood and Elevated All profiles had a significantly higher proportion of youth who identified as Black, Hispanic or Latinx, and whose caregivers reported lower education and household income relative to the Low Threat and Elevated Family profiles. This pattern can be contextualized in light of other research showing that people of color are overrepresented in lower socioeconomic status neighborhoods and exposed to the highest rates of neighborhood violence (Friedson & Sharkey, 2015). These disparities in socioeconomic status and exposure to neighborhood violence across race and ethnicity, which are social constructs (Bryant et al., 2022), are representative of ongoing structural racism in the United States (Riley, 2018) and should not be considered to reflect etiology (Cheng et al., 2015). Although examining group-based differences across sociodemographic factors is beyond the scope of the current study, our results lay the groundwork for future research on interactions between various aspects of youth's intersectional identities (Crenshaw, 2018), multicontextual threats, and development.

Fourth, the magnitude of effects in the current study was small by conventional heuristics. That said, the large ABCD Study has increased statistical power to detect small effects that are thought to have greater accuracy than many previously reported effect sizes that may be inflated due to small sample sizes (Dick et al., 2021; Owens et al., 2021). Further, there is increasing recognition that small effects can have practical significance over time and should not be disregarded (Funder & Ozer, 2019). Nevertheless, more research is needed to examine the extent to which results from the current study are clinically meaningful.

Finally, our analyses are cross-sectional and cannot address temporal relationships. Following from susceptibility models, we evaluated the hypothesis that executive network activation would moderate the association between neighborhood threats and externalizing. A plausible competing hypothesis could have been that executive network activation would mediate the association between neighborhood threats and externalizing. In fact, several prominent developmental theories propose that alterations in neurobiological structure and function may be one way in which early experiences "get under the skin" to influence cognitive, emotional, and behavioral development (e.g., McLaughlin et al., 2019; Nelson & Gabard-Durnam, 2020; Teicher & Samson, 2016). However, a central tenet of these theories is that repeated exposure to threats leads to chronic activation of stress-response systems, which culminates in the release of high levels of stress-hormones that can impact the development of neurobiological systems involved in cognitive, emotional, and behavioral functioning (Lupien et al., 2009). To test these theories, though, mediation with repeated measures (i.e., longitudinal data) would be needed (Cole & Maxwell, 2003). And, even then, mediation with only the variables from the current study may fail to capture the complexity of potential mechanisms by which neighborhood threats influence neurobiological and behavioral development. Future research with forthcoming releases of ABCD Study or other longitudinal data will be important for evaluating the temporal order of relationships among neighborhood threats, executive network function, and externalizing and elucidating the mechanisms linking these variables.

In conclusion, the current study provides novel evidence of relationships between neighborhood threats and behavioral and neurobiological correlates of cognitive processing. Further, results implicate executive network function as a potential neurobiological marker of risk for externalizing in youth living in neighborhoods with higher threats. These findings highlight the importance of distinguishing between youth's experiences of threats in different social contexts to increase understanding of relationships between youth's environmental experiences and brain development. Further, bolstering neighborhoods so youth feel safe going about their daily lives, and addressing differences in cognitive processing may be two important levers of change to support youth living in neighborhoods with higher threats in multisystemic ways. Ultimately, multicontextual approaches may be useful for advancing our understanding of the risks embedded within youth's larger social contexts and informing early interventions tailored to youth's individual needs.

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Data Availability The ABCD data repository grows and changes over time. The ABCD data used in this report came from https://doi.org/10.15154/1519007.

Compliance with Ethical Standards

Ethical Approval All procedures received approval from institutional review boards.

Informed Consent All parents/caregivers and youth provided written informed consent and assent, respectively.

Conflict of Interest The authors have no conflicts of interest or competing interests to report.

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