Health & Place 67 (2021) 102493

Contents lists available at ScienceDirect

Health and Place

journal homepage: http://www.elsevier.com/locate/healthplace

Neighborhood disadvantage is associated with stable deficits in neurocognitive functioning in traumatically-injured adults

E. Kate Webb[a,*], Carissa N. Weis[a], Ashley A. Huggins[a], Elizabeth A. Parisi[a], Kenneth P. Bennett[b], Tara Miskovich[c], Jessica Krukowski[d], Terri A. deRoon-Cassini[e,1], Christine L. Larson[a,1]

[a] *University of Wisconsin-Milwaukee, Department of Psychology, Milwaukee, WI, USA*
[b] *VA Montana Healthcare System, Helena, MT, USA*
[c] *VA Northern California Healthcare System, Martinez, CA, USA*
[d] *Marquette University, Department of Psychology, Milwaukee, WI, USA*
[e] *Medical College of Wisconsin, Department of Surgery, Division of Trauma & Acute Care Surgery, Milwaukee, WI, USA*

A R T I C L E I N F O

Keywords:
Stress
PTSD/Posttraumatic stress disorder
Life events/stress
Assessment/diagnosis
Hierarchical linear modeling

A B S T R A C T

Background: In trauma-exposed adults, the relationship between an individual's socioeconomic position (SEP) and post-traumatic stress disorder (PTSD) has been well demonstrated. One potential mechanism by which the stress associated with lower SEPs may impact trauma outcomes is through changes in neurocognition. In both healthy and clinical samples, area-level factors also appear to be independently related to neurocognition. Far less is known about how neighborhood socioeconomic disadvantage, may impact cognition in traumatically-injured adults. The current study employed hierarchical linear modeling to longitudinally investigate whether neighborhood disadvantage was associated with neurocognitive functioning in five domains: processing speed, sustained attention, controlled attention, cognitive flexibility, and response inhibition.
Methods: One-hundred and ninety-five socioeconomically diverse traumatically-injured subjects (mean age = 32.8, 52.8% female) were recruited from an Emergency Department. Two-weeks, three-months, and six-months post-trauma, participants completed self-report measures and a computerized test battery to evaluate neurocognition. An Area Deprivation Index (ADI) score, a measure of a neighborhood's socioeconomic disadvantage, was derived from each participants' home address.
Results: Greater neighborhood disadvantage was significantly related to lower scores in all domains. Results of hierarchical linear models revealed neighborhood disadvantage was significantly associated with processing speed, controlled attention, cognitive flexibility, and response inhibition across time, even after adjusting for individual annual household income, baseline PTSD symptoms, and previous adverse life experiences. This relationship was stable for all domains except sustained attention, which varied across time.
Conclusion: These findings indicate neighborhood disadvantage contributes uniquely to neurocognitive functioning and, for the majority of domains, these contributions are stable across time. The relationship between area-level variables and cognitive function may underlie individual vulnerability to developing psychiatric disorders. Future work should continue to examine the interaction between socioenvironmental stressors and PTSD symptoms longitudinally.

1. Neighborhood disadvantage is associated with stable deficits in neurocognitive functioning in traumatically-injured adults

The vast majority (approximately 90%) of American adults will experience a traumatic event in their lifetime with nearly 10% of those individuals developing post-traumatic stress disorder (PTSD; Kilpatrick et al., 2013). Adults who experience a traumatic injury (e.g., motor vehicle crash, assault, fall) and are admitted to a Level-1 trauma center are at heightened risk of developing PTSD (deRoon-Cassini et al., 2010). While a number of effective, empirically-based interventions exist,

* Corresponding author.
E-mail address: ekwebb@uwm.edu (E.K. Webb).
[1] denotes shared senior authorship.

https://doi.org/10.1016/j.healthplace.2020.102493
Received 1 June 2020; Received in revised form 9 October 2020; Accepted 26 October 2020

studies show that those with chronic PTSD seek treatment 7 to11 years post-trauma and symptom onset (Lobban and Murphy, 2019; Zoellner et al., 2003), resulting in years of distress and functional impairment. Promising work has suggested intervention delivered in the early aftermath of trauma may be particularly effective, potentially staving off the onset of symptoms altogether, which highlights a need to identify individuals at heightened risk acutely post-trauma (Birur et al., 2017). Research seeking to identify markers of risk and resilience after a trauma is challenging but several robust predictors of PTSD have emerged (e.g., Ben-Zion et al., 2019; Shalev et al., 2019). Individual socioeconomic position (SEP), whether measured by education or income, significantly predicts PTSD symptoms in adult trauma-survivors (Herrara-Escobar et al., 2019; Shalev et al., 2019); still, even the well-documented factors that contribute to PTSD (e.g., age, gender, SEP) do not entirely explain the considerable heterogeneity of the clinical presentation (deRoon-Cassini et al., 2010; Galatzer-Levy and Bryant, 2013).

An individual's mental health outcomes can be impacted by intrapersonal characteristics, interpersonal relationships, organizational and community structures, as well as legal policies at both the state and federal level (McLeroy et al., 1988; Robinson, 2008; Stokols, 1996). Social and physical contexts defined by community and governing structures may lead to sustained stress and contribute risk of poor trauma outcomes (McLeroy et al., 1988; Robinson, 2008; Stokols, 1996). Living in a socioeconomically disadvantaged neighborhood increases the likelihood of experiencing chronic life stressors, such as less access to reliable transportation, healthy foods, and educational or employment opportunities (Farah, 2017; Haley et al., 2017; Krukowski et al., 2010; McEwen, 2004; McEwen, 2012; Xiao et al., 2018). Adults and adolescents residing in more advantaged neighborhoods report fewer mental and physical health symptoms and better post-trauma outcomes compared to residents of more disadvantaged neighborhoods (Ahern and Galea, 2006; Diez Roux and Mair, 2010; Hill et al., 2005; Pabayo et al., 2017; Ross and Mirowsky, 2008; Schuck and Spatz Widom (2019)).

In general – though not exclusively – individuals in lower SEPs also live in areas that are categorized as socioeconomically disadvantaged (Hill et al., 2005; Kind and Buckingham, 2018; Ross and Mirowsky, 2008). The effects observed between mental health and an individual's neighborhood cannot be entirely explained by individual-level variables (Kind and Buckingham, 2018; Ross and Mirowsky, 2008). In other words, the impact of neighborhood poverty on PTSD is not merely synonymous with the impact of individual poverty on PTSD (Ross and Mirowsky, 2008). Rather, the stress of both individual *and* neighborhood socioeconomic positions can independently and concurrently get "under the skin" and impact trauma outcomes.

2. Individual and neighborhood socioeconomic circumstances get "under the skin"

Although the inclusion of contextual factors appears to help capture differences in psychopathology development after a trauma (Gapen et al., 2011; Heid et al., 2017; Smith and Patton, 2016), the various neurobiological mechanisms by which lower individual and neighborhood SEP may impact mental health are still being ascertained. A well-substantiated hypothesis theorizes living in a poorer neighborhood and/or being in a lower SEP is detrimental to mental health because the circumstances are associated with sustained stress as well as exposure to environmental risk factors (Farah, 2017; Harnett, 2020; Parnia and Siddiqi, 2020; Vliegenthart et al., 2016). Indeed, the chronic stress related to low SEP alters numerous biological processes (Farah, 2017; Juster et al., 2010). The allostatic load theory proposes individuals in a lower SEP encounter greater adversity, which ultimately results in persistent and heightened neuroendocrine and neural responding (McEwen, 2004; Selye, 1956). This theory is bolstered by work on the hypothalamic-pituitary-adrenal axis (HPA axis), one of the body's primary stress response pathways, responsible for regulating neurohormones such as cortisol (Juster et al., 2010; Stephens and Wand, 2012). One potential neurobiological pathway by which lower SEP and neighborhood disadvantage may influence PTSD development is through changes in neurocognition: aberrations in HPA axis function (e.g., increased cortisol reactivity) are associated with impairments or diminishments in nearly all neurocognitive domains (Hackman et al., 2012; Isaksson et al., 2012; Mance et al., 2019).

3. PTSD, neurocognition, and neighborhood disadvantage

Neurocognitive functioning underlies critical everyday behaviors (Last et al., 2018). Although neuropsychological test batteries may employ different tasks to evaluate an individual's neurocognitive profile (Evans et al., 2013), several key domains emerge: (1) attention, categorized as either sustained (engaging with stimuli or a task for a prolonged period of time; Rosenberg et al., 2016) or controlled (deliberately focusing on a stimulus or mental representation; Namazi and Thordardottir, 2010), (2) cognitive flexibility, operationally defined as one's ability to adapt to a new task or use new strategies/problem-solving techniques (Buttelmann and Karbach, 2017), (3) information processing speed (Bowling and Mackenzie, 1996), and (4) response inhibition, or withholding an automatic response to complete a goal-directed behavior (Verbruggen and Logan, 2008).

These domains, in addition to language and sensorimotor cognitive functions, harmoniously affect an individual's thinking and emotions. Deficits in these areas are consistently observed in many neurological and psychiatric illnesses, including PTSD (Aupperle et al., 2012; Ben-Zion et al., 2018; 2019; Samuelson et al., 2020; Tomlinson et al., 2020). Prospective longitudinal and retrospective cross-sectional studies have found functional impairments are predictive of (Ben-Zion et al., 2018; 2019; Samuelson et al., 2020), and associated with PTSD (Aupperle et al., 2012). Poorer cognitive flexibility, response inhibition, and sustained attention pre-trauma predicts future PTSD symptoms (Ben-Zion et al., 2018; 2019; Samuelson et al., 2020). Differences in neurocognition that predate the trauma can aggravate PTSD symptoms and may even potentially hinder treatment effectiveness (Aupperle et al., 2012). Neurocognition is also significantly altered by both individual and contextual factors; however, the majority of research on neurocognition and PTSD has not considered neighborhood variables in analyses (c.f., Tomlinson et al., 2020).

Previous work has chronicled the impact of individual SEP on neurocognitive domains (Fiocco et al., 2007; Lupien et al., 2007). In fact, neurocognitive assessments (both computerized and written) normalize their scores using education of the general population because neurocognition and SEP are related (Silverstein et al., 2007; Ursache and Noble, 2016). Normalized neurocognitive scores, in conjunction with other diagnostic measures and self-report questionnaires, are useful in predicting post-trauma outcomes such as concussions (Lau et al., 2011), depression (Williams and Latkin, 2007), and PTSD (Ben-Zion et al., 2018; Samuelson et al., 2020). Individual factors do not sufficiently explain differences in neurocognition in the same manner that these factors do not fully explain development of PTSD (Farah, 2017; Harnett, 2020). The chronic stress of neighborhood socioeconomic disadvantage may impact neurocognition (Farah, 2017) beyond variance captured by individual SEP.

Indeed, recent work has shown a significant association between neurocognition and neighborhood disadvantage in healthy adolescents and adults as well as clinical populations (Aughinbaugh, 2014; Besser, 2017; Gapen et al., 2011; Lang et al., 2008; Lee and Waite, 2018; Lei et al., 2019; Moore et al., 2016; Muñoz et al., 2020; Sharkey and Elwert, 2011; Wight et al., 2006; Wu et al., 2015). A number of studies have demonstrated that neighborhood factors independently contribute to neurocognition over and above individual SEP (e.g., Besser, 2017; Moore et al., 2016; Muñoz et al., 2020; Sharkey and Elwert, 2011). For example, Moore et al. (2016) demonstrated higher neighborhood SEP was a significant predictor, and in fact a *better* predictor than education, race, or age, of better neurocognitive performance in all domains (Moore et al., 2016). In a large sample of healthy adults, subjective neighborhood stress (e.g., feeling as though your neighborhood is unsafe) was significantly related to poorer memory and executive functioning (Muñoz et al., 2020). For older adults cognitive ability is significantly affected by neighborhood context (Besser, 2017; Lee and Waite, 2018; Lei et al., 2019; Wu et al., 2015). Notably, the effect of neighborhood poverty on cognition extends through generations, with measurable impairments of neurocognition observed over two generations (Sharkey and Elwert, 2011).

Research on the impact of neighborhood factors on neurocognitive domains is critical, especially if normalized scores of neurocognitive assessments are to be utilized as predictors of PTSD development. As aforementioned, alterations in neurocognitive performance are associated with PTSD, individual SEP, and neighborhood disadvantage (e.g., Routledge et al., 2017; Samuelson et al., 2020); still, it is unclear how the relationship between neurocognition and multiple levels of SEP, individual and neighborhood, are in turn related to PTSD risk and chronicity. Neighborhood disadvantage may inherently alter an individual's neurocognitive functioning independent of PTSD symptoms and thereby alter the trajectory of the psychological disorder. Investigations of differences in cognitive functioning may inform experiments on underlying neurobiological mechanisms and yield improved community and individual preventative interventions.

4. The current study

In a sample of traumatically-injured adults, we explored the relationship between neighborhood disadvantage and neurocognitive functioning longitudinally. Given the increased interest in documenting socioenvironmental factors which impact trauma outcomes (Maercker and Horn, 2012) determining whether neighborhood disadvantage uniquely impacts cognitive function is critical. The majority of research on contextual-level variables seeks to evaluate whether those factors explain any variability in neurocognitive functioning over and above individual-level variables (Ross and Mirowsky, 2008). Therefore, the primary aim assessed whether neighborhood disadvantage, as measured by the Area Deprivation Index (ADI; Hu et al., 2018; Knighton et al., 2016; Singh, 2003), was significantly associated with neurocognitive domain scores over and above individual annual household income, adverse life experiences, and PTSD symptoms. Based on previous studies (Farah, 2017; Hackman et al., 2012; Hackman and Farah, 2009; Noble et al., 2012), we hypothesized ADI would be significantly associated with lower scores in all of the domains evaluated at three timepoints, including sustained attention, controlled attention, cognitive flexibility, inhibition, and processing speed. We also anticipated baseline PTSD symptoms would be significantly associated with impairments across the domains (Ben-Zion et al., 2018; 2019; Samuelson et al., 2020). The secondary aim was to examine whether the relationship between neighborhood disadvantage and each neurocognitive domain was stable across time. We tested whether there was an effect of time on the relationship between ADI and domain scores and hypothesized there would be a stable effect of ADI.

5. Methods

Participants. Between 2016 and 2020, 232 participants were recruited from an Emergency Department (ED) in southeastern Wisconsin as part of the Imaging Study on Trauma & Resilience (iSTAR). Participants were eligible if they were English-speaking, between 18 and 60 years of age, and able to schedule a research visit within 30 days of the traumatic injury. Subjects must have experienced a traumatic event which met Criterion A of a PTSD diagnosis (as defined in the DSM-5; American Psychological Association, 2013) and scored a minimum of a three on the Predicting PTSD Questionnaire (Rothbaum et al., 2014; indicative of increased risk of developing PTSD) or endorsed that the event was a near-death experience. Notably, this procedure oversampled individuals at risk of PTSD. Participants were excluded if they scored 13 or lower on the Glasgow Coma Scale (Sternbach, 2000; Teasdale et al., 2014), had a spinal cord injury with neurological deficits, or were diagnosed with any neurological condition affecting brain structure or function. Additional exclusion criteria included: a self-inflicted traumatic injury, severe vision or hearing impairments, history of psychotic or manic symptoms, current antipsychotic medication use, obvious substance abuse, or on a police hold to be released to jail.

Table 1
Baseline sample characteristics of traumatically-injured individuals.

Characteristics	Percent (%)	Mean	SD
Age (years)		32.81	10.82
Sex			
Female	52.8		
Race and Ethnicity			
African American and/or Black	58.8		
White and/or Caucasian	26.3		
More than one race	7.7		
Other racial identity	<5		
Hispanic/Latinx	9.4		
Non-Hispanic/Latinx	90.6		
Race Unknown/Not reported	5.7		
Education			
High school/GED or below	44.6		
Some post-secondary education/college	26.2		
Associate degree	12.8		
Bachelor's degree or beyond	16.4		
Annual Household Income			
$0–10,000	20.5		
$10–20,000	15.4		
$20–30,000	16.9		
$30–40,000	7.7		
$40–50,000	8.7		
$50–60,000	6.7		
$60–70,000	6.7		
$70–80,000	6.2		
$80–90,000	<5		
$90–100,000	<5		
$100,000 or higher	5.6		
Area Deprivation Index		68.76	21.80
Mechanism of Injury			
Motor Vehicle Crash	67.2		
Assault/altercation/Domestic Violence	14.9		
Other	17.9		
T1 PTSD Symptoms (PCL-5)		27.09	18.02
Life Events Checklist (Weighted Total)		30.79	16.63

Note. N = 195. ***T1,*** *Timepoint 1 (two-weeks post-injury),* ***PCL-5,*** *PTSD Checklist for DSM-5.*

Procedure. Participants were screened in the ED or contacted via telephone after discharge. Individuals provided written informed consent prior to participating in research activities. Two-weeks (i.e., T1), three-months (i.e. T2) and six-months (i.e., T3) post-injury subjects completed self-report measures and neurocognitive assessments (sample characteristics for participants included in the analysis are presented in Table 1). All subjects were financially compensated for their time. The study's protocol was approved by the Medical College of Wisconsin Institutional Review Board.

Measures. *Dependent Variables: Neurocognitive Assessments***.** The WebNeuro test battery is a conventional, validated, online assessment of various neurocognitive domains (Mathersul et al., 2009; Silverstein et al., 2007; Williams et al., 2005). The following is a brief description of each of the tasks used in each domain (Brain Resource. BRISC and WebNeuro Assessment Manual, Brain Resource Ltd., V1.7; 2010.; Mathersul et al., 2009; Williams et al., 2010):

Processing Speed: A choice reaction time task was presented in which participants were asked to select whether a specific stimulus (e.g., red circle) was on the left or right side of the screen.

Sustained Attention: Participants completed a continuous performance test (also known as an n-back task). Four letters (B, C, D, or G) were presented randomly every 2.5 s. Subjects were instructed to respond if the same stimuli was presented twice in a row.

Controlled Attention: Subjects completed a Stroop task (Stroop, 1935). Names of color (e.g., "Blue") were presented in a color that matched (e.g., "Blue" displayed in blue font color) or mismatched (e.g., "Blue" displayed in red font color) and participants answered whether the pair was congruent or incongruent. First, participants were asked to attend to the meaning of the word and ignore the font color and then they were required to disregard the meaning of the word, and attend to the font color.

Cognitive Flexibility: Participants completed a trail-making task (Reitan, 1992) in which they were required to alternate between numbers and letters and select responses in ascending sequential order (e.g., 1-A).

Response Inhibition: A go/no-go task was presented. Participants were asked to respond as quickly as possible when a red word was presented and inhibit the response when the word was presented in a green font color.

WebNeuro domain summary scores are provided by the battery's automated algorithms (Gordon et al., 2013; Burger et al., 2014; Mathersul et al., 2009; Silverstein et al., 2007; Williams et al., 2005; Williams et al., 2010). The outputted scores are provided as normalized scores. Gender, age, and educational level, are used to normalize each domain score to the WebNeuro normative sample of 1000 participants (Gordon et al., 2013; Mathersul et al., 2009; Williams et al., 2010); thus, these variables are accounted for in the final z-scores output (dependent variable) for each participant. Although education is inherently related to the z-score through the normalization procedure, there was still significant variability in education associated with all of the domain scores (Table 2). We have included analyses that also include education as a covariate in the Supplemental Material.

Covariates: Individual Factors. Annual household income was provided on a semi-continuous scale (1–11) where 1 reflected a $0–10,000 income bracket and 11 represented an income of $100,000 and above. Education was also reported on a semi-continuous scale and reflected the number of educational years completed. For example, a score of 12 reflected a high school diploma or equivalency. Participants provided contact information, including their home addresses.

To assess acute posttraumatic stress symptoms at T1, the PTSD Checklist was administered (PCL-5; Weathers et al., 2018). This well-validated self-report measure required participants to indicate how much specific symptoms (related to PTSD symptom clusters described in DSM-5) bothered them. Twenty items were presented, and participants responded using a Likert scale, with higher scores indicating greater symptom severity. In our sample, the PCL-5 had excellent internal consistency (Cronbach's alpha = 0.95; Cronbach, 1951; Lance et al., 2006). At T1, the 17-item Life Events Checklist (LEC) was also administered (Gray et al., 2004). The measure screens for life-time exposure to potentially stressful or traumatic events. Participants are asked to endorse whether the event (e.g., a natural disaster) was directly experienced, witnessed, or learned about. A newly developed weighted total score was created in which higher scores were indicative of a closer proximity to the event (items experienced were weighted the heaviest; Weis et al., *under review*). The maximum weighted score was 102 (Weis et al., *under review*). This weighted score has high reliability in this sample (Cronbach's alpha = 0.87; Weis et al., *under review*).

Independent Variable: Neighborhood Disadvantage. An Area Deprivation Index (ADI) Score, a validated measure of neighborhood socioeconomic disadvantage, was calculated for each participant (Hu et al., 2018; Kind et al., 2014; Kind and Buckingham, 2018; Singh, 2003). The 2015 ADI scores were derived from variables measured in the 2011–2015 American Community Survey (ACS; part of the United States Government Census) and publicly available online: https://www.neighborhoodatlas.medicine.wisc.edu/(accessed February 2020). One factor-based index score (Kind et al., 2014; Singh, 2003) is calculated for each individual block-group units, which include between 600 and 3000

Table 2
Bivariate relationships between study measures.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. Gender	–																					
2. Age	.08	–																				
3. Education	.16	.16	–																			
4. Income	-.10	.03	.49	–																		
5. ADI	-.01	.01	-.33	-.45	–																	
6. LEC	-.06	.01	.09	<.01	-.07	–																
7. PCL-5	.13	-.19	-.06	-.10	<.01	.26	–															
8. PS (T1)	.16	-.08	.12	.21	-.20	-.04	-.07	–														
9. PS (T2)	.13	-.03	.20	.25	-.26	<.01	-.02	.47	–													
10. PS (T3)	.19	.06	.21	.20	-.30	.11	-.02	.40	.37	–												
11. SA (T1)	.10	.02	.29	.29	-.26	.03	<.01	.32	.17	.24	–											
12. SA (T2)	<.01	.09	.26	.31	-.28	-.02	-.11	.23	.26	.27	.40	–										
13. SA (T3)	.12	.06	.28	.29	-.39	.12	.06	.24	.22	.47	.34	.51	–									
14. CA (T1)	.03	-.12	.28	.24	-.24	.06	.05	.25	.31	.22	.32	.25	.25	–								
15. CA (T2)	.17	-.23	.31	.27	-.29	.09	.15	.20	.34	.24	.27	.35	.36	.53	–							
16. CA (T3)	.04	-.20	.38	.34	-.36	.09	.08	.32	.29	.41	.29	.34	.47	.53	.62	–						
17. CF (T1)	.10	-.23	.24	.22	-.33	.10	.15	.35	.32	.29	.36	.35	.36	.55	.60	.57	–					
18. CF (T2)	.13	-.27	.34	.30	-.32	.13	.09	.40	.41	.35	.45	.43	.43	.50	.61	.55	.78	–				
19. CF (T3)	.06	-.29	.28	.34	-.33	.13	.13	.35	.40	.44	.27	.40	.51	.46	.56	.64	.72	.74	–			
20. RI (T1)	-.03	-.07	.34	.30	-.35	.19	.05	.30	.32	.31	.47	.42	.47	.36	.38	.43	.43	.52	.39	–		
21. RI (T2)	<.01	.10	.31	.25	-.34	.15	-.03	.25	29	.35	.31	.55	.52	.28	.40	.41	.37	.46	.35	.58	–	
22. RI (T3)	.06	.03	.28	.30	-.50	.20	.04	.35	.34	.50	.36	.40	.65	.28	.39	.52	.42	.42	.47	.66	.68	–

Note: N = 195; Point biserial correlations are reported for gender, all correlations with continuous variables are Pearson's correlations; Missing variables removed case-wise; **ADI:** Area Deprivation Index, **PCL-5:** PTSD Checklist for DSM-5, **LEC:** weighted Life Events Checklist scores, **PS:** Processing Speed, **SA:** Sustained Attention, **CA:** Controlled Attention, **CF:** Cognitive Flexibility, **RI:** Response Inhibition, **T1:** Time 1 (two-weeks post-trauma), **T2:** Time 2 (three-months post-trauma), **T3:** Time 3 (six-months post-trauma); **bolded coefficients:** $p < .05$.

people (US Census Bureau, 2020. Retrieved from: https://www.census.gov/programs-surveys/geography/about/glossary.html). The block-group factor-based index represents 17 variables from the US Census including measurements of poverty, education, housing, and employment (Kind et al., 2014). National ADI rankings ranged from 1 to 100 (higher scores indicating more disadvantage).

Data Preparation. Participants were excluded if they designated a post office box as their primary residence, lived outside of Wisconsin, or if their address was not associated with a block-group ID. The initial address provided by the participant was geocoded and participants were included regardless of residential stability. A total of 224 participant's addresses were successfully geocoded. The distribution of ADI rankings for all participants in this study is presented in Fig. 1. The distributions of ADI by participant gender and racial identity are displayed in Figs. 2 and 3, respectively. Of the participants with ADI scores, four did not complete self-report or demographic data at T1. One-hundred and ninety-five subjects started (i.e., opened the program and completed at least one domain) T1 WebNeuro assessments. Sample characteristics for these participants can be found in Table 1. The selected analysis approach permits some missing data, therefore, no subjects were excluded for missing neurocognitive scores.

Prior to conducting analyses, we centered the time variable at T1, allowing the intercept to indicate average scores at the initial study visit. National ADI scores, annual household income, weighted life events scores, and PCL-5 total scores, were treated as continuous variables and were grand-mean centered.

Analysis Strategy. Hierarchical linear modeling (HLM) was used to investigate the relationship between neighborhood socioeconomic disadvantage and neurocognitive domains following trauma exposure. HLM offers several advantages over traditional longitudinal analysis methods (e.g., repeated measures ANOVA); this type of modeling allows for missing data (Gallop and Tasca, 2009; Pickett, 2001) and provides estimates for individual subject variation across time (Lininger et al., 2015).

All models were fitted using Maximum Likelihood estimation and an unstructured covariance structure in the R package "lmerTest" (provides *p*-values, in addition to the confidence intervals provided in the "lme4" package) using R Version 3.5.3 (R Core Team, 2020). An unconditional model (i.e., "null model") was fit and intraclass correlation coefficients (ICC), were calculated using the "icc" function in the "sjstats" package. ICCs provided an index of how much variability was attributed to individual differences. A low ICC (<0.20) suggests people are similar across time while a moderate to high ICC suggests there is considerable within-subject variability.

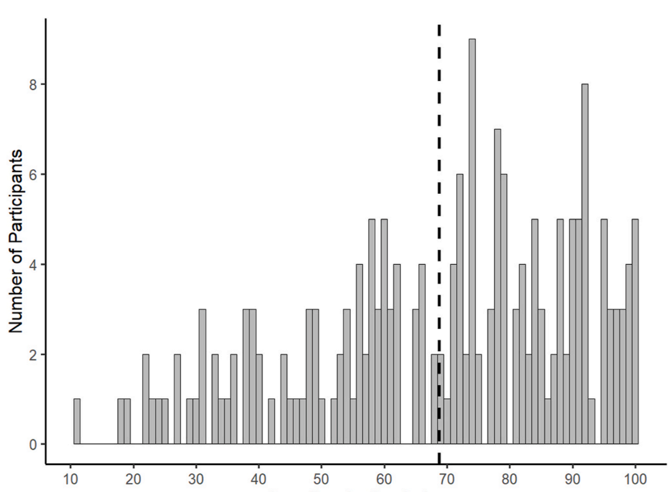

Fig. 1. Distribution of area deprivation index rankings (mean = 68.76, standard deviation = 21.80).

Fig. 2. Distribution of area deprivation index rankings by gender (Male mean = 69.24, standard deviation = 22.31, N = 93; female M = 68.32, SD = 21.42, N = 102).

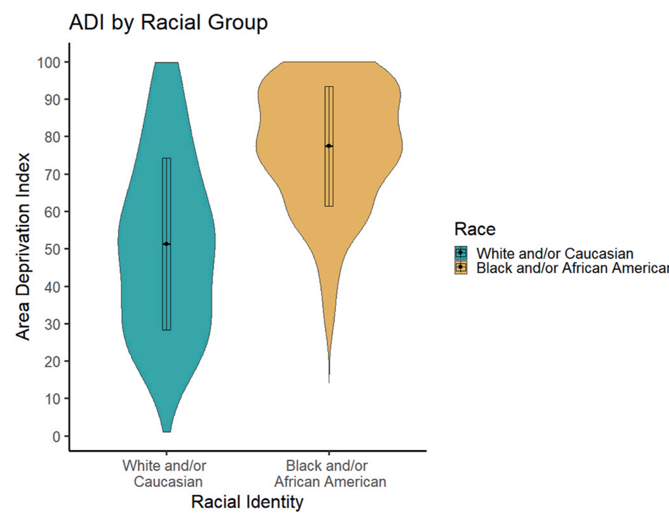

Fig. 3. Distribution of Area Deprivation Index Rankings by Racial Identity (White and/or Caucasian Participants Mean = 51.24, Standard Deviation = 22.94, N = 51; Black and/or African American Participants M = 77.39, SD = 16.00, N = 114). *Note: ADIs of participants identifying as another reported racial and ethnic group were excluded due to small sample sizes.*

Prior to analyzing study variables, we tested whether there was significant variability in the slopes for time by comparing a model treating slopes as a fixed factor (reduced model) to a model treating slopes as a random factor (full model). Our results suggest that there is no significant variability in time slopes for predicting processing speed ($\chi^2(1) = 1.88$, $p = .391$), response inhibition ($\chi^2(1) = 0.27$, $p = .872$), and cognitive flexibility ($\chi^2(1) = 0.16$, $p = .923$). Including time as both a random and fixed variable in a model predicting controlled attention resulted in a singular fit. Therefore, in an attempt to create the most parsimonious model and avoid overfitting models, all subsequent models with these outcome variables included time as fixed variable (Matuschek et al., 2017). However, in predicting sustained attention, the inclusion of time as a random factor significantly improved the model ($\chi^2(1) = 6.81$, $p = .033$), suggesting there was a significant effect of time on individual slopes and it should be included in the model.

We conducted five separate analyses and examined the relationship between our study variables and each neurocognitive domain independently. For each domain analysis, the following models were conducted: prior to examining study variables an Unconditional Model, (in which all predictors were excluded) was conducted. A Level 1 Model was then assessed, which added a time variable to examine if neurocognitive scores changed over time without considering level 2 factors (i.e., ADI, baseline PTSD, weighted life event scores, and annual household income). In Model 1, we examined how income, weighted life events checklist scores, and baseline PCL-5 scores explained individual differences in changes of neurocognitive functioning across time (fixed variable for processing speed, response inhibition, and cognitive flexibility and a random variable in the models for sustained and controlled attention). In Model 2, national ADI scores were added. We conducted a model comparison to determine whether neighborhood socioeconomic disadvantage contributed to neurocognitive functioning over and above the other covariates. Finally, in Model 3 we included the cross-level interaction term ADI x Time as a predictor and compared this model to Model 2. We hypothesized there would be a non-significant interaction between these variables, indicating the relationship between ADI and the neurocognitive domain was stable across time.

Marginal R^2 (proportion of variance explained by fixed factors) and Conditional R^2 (proportion of variance explained by all factors) were calculated for every model whereas effect sizes (Cohen's D calculated using "lme.dscore"; Cohen, 1962), were derived for variables in the final significant model (which varied by neurocognitive domain). All assumptions for HLM were sufficiently met and all statistical tests were two-tailed and an alpha of .05 was considered significant. To control for multiple comparisons, we applied the Benjamini-Hochberg False Discovery Rate (Benjamini and Hochberg, 2000); however, the results remained unchanged, therefore we have reported uncorrected p-values.

6. Results

Study Sample. Of the 195 participants who completed the T1 assessment, not all completed T2 and T3. At T2, 29 participants did not complete the study visit (T2 N = 166). Thirteen of the participants who did not complete T2 did return for the T3 appointment. Twenty-two participants were absent from the T3 visit (T3 N = 173). Independent samples *t*-tests were conducted to assess potential differences between the participants who completed all study visits and those who missed one or both follow-up assessments. Individuals who did not complete all assessments had significantly lower household income (N = 35; M = 3.34, SD = 2.78) compared to those who attended all visits, (N = 160; M = 4.50, SD = 3.05; $t(193) = 2.07$, $p = .040$. In addition, these individuals were significantly younger (N = 35; M = 27.62, SD = 7.8) compared to participants who returned for all follow-up visits (N = 160; M = 33.94, SD = 11.07; $t(193) = 3.21$, $p = .002$). Regarding the outcome variables, those who did not return for one, or both study visits, significantly

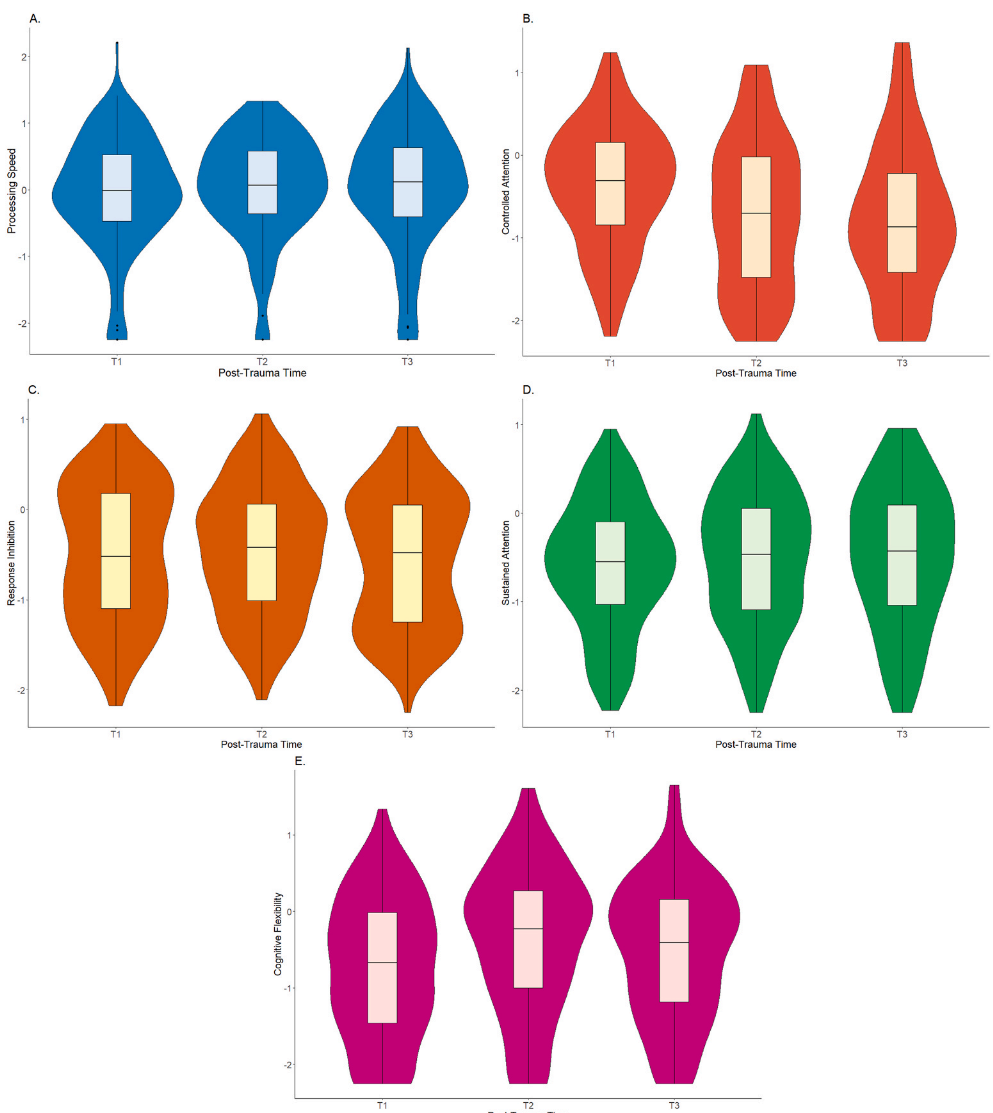

Fig. 4. Violin plots of mean normalized neurocognitive z-scores across time. Black dots represent outliers. [A] Processing Speed (Mean T1 (two-weeks post-trauma) = −0.046, SD = 0.834, N = 186; M T2 (three-months post-trauma) = 0.026, SD = 0.775, N = 159; M T3 (six-months post-trauma) = 0.032, SD = 0.900, N = 166), [B] Controlled Attention (M T1 = −0.378, SD = 0.739, N = 194; M T2 = −0.719, SD = 0.900, N = 166; M T3 = −0.719, SD = .895, N = 173), [C] Response Inhibition (M T1 = −0.493, SD = 0.757, N = 193; M T2 = −0.463, SD = 0.703, N = 161; M T3 = −0.562, SD = 0.734, N = 168, [D] Sustained Attention (M T1 = −0.592, SD = 0.716, N = 191; M T2 = −0.509, SD = 0.746, N = 160; M T3 = −0.489, SD = 0.802, N = 167), [E] Cognitive Flexibility (M T1 = −0.727, SD = 0.909, N = 195; M T2 = −0.382, SD = 0.946, N = 165; M T3 = −0.500, SD = 0.884, N = 173).

differed on the baseline controlled attention z-scores (N = 35; M = -.63, SD = .73) compared to the participants who did not drop-out during any time (N = 159; M = -.32, SD = .73; $t(192) = 2.23$, $p = .027$). Neurocognitive scores across time are displayed in Fig. 4 and bivariate relationships (Pearson's and Point Bi-serial Correlations) between study variables are presented in Table 2.

7. Processing Speed

Results of the unconditional model indicated approximately 42% (ICC = 0.42) of the variation in processing speed could be accounted for by the individual differences between participants.

Processing Speed Scores are Stable Across Study Visits. A Level 1 model with only time showed that the average processing speed z-score for an individual at T1 was −0.05. Across study visits, processing speed scores were not predicted to significantly change ($B = 0.04$; $t(335) = 1.13$, $p = .261$).

Processing Speed was Impacted by ADI and Income. A model comparison revealed the addition of national ADI scores (Model 2) to a model with time (fixed effect only), income, baseline PCL-5, weighted life events checklist scores (Model 1), significantly improved the model predicting processing speed ($\chi^2(1) = 14.93$, $p < .001$); however, the addition of a Time x ADI cross-level interaction term did not significantly improve model fit ($\chi^2(1) = 3.6$, $p = .011$; Model 3), therefore this term was dropped.

The standardized and unstandardized coefficients, 95% confidence intervals, and *p*-values are provided in Table 3. For an individual with average weighted life events checklist, PCL-5, and ADI scores, every \$10,000 increase in income was associated with a 0.04 increase in processing speed z-score at baseline (unstandardized coefficient $B = 0.04$; $t(184) = 2.17$, $p = .030$, unstandardized 95% Confidence Interval: CI[0.003, 0.070], Cohen's $d = 0.32$). As the average participants' ADI score increased by one, processing speed at baseline decreased by −0.01 ($B = -0.01$; $t(189) = -3.24$, $p = .001$, CI[-0.012, −0.002], $d = -0.47$). There was not a significant effect of time ($B = 0.04$; $t(339) = 1.06$, $p = .268$, CI[-0.030, 0.106], $d = 0.12$), weighted life events checklist ($B < 0.010$ $t(188) = 0.49$, $p = .621$, CI[-0.004, 0.007], $d = 0.07$), or baseline PTSD symptoms ($B < -0.01$; $t(182) = -0.62$, $p = .534$, CI[-0.006, −0.004], $d = -0.09$) on processing speed.

8. Controlled Attention

The unconditional model indicated approximately 49% (ICC = 0.49) of the variation in controlled attention could be accounted for by the individual differences between participants.

Controlled Attention Scores Significantly Changed Across Study Visits. The addition of time as a fixed variable (Level 1 Model) yielded a significantly better fit than the unconditional model, $\chi^2(1) = 47.72$, $p < .001$. The average controlled attention z-score for an individual at T1 was −0.04. From one study time-point the next, controlled attention significantly decreased by −0.22 ($B = -0.22$; $t(297) = -7.07$, $p < .001$.

Controlled Attention was Impacted by Time, ADI, and Income. Including national ADI scores in a model with time (fixed effect *only*), income, baseline PCL-5, and weighted life events checklist scores, significantly improved model fit compared to the unconditional model predicting controlled attention ($\chi^2(1) = 10.22$, $p = .001$). The addition of a Time x ADI cross-level term significantly improved model fit ($\chi^2(1) = 5.44$, $p = .019$), therefore this term was included in the final model.

Results of the final model is displayed in Table 4. For every one unit in time, an individual's controlled attention score decreased by −0.22 ($B = -0.22$; $t(317) = -7.24$, $p < .001$, CI[-0.28, −0.16], $d = -.77$). For the average individual every \$10,000 increase in income was significantly associated with a 0.05 increase in controlled attention z-score at baseline ($B = 0.05$; $t(196) = 3.13$, $p = .002$, CI[0.016, 0.086], $d = 0.44$). The impact of ADI on controlled attention approached significance ($B = -0.01$; $t(219) = -1.96$, $p = .080$, CI[-0.010, <0.001], $d = -0.19$). There was not a significant effect of weighted life events checklist ($B = 0.002$; $t(194) = 0.84$, $p = .400$, CI[-0.003, 0.010], $d = 0.12$) or PCL-5 scores ($B = 0.005$; $t(192) = 1.81$, $p = .072$, CI[>-0.001, −0.010], $d = 0.26$). There was a significant effect of ADI scores on the relationship between time and controlled attention (ADI x Time: $B = -0.003$; $t(316) = -2.29$, $p = .020$, CI[-0.006, >-0.001], $d = -0.25$).

9. Sustained Attention

Results of the unconditional model revealed approximately 42% (ICC = 0.42) of the variation in sustained attention could be accounted for by the individual differences between participants.

Sustained Attention Scores are Stable Across Study Visits. The addition of time as a random and fixed variable (Level 1 Model) yielded a significantly better fit than the unconditional model, $\chi^2(1) = 9.37$, $p = .025$. The average sustained attention z-score for an individual at T1 was −0.60. Sustained attention scores did not significantly change across study visits ($B = -0.05$; $t(342) = 1.60$, $p = .110$).

Sustained Attention was Impacted by Income and ADI. The addition of national ADI scores to a model with time (fixed *and* random effect), income, baseline PCL-5, and weighted life events checklist scores, significantly improved the model predicting sustained attention, $\chi^2(1) = 11.85$, $p < 0.001$. The addition of a Time x ADI cross-level term did not significantly improve model fit ($\chi^2(1) = 3.55$, $p = .070$), therefore this term was dropped. The final model is presented in Table 5. There was non-significant effect of time on sustained attention scores ($B = 0.05$; t

Table 3
Parameter estimates for different HLM models associated with processing speed.

	Model 1					Model 2				
Predictor	B	ß	CI(95%)	std. CI	p-value	B	ß	CI(95%)	std. CI	p-value
Intercept	−0.06	−0.01	−0.17, 0.06	−0.12, 0.10	0.329	−0.05	−0.01	−0.16, 0.06	−0.12, 0.10	0.329
Time	0.04	0.04	−0.03, 0.11	−0.03, 0.10	0.271	0.04	0.04	−0.03, 0.11	−0.03, 0.10	0.268
Income	**0.06**	**0.23**	**0.03, 0.09**	**0.12, 0.34**	<0.001	**0.04**	**0.13**	**0.00, 0.07**	**0.01, 0.26**	0.030
LEC	0.00	0.04	−0.00, 0.01	−0.07, 0.15	0.480	0.00	0.03	−0.00, 0.01	−0.08, 0.14	0.621
PCL-5	−0.00	−0.03	−0.01, 0.00	−0.14, 0.09	0.648	−0.00	−0.04	−0.01, 0.00	−0.15, 0.08	0.534
ADI						**−0.01**	**−0.20**	**−0.01, -0.00**	**−0.32, -0.08**	0.001
Random Effects										
σ^2	0.41					0.41				
τ_{00}	0.26 Subject					0.24 Subject				
ICC	0.39					0.37				
N	193 Subject					193 Subject				
Observations	513					513				
Marginal R^2/Conditional R^2	0.056/0.424					0.086/0.424				

Note: **ADI:** Area Deprivation Index, **PCL-5:** PTSD Checklist for DSM-5, **LEC:** weighted Life Events Checklist, **B:** unstandardized coefficient, **ß:** standardized coefficient, **CI:** confidence interval, **ICC**: intraclass correlation coefficient; **τ00**: between-individual variance, $\boldsymbol{\sigma^2}$: within-individual variance.

Table 4
Parameter estimates for different HLM models associated with controlled attention.

Predictor	Model 1					Model 2					Model 3				
	B	*β*	*CI(95%)*	*std. CI*	*p-value*	*B*	*β*	*CI(95%)*	*std. CI*	*p-value*	*B*	*β*	*CI(95%)*	*std. CI*	*p-value*
Intercept	**−0.43**	**−0.01**	**−0.53, -0.32**	**−0.12, 0.10**	<0.001	**−0.43**	**−0.01**	**−0.53, -0.32**	**−0.12, 0.09**	<0.001	**−0.43**	**−0.01**	**−0.53, -0.32**	**−0.12, 0.09**	<0.001
Time	**−0.22**	**−0.21**	**−0.28, -0.16**	**−0.27, -0.15**	<0.001	**−0.22**	**−0.21**	**−0.28, -0.16**	**−0.27, -0.15**	<0.001	**−0.22**	**−0.21**	**−0.28, -0.16**	**−0.27, -0.15**	<0.001
Income	**0.08**	**0.28**	**0.05, 0.11**	**0.17, 0.39**	<0.001	**0.05**	**0.19**	**0.02, 0.09**	**0.07, 0.31**	0.002	**0.05**	**0.19**	**0.02, 0.09**	**0.07, 0.31**	0.002
LEC	0.00	0.06	-0.00, 0.01	-0.05, 0.17	0.301	0.00	0.05	-0.00, 0.01	-0.06, 0.16	0.397	0.00	0.05	-0.00, 0.01	-0.06, 0.16	0.400
PCL-5	0.01	0.11	-0.00, 0.01	-0.00, 0.22	0.055	0.00	0.10	-0.00, 0.01	-0.01, 0.21	0.066	0.00	0.10	-0.00, 0.01	-0.01, 0.21	0.071
ADI						**−0.01**	**−0.20**	**−0.01, -0.00**	**−0.31, -0.08**	0.001	-0.00	-0.20	-0.01, 0.00	-0.32, −0.08	0.080
ADI x Time											**−0.00**	**−0.07**	**−0.01, -0.00**	**−0.12, -0.01**	0.019
Random Effects															
σ^2	0.33					0.33					0.32				
τ_{00}	0.31 Subject					0.29 Subject					0.29 Subject				
ICC	0.49					0.47					0.47				
N	195 Subject					195 Subject					195 Subject				
Observations	535					535					535				
Marginal R^2/Conditional R^2	0.134/0.556					0.165/0.556					0.170/0.562				

Note: **ADI:** Area Deprivation Index, **PCL-5:** PTSD Checklist for DSM-5, **LEC:** weighted Life Events Checklist, **B:** unstandardized coefficient, **β:** standardized coefficient, **CI:** confidence interval, **ICC:** intraclass correlation coefficient; **τ00**: between-individual variance, **σ²**: within-individual variance.

(179) = −1.46, *p* = .144, CI[-0.020, 0.112], *d* = .22). For an participant with average weighted life events checklist, PCL-5, and ADI scores, every $10,000 increase in income was significantly associated with a 0.05 increase in sustained attention z-score at baseline (*B* = 0.05; *t*(187) = 3.47, *p* < .001, CI[0.022, 0.079], *d* = .51). The impact of ADI on sustained attention was also significant (*B* = −0.01; *t*(190) = −3.53, *p* = .001, CI[-0.011, −0.003], *d* = -.51); however, there was not a significant effect of weighted life events checklist (*B* = 0.002; *t*(186) = 0.83, *p* = .404, CI[-0.003, 0.007], *d* = .12) or PCL-5 scores (*B* < −0.01; *t*(183) = −0.02, *p* = .988, CI[-0.004, 0.004], *d* < -.01).

10. Response Inhibition

Results of the unconditional model indicated approximately 63% (ICC = 0.63) of the variation in response inhibition could be accounted for by the individual differences between participants.

Response Inhibition Scores were Stable Across Study Visits. In a model with only time (Level 1 Model), the average response inhibition z-score for an individual at T1 was −0.49; however, these scores did not significantly change across time (*B* = −0.04; *t*(342) = 1.60, *p* = .116).

Response Inhibition was Impacted by Income, ADI, and Lifetime Trauma Exposure. The addition of national ADI scores to a model with time (fixed effect only), income, baseline PCL-5, and weighted life events checklist scores, significantly improved the model predicting response inhibition (χ^2(1) = 24.61, *p* < .001). The addition of a Time x ADI cross-level term did not significantly improve model fit (χ^2(1) = 3.03, *p* = .080), therefore this term was excluded. In the final model (presented in Table 6) there was non-significant effect of time on response inhibition scores (*B* = −0.04; *t*(344) = −1.69, *p* = .096, CI[-0.090, 0.006], *d* = −0.18). Income was significantly associated with a 0.03 increase in response inhibition at baseline (*B* = 0.03; *t*(194) = 2.17, *p* = .030, CI[0.003, 0.062], *d* = .31) whereas greater neighborhood disadvantage was significantly associated with a -.01 decrease (*B* = −0.01; *t*(197) = −5.13, *p* < .001, CI [-0.015, −0.007], *d* = -.73). A one unit increase in weighted life events checklist significantly predicted an 0.01 increase in response inhibition (*B* = 0.01; *t*(193) = 3.31, *p* = .001, CI[0.003, 0.013], *d* = .48). There was no significant impact of baseline PTSD symptoms on response inhibition (*B* < 0.01; *t*(190) = 0.02, *p* = .986, CI[-0.004, 0.004], *d* < 0.01).

11. Cognitive Flexibility

Approximately 73% (ICC = 0.73) of the variation in cognitive flexibility could be accounted for by the individual differences between participants (unconditional model).

Cognitive Flexibility Scores Changed Across Study Visits. A model with only time (fixed variable; Level 1 Model) revealed that the average cognitive flexibility z-score for an individual at T1 was −0.67 and scores were expected to significantly increase across time (*B* = 0.10; *t*(347) = 3.99, *p* < .001).

Cognitive Flexibility was Impacted by Income, ADI, and PTSD Symptoms. Including ADI scores to a model with time (fixed effect only), income, baseline PCL-5, and weighted life events checklist scores, significantly improved model fit (χ^2(1) = 13.78, *p* < .001). The addition of Time x ADI did not significantly improve the model (χ^2(1) = 0.05, *p* = .820), therefore the interaction term was dropped from the final model (Table 7). There was a significant effect of time on cognitive flexibility scores (*B* = .010; *t*(348) = 3.96, *p* < .001, CI[0.049, 0.147], *d* = 0.42). Income (*B* = 0.05; *t*(194) = 2.65, *p* = .008, CI[0.014, 0.094], *d* = 0.38) and baseline PCL-5 scores (*B* = 0.01; *t*(192) = 2.12, *p* = .034, CI[<0.001, 0.010], *d* = 0.31) were significantly associated with an increase in cognitive flexibility at baseline. ADI was significantly associated with a -.01 decrease in cognitive flexibility (*B* = 0.01; *t*(196) = −3.77, *p* < .001, CI[-0.016, −0.005], *d* = −0.54). There was no significant impact of weighted life events checklist scores on cognitive flexibility (*B* < 0.01; *t* (193) = 0.96, *p* = .336, CI[-0.060, 0.181], *d* = .14).

Table 5
Parameter estimates for different HLM models associated with sustained attention.

	Model 1					Model 2				
Predictor	B	ß	CI(95%)	std. CI	p-value	B	ß	CI(95%)	std. CI	p-value
Intercept	**−0.60**	**−0.01**	**−0.69, -0.50**	**−0.12, 0.09**	<0.001	**−0.60**	**−0.01**	**−0.69, -0.51**	**−0.11, 0.09**	<0.001
Time	0.05	0.05	−0.02, 0.11	−0.02, 0.12	0.158	0.05	0.05	−0.02, 0.11	−0.02, 0.12	0.144
Income	**0.07**	**0.30**	**0.05, 0.10**	**0.19, 0.40**	<0.001	**0.05**	**0.20**	**0.02, 0.08**	**0.09, 0.32**	0.001
LEC	0.00	0.06	−0.00, 0.01	−0.05, 0.16	0.315	0.00	0.04	−0.00, 0.01	−0.06, 0.15	0.404
PCL-5	0.00	0.01	−0.00, 0.00	−0.10, 0.11	0.922	−0.00	−0.00	−0.00, 0.00	−0.11, 0.11	0.988
ADI						**−0.01**	**−0.20**	**−0.01, -0.00**	**−0.32, -0.09**	<0.001
Random Effects										
σ^2	0.28					0.28				
τ_{00}	0.19 $_{\text{Subject}}$					0.18 $_{\text{Subject}}$				
τ_{11}	0.05 $_{\text{Subject\_Time}}$					0.05 $_{\text{Subject\_Time}}$				
ρ_{01}	−0.16 $_{\text{Subject}}$					−0.24 $_{\text{Subject}}$				
ICC	0.46					0.43				
N	194 $_{\text{Subject}}$					194 $_{\text{Subject}}$				
Observations	520					520				
Marginal R^2/Conditional R^2	0.094/0.509					0.127/0.506				

Note: **ADI:** Area Deprivation Index, **PCL-5:** PTSD Checklist for DSM-5, **LEC:** weighted Life Events Checklist, **B:** unstandardized coefficient, **ß:** standardized coefficient, **CI:** confidence interval, **ICC:** intraclass correlation coefficient, **τ00:** between-individual variance, **σ2:** within-individual variance, **τ11**: time-by-subject variance in slopes, **ρ01:** Correlation between random slope and intercept.

Table 6
Parameter estimates for different HLM models associated with response inhibition.

	Model 1					Model 2				
Predictor	B	ß	CI(95%)	std. CI	p-value	B	ß	CI(95%)	std. CI	p-value
Intercept	**−0.49**	**−0.01**	**−0.58, -0.39**	**−0.12, 0.10**	<0.001	**−0.49**	**−0.01**	**−0.58, -0.40**	**−0.12, 0.09**	<0.001
Time	−0.04	−0.05	−0.09, 0.01	−0.10, 0.01	0.090	−0.04	−0.05	−0.09, 0.01	−0.10, 0.01	0.096
Income	**0.07**	**0.28**	**0.04, 0.10**	**0.17, 0.40**	<0.001	**0.03**	**0.13**	**0.00, 0.06**	**0.01, 0.26**	0.030
LEC	**0.01**	**0.21**	**0.00, 0.01**	**0.09, 0.32**	0.001	**0.01**	**0.19**	**0.00, 0.01**	**0.08, 0.30**	0.001
PCL-5	0.00	0.01	−0.00, 0.01	−0.11, 0.13	0.830	0.00	0.00	−0.00, 0.00	−0.11, 0.11	0.986
ADI						**−0.01**	**−0.31**	**−0.01, -0.01**	**−0.43, -0.19**	<0.001
Random Effects										
σ^2	0.20					0.20				
τ_{00}	0.27 $_{\text{Subject}}$					0.23 $_{\text{Subject}}$				
ICC	0.58					0.54				
N	195 $_{\text{Subject}}$					195 $_{\text{Subject}}$				
Observations	524					524				
Marginal R^2/Conditional R^2	0.121/0.630					0.198/0.629				

Note: **ADI:** Area Deprivation Index, **PCL-5:** PTSD Checklist for DSM-5, **LEC:** weighted Life Events Checklist, **B:** unstandardized coefficient, **ß:** standardized coefficient, **CI:** confidence interval, **ICC**: intraclass correlation coefficient; **τ00**: between-individual variance, **σ^2:** within-individual variance.

Table 7
Parameter estimates for different HLM models associated with cognitive flexibility.

	Model 1					Model 2				
Predictor	B	ß	CI(95%)	std. CI	p-value	B	ß	CI(95%)	std. CI	p-value
Intercept	**−0.67**	**−0.01**	**−0.79, -0.55**	**−0.13, 0.11**	<0.001	**−0.67**	**−0.02**	**−0.78, -0.55**	**−0.13, 0.10**	<0.001
Time	**0.10**	**0.09**	**0.05, 0.15**	**0.04, 0.13**	<0.001	**0.10**	**0.09**	**0.05, 0.15**	**0.04, 0.13**	<0.001
Income	**0.09**	**0.29**	**0.05, 0.13**	**0.17, 0.41**	<0.001	**0.05**	**0.18**	**0.01, 0.09**	**0.05, 0.31**	0.008
LEC	0.00	0.07	−0.00, 0.01	−0.05, 0.20	0.245	0.00	0.06	−0.00, 0.01	−0.06, 0.18	0.336
PCL-5	**0.01**	**0.14**	**0.00, 0.01**	**0.01, 0.27**	0.028	**0.01**	**0.13**	**0.00, 0.01**	**0.01, 0.25**	0.034
ADI						**−0.01**	**−0.25**	**−0.02, -0.01**	**−0.38, -0.12**	<0.001
Random Effects										
σ^2	0.22					0.22				
τ_{00}	0.53 $_{\text{Subject}}$					0.49 $_{\text{Subject}}$				
ICC	0.71					0.69				
N	195 $_{\text{Subject}}$					195 $_{\text{Subject}}$				
Observations	535					535				
Marginal R^2/Conditional R^2	0.117/0.741					0.166/0.741				

Note: **ADI:** Area Deprivation Index, **PCL-5:** PTSD Checklist for DSM-5, **LEC:** weighted Life Events Checklist, **B:** unstandardized coefficient, **ß:** standardized coefficient, **CI:** confidence interval, **ICC**: intraclass correlation coefficient; **τ00**: between-individual variance, **σ^2:** within-individual variance.

12. Discussion

The current study adds to the growing body of work suggesting living in a socioeconomically-disadvantaged neighborhood is associated with impairments in neurocognition (e.g., Moore et al., 2016; Muñoz et al., 2020). In a group of traumatically-injured socioeconomically diverse adults, we explored the relationship between ADI and five neurocognitive domains. At the bivariate level (Table 2), living in a more advantaged neighborhoods was associated with more efficient information processing speed, greater sustained and controlled attention, and better cognitive flexibility and response inhibition at two-weeks, three-months, and six-months post-injury. These initial correlations provided little information as to whether neighborhood disadvantage contributes to neurocognitive functioning over and above other relevant individual variables. Using additional hierarchical linear modeling analyses we observed stable deficits in cognitive domains uniquely attributable to neighborhood disadvantage across the three time-points following trauma exposure.

Notably, for all neurocognitive domains, the addition of ADI significantly improved the models' fit, indicating that neighborhood disadvantage is robustly and uniquely linked to neurocognition. Our findings support conceptualizing neurocognition within the multi-level socio-ecological model and suggest variables at various levels must be critically assessed when considering mental health outcomes (Maercker and Horn, 2012). The implementation of a longitudinal design allowed our results to reflect stable impairments associated with neighborhood disadvantage in processing speed, sustained attention, response inhibition, and cognitive flexibility. Interestingly, the relationship between ADI and controlled attention was significantly moderated by the passing of time. For individuals living in more disadvantaged neighborhoods, there was a negative relationship between post-injury study visits and controlled attention scores.

Living in a socioeconomically disadvantaged neighborhood is a unique form of chronic stress (Diez Roux and Mair, 2010; Farah, 2017; Hu et al., 2018; Hunt et al., 2020; Kind and Buckingham, 2018; Ross and Mirowsky, 2008). Cognitive flexibility facilitates an individual's adaption to a new situation or task (Whiting et al., 2017). More broadly, it promotes the ability to change actions and thoughts in response to new environments or stimuli (Whiting et al., 2017). Both acute and chronic stress have been linked to less cognitive flexibility in animal models and humans (Goldfarb et al., 2017; Jett et al., 2017; Kalia and Knauft, 2020). Surprisingly, we did not replicate work demonstrating cognitive flexibility is associated with PTSD symptoms (c.f. Ben-Zion et al., 2019; Samuelson et al., 2020; Whiting et al., 2017). In fact, in our sample, higher baseline PTSD symptoms were related to significantly better cognitive flexibility. More research is necessary to determine the longitudinal relationship between cognitive flexibility and PTSD symptoms, particularly as there is little known about relations between PTSD and neurocognition in the acute post-trauma window.

Reduced response inhibition was also significantly associated with ADI. Impaired inhibitory control is observed in individuals diagnosed with major depressive disorder (Eugene, Cooney, Atlas, 2010) and PTSD (Van Rooji, Geuze, Kennis, Radenmaker and Vink, 2015), with previous work suggesting preexisting deficits in inhibition may bestow susceptibility for PTSD development (Aupperle, Melrose, Stein and Paulus, 2012). Although a more extensive investigation is necessary, studies with children have suggested that there is a substantial relationship between neighborhood poverty and inhibitory control (Tomlinson et al., 2020). Response inhibition can also be impacted by neighborhood crime (Gudiño, 2013). Chronic exposure to violence, a separable component from neighborhood disadvantage that is not incorporated in the ADI, may be associated with heightened reactivity and impair the ability to inhibit automatic responses (Gudiño, 2013). To date, there have been few studies that have specifically examined how exposure to community violence (both objectively and subjectively measured) and neighborhood socioeconomic disadvantage impact any of the neurocognitive domains in adults, traumatically-injured or otherwise.

In the United States, individuals identifying as a racial or ethnic minority disproportionately live in disadvantaged neighborhoods (Houston et al., 2004; Pager and Shepherd, 2008). Our research design assessing whether neighborhood disadvantage explained variation in neurocognition over and above individual SEP was correlational - rather than casual or comparative - in nature. We did not group individuals by race, gender, or SEP. While our full sample had sufficient variability in ADI to address the research question, it also reflected this reality, and therefore stratifying participants by race was impractical. In our sample, as in other studies (e.g., Kind et al., 2014), the participants with higher ADI scores were more likely to be Black individuals whereas White participants were more apt to live in advantaged neighborhoods. Practices such as redlining (i.e., the denial of services such as mortgages based on onerous terms, namely an individual's race or ethnicity) have facilitated residential racial segregation in the United States (Squires and Woodruff, 2019), thereby confounding neighborhood disadvantage and race and ethnicity, especially in southeastern Wisconsin (Squires & O";Connor, 2001).

We did not directly assess the effects of race and ethnicity on neurocognition nor the interaction between race and ethnicity and ADI. Race-corrected norms are commonly used in clinical assessments due to significant racial and ethnic differences observed in neurocognitive function (Rivera Mindt et al., 2010). These group differences reflect profound measurement biases; the majority of neuropsychological test batteries were developed for White people in middle/upper SEP and were not validated in diverse samples (Manly and Echemendia, 2007; Pedraza and Mungas, 2008). The observed differences across racial and ethnic groups (social constructs) are not explained by underlying biological factors, but rather reflect other critical variables (e.g., quality of education, discrimination) or poor construct validity across different cultural groups (Krieger, 2005; Manly and Echemendia, 2007; Smedley and Smedley, 2005). As such, the differences observed in neurocognitive functioning between groups of people may be indicative of test biases and/or societal inequities. Research on addressing this consequential issue has proposed methods to minimize assessment bias, such as the use of race- and ethnic-specific norms, and validating measures in samples that are not only non-Hispanic White individuals (Pedraza and Mungas, 2008; Rivera Mindt et al., 2010). Studies focusing on biases in assessments is critically important to the field and has vast implications on the interpretation of neurocognitive performance.

Despite this racial inequality in neighborhood advantage, in large samples neighborhood SEP has explained variability in neurocognition over and above race and ethnicity (Moore et al., 2016). Given the substantial, and confounding, overlap between race and ethnicity and ADI in our sample, we did not investigate this question. Although we cannot conclude or interpret how the social construct of race may be impacting our results, we have illustrated the importance of assessing contextual-factors. Moving forward, research would benefit from examining large datasets with considerable variability in individual- and contextual-level variables to make more meaningful conclusions about the complex interplay of race, individual SEP, neighborhood advantage, and neurocognition. Moreover, research that values intersectionality (Cho et al., 2013; Crenshaw, 1991) will better inform the development of interventions, both at the community- and individual-level.

Although this longitudinal study had several advantages, such as the inclusion of important individual-level variables, including the LEC, several limitations did exist. The neurocognitive test battery was delivered shortly after participants experienced a trauma. Even though we statistically controlled for relevant variables, including acute PTSD symptoms, we did not capture a true symptom baseline. While we also excluded participants who experienced a serious injury to their spinal cord and/or head, the effect of experiencing a traumatic injury (e.g., mild traumatic brain injury (mTBI), medication), irrespective of PTSD symptoms was not taken into account. However, if mTBI were impacting neurocognition, we would expect to see improvements across timepoints (Karr et al., 2014). Depressive symptoms, as well as physical health status (Stillman et al., 2016) also impact neurocognition (Gualtieri et al., 2006) and are often highly correlated with PTSD (Breslau, 2002), therefore future work should attempt to disentangle the role depression may play in the association between socioeconomic position, (individual and neighborhood) and neurocognition.

This study was conducted with adult participants, and we did not collect information on childhood SEP, a factor that likely impacts adult SEP and shapes neurocognition in adulthood (Luo and Waite, 2005). We demonstrated that adult individual SEP, or as operationalized in this study, annual household income (and education, refer to Supplemental Material), was significantly associated with ADI. We opted to include participants regardless of their residential stability. Future work should proactively seek additional information regarding participant's residential stability, which has been found to improve trauma-outcomes (Ford, 2008), including how long they have resided at their current address. The fact that individuals in lower SEP live in more socioeconomically disadvantaged neighborhoods and are more likely to identify as racially or ethnically minoritized creates confounds that need to be considered both theoretically and statistically. As discussed above, racial and ethnic identity may influence neurocognitive test performance due to assessment biases (Rivera Mindt et al., 2010).

Our results suggest that neighborhood SEP should be considered when conducting post-trauma neurocognitive assessments with participants or developing a patient's neurobehavioral profile. In traumatically-injured adults, ADI significantly explains variability in neurocognitive domains, independent of factors traditionally assessed (e.g. income, adverse life experiences; Shalev et al., 2019). Where a patient or participant lives may be impacting their behavior and their post-trauma recovery in manners not yet fully understood. Previous efforts to predict risk and resilience of PTSD development may have been partly limited because they *over*emphasized the individual and *under*emphasized the environment. Uncovering the impact of neighborhoods, and more broadly society, on neurocognition may prove pivotal in improving trauma outcomes.

Data Availability Statement

Data available on request from the authors.

Funding

This research was supported by: U.S. Department of Health and Human Services, National Institutes of Health, National Institute of Mental Health (R01 MH106574; PI: Larson), Medical College of Wisconsin CTSI grant (PI: Larson), Medical College of Wisconsin Injury Research Center grant (PI: deRoon-Cassini). E.K.W was supported by the National Center for Advancing Translational Sciences, National Institutes of Health, through Grant Numbers 2UL1TR001436 and 2TL1TR001437. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the NIH.

Declaration of competing interest

All authors report no financial disclosures or potential conflicts of interest.

Acknowledgments

We would like to extend a special thanks to the iSTAR research team, especially Kate Isely, Maddy Kallenbach, and Sarah Damiano. The authors are also grateful to the Milwaukee Trauma Outcomes Project, which has provided a space for intellectual growth and collaboration.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2020.102493.

References

Ahern, J., Galea, S., 2006. Social context and depression after a disaster: the role of income inequality. J. Epidemiol. Community 60 (9), 766–770. https://doi.org/10.1136/jech.2006.042069.

Association, A.P., 2013. Diagnostic and Statistical Manual of Mental Health Disorders: DSM-5. American Psychiatric Publishing, Washington, DC.

Aughinbaugh, A., 2014. Do cognitive skills moderate the influence of neighborhood disadvantage on subsequent educational attainment? Econ. Educ. Rev. 17.

Aupperle, R.L., Melrose, A.J., Stein, M.B., Paulus, M.P., 2012. Executive function and PTSD: disengaging from trauma. Neuropharmacology 62 (2), 686–694.

Ben-Zion, Z., Fine, N.B., Keynan, N.J., Admon, R., Green, N., Halevi, M., Fonzo, G.A., Achituv, M., Merin, O., Sharon, H., 2018. Cognitive flexibility predicts PTSD symptoms: observational and interventional studies. Front. Psychiatr. 9, 477.

Ben-Zion, Z., Fine, N.B., Keynan, N.J., Admon, R., Halpern, P., Liberzon, I., Hendler, T., Shalev, A.Y., 2019. Neurobehavioral moderators of post-traumatic stress disorder (PTSD) trajectories: study protocol of a prospective MRI study of recent trauma survivors. Eur. J. Psychotraumatol. 10 (1), 1683941. https://doi.org/10.1080/20008198.2019.1683941.

Benjamini, Y., Hochberg, Y., 2000. On the adaptive control of the false discovery rate in multiple testing with independent statistics. J. Educ. Behav. Stat. 25 (1), 60–83. https://doi.org/10.2307/1165312.

Besser, L.M., 2017. Neighborhood environment and cognition in older adults_ A systematic review. Am. J. Prev. Med. 11.

Birur, B., Moore, N.C., Davis, L.L., 2017. An evidence-based review of early intervention and prevention of posttraumatic stress disorder. Community Ment. Health J. 53 (2), 183–201. https://doi.org/10.1007/s10597-016-0047-x.

Bowling, A.C., Mackenzie, B.D., 1996. The relationship between speed of information processing and cognitive ability. Pers. Indiv. Differ. 20 (6), 775–800.

Breslau, N., 2002. Epidemiologic studies of trauma, posttraumatic stress disorder, and other psychiatric disorders. Canadian Journal of Psychiatry. Revue Canadienne De Psychiatrie 47 (10), 923–929. https://doi.org/10.1177/070674370204701003.

Buttelmann, F., Karbach, J., 2017. Development and plasticity of cognitive flexibility in early and middle childhood. Front. Psychol. 8, 1040.

Cho, S., Crenshaw, K.W., McCall, L., 2013. Toward a field of intersectionality studies: theory, applications, and praxis. *Signs*. Journal of Women in Culture and Society 38 (4), 785–810. https://doi.org/10.1086/669608.

Cohen, J., 1962. The statistical power of abnormal-social psychological research: a review. J. Abnorm. Soc. Psychol. 65 (3), 145–153. https://doi.org/10.1037/h0045186.

Crenshaw, K., 1991. Mapping the margins: intersectionality, identity politics, and violence against women of color. Stanford Law Rev. 43 (6), 1241. https://doi.org/10.2307/1229039.

Cronbach, L.J., 1951. Coefficient alpha and the internal structure of tests. Psychometrika 16 (3), 297–334.

deRoon-Cassini, T.A., Mancini, A.D., Rusch, M.D., Bonanno, G.A., 2010. Psychopathology and resilience following traumatic injury: a latent growth mixture model analysis. Rehabil. Psychol. 55 (1), 1–11. https://doi.org/10.1037/a0018601.

Diez Roux, A.V., Mair, C., 2010. Neighborhoods and health: neighborhoods and health. Ann. N. Y. Acad. Sci. 1186 (1), 125–145. https://doi.org/10.1111/j.1749-6632.2009.05333.x.

Evans, V.C., Chan, S.S., Iverson, G.L., Bond, D.J., Yatham, L.N., Lam, R.W., 2013. Systematic review of neurocognition and occupational functioning in major depressive disorder. Neuropsychiatry 3 (1), 97.

Farah, M.J., 2017. The neuroscience of socioeconomic status: correlates, causes, and consequences. Neuron 96 (1), 56–71. https://doi.org/10.1016/j.neuron.2017.08.034.

Fiocco, A.J., Joober, R., Poirier, J., Lupien, S., 2007. Polymorphism of the 5-HT2A receptor gene: association with stress-related indices in healthy middle-aged adults. Front. Behav. Neurosci. 1, 3.

Ford, J.D., 2008. Ethnoracial minority background, psychological trauma, PTSD, and DESNOS among urban low-income women with severe mental illness. J. Psychol. Trauma 7 (3), 170–184. https://doi.org/10.1080/19322880802266805.

Galatzer-Levy, I.R., Bryant, R.A., 2013. 636,120 ways to have posttraumatic stress disorder. Perspect. Psychol. Sci. 8 (6), 651–662.

Gallop, R., Tasca, G.A., 2009. Multilevel modeling of longitudinal data for psychotherapy researchers: II. The complexities. Psychother. Res. 19 (4–5), 438–452. https://doi.org/10.1080/10503300902849475.

Gapen, M., Cross, D., Ortigo, K., Graham, A., Johnson, E., Evces, M., Ressler, K.J., Bradley, B., 2011. Perceived neighborhood disorder, community cohesion, and PTSD symptoms among low-income African Americans in an urban health setting. Am. J. Orthopsychiatry 81 (1), 31–37. https://doi.org/10.1111/j.1939-0025.2010.01069.x.

Goldfarb, E.V., Froböse, M.I., Cools, R., Phelps, E.A., 2017. Stress and cognitive flexibility: cortisol increases are associated with enhanced updating but impaired switching. J. Cognit. Neurosci. 29 (1), 14–24. https://doi.org/10.1162/jocn_a_01029.

Gordon, E., Palmer, D.M., Liu, H., Rekshan, W., DeVarney, S., 2013. Online cognitive brain training associated with measurable improvements IN cognition and emotional well-being. Technol. Innovat. 15 (1), 53–62. https://doi.org/10.3727/194982413X13608676060574.

Gray, M.J., Litz, B.T., Hsu, J.L., Lombardo, T.W., 2004. Psychometric properties of the life events checklist. Assessment 11 (4), 330–341. https://doi.org/10.1177/1073191104269954.

Gualtieri, C.T., Johnson, L.G., Benedict, K.B., 2006. Neurocognition in depression: patients on and off medication versus healthy comparison subjects. J. Neuropsychiatry 18 (2), 217–225. https://doi.org/10.1176/jnp.2006.18.2.217.

Gudiño, O.G., 2013. Behavioral inhibition and risk for posttraumatic stress symptoms in Latino children exposed to violence. J. Abnorm. Child Psychol. 41 (6), 983–992. https://doi.org/10.1007/s10802-013-9731-2.

Hackman, D.A., Farah, M.J., 2009. Socioeconomic status and the developing brain. Trends Cognit. Sci. 13 (2), 65–73. https://doi.org/10.1016/j.tics.2008.11.003.

Hackman, D.A., Betancourt, L.M., Brodsky, N.L., Hurt, H., Farah, M.J., 2012. Neighborhood disadvantage and adolescent stress reactivity. Front. Hum. Neurosci. 6 https://doi.org/10.3389/fnhum.2012.00277.
Haley, D.F., Linton, S., Luo, R., Hunter-Jones, J., Adimora, A.A., Wingood, G.M., Bonney, L., Ross, Z., Cooper, H.L.F., 2017. Public housing relocations and relationships of changes in neighborhood disadvantage and transportation access to unmet need for medical care. J. Health Care Poor Underserved 28 (1), 315–328. https://doi.org/10.1353/hpu.2017.0026.
Harnett, N.G., 2020. Neurobiological consequences of racial disparities and environmental risks: a critical gap in understanding psychiatric disorders. Neuropsychopharmacology 45 (8), 1247–1250. https://doi.org/10.1038/s41386-020-0681-4. PMID: 32330926; PMCID: PMC7411049.
Heid, A.R., Pruchno, R., Cartwright, F.P., Wilson-Genderson, M., 2017. Exposure to Hurricane Sandy, neighborhood collective efficacy, and post-traumatic stress symptoms in older adults. Aging Ment. Health 21 (7), 742–750. https://doi.org/10.1080/13607863.2016.1154016.
Herrara-Escobar, J.P., et al., 2019. Lower education and income predict worse long-term outcomes after injury. The Journal of Trauma and Acute Care Surgery 87 (1), 104–110. https://doi.org/10.1097/ta.0000000000002329.
Hill, T.D., Ross, C.E., Angel, R.J., 2005. Neighborhood disorder, psychophysiological distress, and health. J. Health Soc. Behav. 46 (2), 170–186. https://doi.org/10.1177/002214650504600204.
Houston, D., Wu, J., Ong, P., Winer, A., 2004. Structural disparities of urban traffic in southern California: implications for vehicle-related air pollution exposure in minority and high-poverty neighborhoods. J. Urban Aff. 26 (5), 565–592.
Hu, J., Kind, A.J.H., Nerenz, D., 2018. Area deprivation index (ADI) predicts readmission risk at an urban teaching hospital. Am. J. Med. Qual.: The Official Journal of the American College of Medical Quality 33 (5), 493–501. https://doi.org/10.1177/1062860617753063.
Hunt, J.F.V., Buckingham, W., Kim, A.J., Oh, J., Vogt, N.M., Jonaitis, E.M., Hunt, T.K., Zuelsdorff, M., Powell, R., Norton, D., Rissman, R.A., Asthana, S., Okonkwo, O.C., Johnson, S.C., Kind, A.J.H., Bendlin, B.B., 2020. Association of neighborhood-level disadvantage with cerebral and hippocampal volume. JAMA Neurology 77 (4), 451. https://doi.org/10.1001/jamaneurol.2019.4501.
Isaksson, J., Nilsson, K.W., Nyberg, F., Hogmark, \AAsa, Lindblad, F., 2012. Cortisol levels in children with attention-deficit/hyperactivity disorder. J. Psychiatr. Res. 46 (11), 1398–1405.
Jett, J.D., Bulin, S.E., Hatherall, L.C., McCartney, C.M., Morilak, D.A., 2017. Deficits in cognitive flexibility induced by chronic unpredictable stress are associated with impaired glutamate neurotransmission in the rat medial prefrontal cortex. Neuroscience 346, 284–297. https://doi.org/10.1016/j.neuroscience.2017.01.017.
Juster, R.-P., McEwen, B.S., Lupien, S.J., 2010. Allostatic load biomarkers of chronic stress and impact on health and cognition. Neurosci. Biobehav. Rev. 35 (1), 2–16. https://doi.org/10.1016/j.neubiorev.2009.10.002.
Kalia, V., Knauft, K., 2020. Emotion regulation strategies modulate the effect of adverse childhood experiences on perceived chronic stress with implications for cognitive flexibility. PloS One 15 (6). https://doi.org/10.1371/journal.pone.0235412.
Karr, J.E., Areshenkoff, C.N., Garcia-Barrera, M.A., 2014. The neuropsychological outcomes of concussion: a systematic review of meta-analyses on the cognitive sequelae of mild traumatic brain injury. Neuropsychology 28 (3), 321–336. https://doi.org/10.1037/neu0000037.
Kilpatrick, D.G., Resnick, H.S., Milanak, M.E., Miller, M.W., Keyes, K.M., Friedman, M.J., 2013. National estimates of exposure to traumatic events and PTSD prevalence using DSM-IV and DSM-5 criteria. J. Trauma Stress 26 (5), 537–547. https://doi.org/10.1002/jts.21848.
Kind, A.J.H., Buckingham, W.R., 2018. Making neighborhood-disadvantage metrics accessible—the neighborhood Atlas. N. Engl. J. Med. 378 (26), 2456–2458. https://doi.org/10.1056/NEJMp1802313.
Kind, A.J., Jencks, S., Brock, J., Yu, M., Bartels, C., Ehlenbach, W., Greenberg, C., Smith, M., 2014. Neighborhood socioeconomic disadvantage and 30 Day rehospitalizations: an analysis of medicare data. Ann. Intern. Med. 161 (11), 765–774. https://doi.org/10.7326/M13-2946.
Knighton, A.J., Savitz, L., Belnap, T., Stephenson, B., VanDerslice, J., 2016. Introduction of an area deprivation index measuring patient socioeconomic status in an integrated health system: implications for population health. EGEMs 4 (3). https://doi.org/10.13063/2327-9214.1238.
Krieger, N., 2005. Stormy weather: race, gene expression, and the science of health disparities. Am. J. Publ. Health 95 (12), 2155–2160. https://doi.org/10.2105/AJPH.2005.067108.
Krukowski, R.A., West, D.S., Harvey-Berino, J., Prewitt, T.E., 2010. Neighborhood impact on healthy food availability and pricing in food stores. J. Community Health 35 (3), 315–320. https://doi.org/10.1007/s10900-010-9224-y.
Lance, C.E., Butts, M.M., Michels, L.C., 2006. The sources of four commonly reported cutoff criteria: what did they really say? Organ. Res. Methods 9 (2), 202–220.
Lang, I.A., Llewellyn, D.J., Langa, K.M., Wallace, R.B., Huppert, F.A., Melzer, D., 2008. Neighborhood deprivation, individual socioeconomic status, and cognitive function in older people: analyses from the English longitudinal study of ageing. J. Am. Geriatr. Soc. 56 (2), 191–198. https://doi.org/10.1111/j.1532-5415.2007.01557.x.
Last, B.S., Lawson, G.M., Breiner, K., Steinberg, L., Farah, M.J., 2018. Childhood socioeconomic status and executive function in childhood and beyond. PloS One 13 (8), e0202964. https://doi.org/10.1371/journal.pone.0202964.
Lau, B.C., Collins, M.W., Lovell, M.R., 2011. Sensitivity and Specificity of Subacute Computerized Neurocognitive Testing and Symptom Evaluation in Predicting Outcomes after Sports-Related Concussion: *the American Journal of Sports Medicine*. https://doi.org/10.1177/0363546510392016.
Lee, H., Waite, L.J., 2018. Cognition in context: the role of objective and subjective measures of neighborhood and household in cognitive functioning in later life. Gerontol. 58 (1), 159–169. https://doi.org/10.1093/geront/gnx050.
Lei, M.-K., Simons, R.L., Beach, S.R.H., Philibert, R.A., 2019. Neighborhood disadvantage and biological aging: using marginal structural models to assess the link between neighborhood census variables and epigenetic aging. J. Gerontol.: Ser. Bibliogr. 74 (7), e50–e59. https://doi.org/10.1093/geronb/gbx015.
Lininger, M., Spybrook, J., Cheatham, C.C., 2015. Hierarchical linear model: thinking outside the traditional repeated-measures analysis-of-variance box. J. Athl. Train. 50 (4), 438–441. https://doi.org/10.4085/1062-6050-49.5.09.
Lobban, J., Murphy, D., 2019. Understanding the role art therapy can take in treating veterans with chronic post-traumatic stress disorder. Arts Psychother. 62, 37–44. https://doi.org/10.1016/j.aip.2018.11.011.
Luo, Y., Waite, L.J., 2005. The impact of childhood and adult SES on physical, mental, and cognitive well-being in later life. J. Gerontol. B Psychol. Sci. Soc. Sci. 60 (2), S93–S101.
Lupien, S.J., Maheu, F., Tu, M., Fiocco, A., Schramek, T.E., 2007. The effects of stress and stress hormones on human cognition: implications for the field of brain and cognition. Brain Cognit. 65 (3), 209–237. https://doi.org/10.1016/j.bandc.2007.02.007.
Maercker, A., Horn, A.B., 2012. A sociointerpersonal perspective on PTSD: the case for environments and interpersonal processes. Clin. Psychol. Psychother. 17.
Mance, G.A., Grant, K.E., Roberts, D., Carter, J., Turek, C., Adam, E., Thorpe, R.J., 2019. Environmental stress and socioeconomic status: does parent and adolescent stress influence executive functioning in urban youth? J. Prev. Interv. Community 47 (4), 279–294. https://doi.org/10.1080/10852352.2019.1617386.
Manly, J.J., Echemendia, R.J., 2007. Race-specific norms: using the model of hypertension to understand issues of race, culture, and education in neuropsychology. Arch. Clin. Neuropsychol. 22 (3), 319–325. https://doi.org/10.1016/j.acn.2007.01.006.
Mathersul, D., Palmer, D.M., Gur, R.C., Gur, R.E., Cooper, N., Gordon, E., Williams, L.M., 2009. Explicit identification and implicit recognition of facial emotions: II. Core domains and relationships with general cognition. J. Clin. Exp. Neuropsychol. 31 (3), 278–291. https://doi.org/10.1080/13803390802043619.
Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., Bates, D., 2017. Balancing Type I error and power in linear mixed models. J. Mem. Lang. 94, 305–315. https://doi.org/10.1016/j.jml.2017.01.001.
McEwen, B.S., 2004. Protection and damage from acute and chronic stress: allostasis and allostatic overload and relevance to the pathophysiology of psychiatric disorders. Ann. N. Y. Acad. Sci. 1032 (1), 1–7. https://doi.org/10.1196/annals.1314.001.
McEwen, B.S., 2012. Brain on stress: how the social environment gets under the skin. Proc. Natl. Acad. Sci. Unit. States Am. 109 (Suppl. 2), 17180–17185. https://doi.org/10.1073/pnas.1121254109.
McLeroy, K.R., Bibeau, D., Steckler, A., Glanz, K., 1988. An ecological perspective on health promotion programs. Health Educ. Q. 15 (4), 351–377. https://doi.org/10.1177/109019818801500401.
Moore, T.M., Martin, I.K., Gur, O.M., Jackson, C.T., Scott, J.C., Calkins, M.E., Ruparel, K., Port, A.M., Nivar, I., Krinsky, H.D., Gur, R.E., Gur, R.C., 2016. Characterizing social environment's association with neurocognition using census and crime data linked to the Philadelphia Neurodevelopmental Cohort. Psychol. Med. 46 (3), 599–610. https://doi.org/10.1017/S0033291715002111.
Muñoz, E., Scott, S.B., Corley, R., Wadsworth, S.J., Sliwinski, M.J., Reynolds, C.A., 2020. The role of neighborhood stressors on cognitive function: a coordinated analysis. Health Place 66, 102442. https://doi.org/10.1016/j.healthplace.2020.102442.
Namazi, M., Thordardottir, E., 2010. A working memory, not bilingual advantage, in controlled attention. Int. J. Biling. Educ. BiLing. 13 (5), 597–616. https://doi.org/10.1080/13670050.2010.488288.
Noble, K.G., Houston, S.M., Kan, E., Sowell, E.R., 2012. Neural correlates of socioeconomic status in the developing human brain: neural correlates of socioeconomic status. Dev. Sci. 15 (4), 516–527. https://doi.org/10.1111/j.1467-7687.2012.01147.x.
Pabayo, R., Fuller, D., Goldstein, R.B., Kawachi, I., Gilman, S.E., 2017. Income inequality among American states and the conditional risk of post-traumatic stress disorder. Soc. Psychiatr. Psychiatr. Epidemiol. 52 (9), 1195–1204. https://doi.org/10.1007/s00127-017-1413-x.
Pager, D., Shepherd, H., 2008. The sociology of discrimination: racial discrimination in employment, housing, credit, and consumer markets. Annu. Rev. Sociol. 34, 181–209.
Parnia, A., Siddiqi, A., 2020. Socioeconomic disparities in smoking are partially explained by chronic financial stress: marginal structural model of older US adults. J. Epidemiol. Community 74 (3), 248–254. https://doi.org/10.1136/jech-2019-213357.
Pedraza, O., Mungas, D., 2008. Measurement in cross-cultural neuropsychology. Neuropsychol. Rev. 18 (3), 184–193. https://doi.org/10.1007/s11065-008-9067-9.
Pickett, K.E., 2001. Multilevel analyses of neighbourhood socioeconomic context and health outcomes: a critical review. J. Epidemiol. Community 55 (2), 111–122. https://doi.org/10.1136/jech.55.2.111.
Reitan, R.M., 1992. Trail Making Test: Manual for Administration and Scoring. Reitan Neuropsychology Laboratory.
Resource, Brain, 2010. BRISC and WebNeuroTM Assessment Manual, V1.7. Brain Resource Ltd.
Rivera Mindt, M., Byrd, D., Saez, P., Manly, J., 2010. Increasing culturally competent neuropsychological services for ethnic minority populations: a call to action. Clin. Neuropsychol. 24 (3), 429–453. https://doi.org/10.1080/13854040903058960.

Robinson, T., 2008. Applying the socio-ecological model to improving fruit and vegetable intake among low-income African Americans. J. Community Health 33 (6), 395–406. https://doi.org/10.1007/s10900-008-9109-5.

Rosenberg, M.D., Finn, E.S., Scheinost, D., Papademetris, X., Shen, X., Constable, R.T., Chun, M.M., 2016. A neuromarker of sustained attention from whole-brain functional connectivity. Nat. Neurosci. 19 (1), 165–171. https://doi.org/10.1038/nn.4179.

Ross, C.E., Mirowsky, J., 2008. Neighborhood socioeconomic status and health: context or composition? City Community 7 (2), 163–179. https://doi.org/10.1111/j.1540-6040.2008.00251.x.

Rothbaum, B.O., Kearns, M.C., Reiser, E., Davis, J.S., Kerley, K.A., Rothbaum, A.O., Mercer, K.B., Price, M., Houry, D., Ressler, K.J., 2014. Early intervention following trauma may mitigate genetic risk for PTSD in civilians: a pilot prospective emergency department study. J. Clin. Psychiatr. 75 (12), 1380–1387. https://doi.org/10.4088/JCP.13m08715.

Routledge, K.M., Burton, K.L.O., Williams, L.M., Harris, A., Schofield, P.R., Clark, C.R., Gatt, J.M., 2017. The shared and unique genetic relationship between mental well-being, depression and anxiety symptoms and cognitive function in healthy twins. Cognit. Emot. 31 (7), 1465–1479. https://doi.org/10.1080/02699931.2016.1232242.

Samuelson, K.W., Newman, J., Abu Amara, D., Qian, M., Li, M., Schultebraucks, K., Purchia, E., Genfi, A., Laska, E., Siegel, C., Hammamieh, R., Gautam, A., Jett, M., Marmar, C.R., 2020. Predeployment neurocognitive functioning predicts postdeployment posttraumatic stress in Army personnel. Neuropsychology 34 (3), 276–287. https://doi.org/10.1037/neu0000603.

Schuck, A.M., Spatz Widom, C., 2019. Posttraumatic stress disorder in maltreated children grown up: the influence of neighborhood. J. Trauma Stress 32 (1), 78–87. https://doi.org/10.1002/jts.22355.

Selye, H., 1956. The Stress of Life. McGraw-Hill, p. 324.

Shalev, A.Y., Gevonden, M., Ratanatharathorn, A., Laska, E., Mei, W. F. van der, Qi, W., Lowe, S., Lai, B.S., Bryant, R.A., Delahanty, D., Matsuoka, Y.J., Olff, M., Schnyder, U., Seedat, S., deRoon-Cassini, T.A., Kessler, R.C., Koenen, K.C., 2019. Estimating the risk of PTSD in recent trauma survivors: results of the international consortium to predict PTSD (ICPP). World Psychiatr. 18 (1), 77–87. https://doi.org/10.1002/wps.20608.

Sharkey, P., Elwert, F., 2011. The legacy of disadvantage: multigenerational neighborhood effects on cognitive ability. Am. J. Sociol. 116 (6), 1934–1981. https://doi.org/10.1086/660009.

Silverstein, S.M., Berten, S., Olson, P., Paul, R., Williams, L.M., Cooper, N., Gordon, E., 2007. Development and validation of a World-Wide-Web-based neurocognitive assessment battery: WebNeuro. Behav. Res. Methods 39 (4), 940–949. https://doi.org/10.3758/BF03192989.

Singh, G.K., 2003. Area deprivation and widening inequalities in US mortality, 1969–1998. Am. J. Publ. Health 93 (7), 1137–1143. https://doi.org/10.2105/AJPH.93.7.1137.

Smedley, A., Smedley, B.D., 2005. Race as biology is fiction, racism as a social problem is real: anthropological and historical perspectives on the social construction of race. Am. Psychol. 60 (1), 16–26. https://doi.org/10.1037/0003-066X.60.1.16.

Smith, J.R., Patton, D.U., 2016. Posttraumatic stress symptoms in context: examining trauma responses to violent exposures and homicide death among Black males in urban neighborhoods. Am. J. Orthopsychiatry 86 (2), 212–223. https://doi.org/10.1037/ort0000101.

Squires, G.D., Woodruff, F., 2019. Redlining. The Wiley Blackwell Encyclopedia of Urban and Regional Studies, pp. 1–8.

Squires, Gregory D., O"Connor, Sally, 2001. Color and Money: Politics and Prospects for Community Reinvestment in Urban America. State University of New York Press, Albany.

Sternbach, G.L., 2000. The Glasgow coma scale. J. Emerg. Med. 19 (1), 67–71. https://doi.org/10.1016/s0736-4679(00)00182-7.

Stillman, C.M., Cohen, J., Lehman, M.E., Erickson, K.I., 2016. Mediators of physical activity on neurocognitive function: a review at multiple levels of analysis. Front. Hum. Neurosci. 10 https://doi.org/10.3389/fnhum.2016.00626.

Stokols, D., 1996. Translating social ecological theory into guidelines for community health promotion. Am. J. Health Promot.: Aust. J. Hosp. Pharm. 10 (4), 282–298. https://doi.org/10.4278/0890-1171-10.4.282.

Stroop, J.R., 1935. Studies of interference in serial verbal reactions. J. Exp. Psychol. 18 (6), 643–662. https://doi.org/10.1037/h0054651.

Teasdale, G., Maas, A., Lecky, F., Manley, G., Stocchetti, N., Murray, G., 2014. The Glasgow coma scale at 40 years: standing the test of time. *The lancet*. Neurology 13 (8), 844–854. https://doi.org/10.1016/S1474-4422(14)70120-6.

Tomlinson, R.C., Burt, S.A., Waller, R., Jonides, J., Miller, A.L., Gearhardt, A.N., Peltier, S.J., Klump, K.L., Lumeng, J.C., Hyde, L.W., 2020. Neighborhood poverty predicts altered neural and behavioral response inhibition. Neuroimage 209, 116536. https://doi.org/10.1016/j.neuroimage.2020.116536.

Ursache, A., Noble, K.G., 2016. Neurocognitive development in socioeconomic context: multiple mechanisms and implications for measuring socioeconomic status. Psychophysiology 53 (1), 71–82. https://doi.org/10.1111/psyp.12547.

Verbruggen, F., Logan, G.D., 2008. Response inhibition in the stop-signal paradigm. Trends Cognit. Sci. 12 (11), 418–424. https://doi.org/10.1016/j.tics.2008.07.005.

Vliegenthart, J., Noppe, G., van Rossum, E.F.C., Koper, J.W., Raat, H., van den Akker, E. L.T., 2016. Socioeconomic status in children is associated with hair cortisol levels as a biological measure of chronic stress. Psychoneuroendocrinology 65, 9–14. https://doi.org/10.1016/j.psyneuen.2015.11.022.

Weathers, F.W., Bovin, M.J., Lee, D.J., Sloan, D.M., Schnurr, P.P., Kaloupek, D.G., Keane, T.M., Marx, B.P., 2018. The Clinician-Administered PTSD Scale for DSM-5 (CAPS-5): development and initial psychometric evaluation in military veterans. Psychol. Assess. 30 (3), 383–395. https://doi.org/10.1037/pas0000486.

Whiting, D.L., Deane, F.P., Simpson, G.K., McLeod, H.J., Ciarrochi, J., 2017. Cognitive and psychological flexibility after a traumatic brain injury and the implications for treatment in acceptance-based therapies: a conceptual review. Neuropsychol. Rehabil. 27 (2), 263–299. https://doi.org/10.1080/09602011.2015.1062115.

Wight, R.G., Aneshensel, C.S., Miller-Martinez, D., Botticello, A.L., Cummings, J.R., Karlamangla, A.S., Seeman, T.E., 2006. Urban neighborhood context, educational attainment, and cognitive function among older adults. Am. J. Epidemiol. 163 (12), 1071–1078. https://doi.org/10.1093/aje/kwj176.

Williams, C.T., Latkin, C.A., 2007. Neighborhood socioeconomic status, personal network attributes, and use of heroin and cocaine. Am. J. Prev. Med. 32 (6), S203–S210. https://doi.org/10.1016/j.amepre.2007.02.006.

Williams, L.M., Simms, E., Clark, C.R., Paul, R.H., Rowe, D., Gordon, E., 2005. The test-retest reliability of a standardized neurocognitive and neurophysiological test battery: "Neuromarker. Int. J. Neurosci. 115 (12), 1605–1630. https://doi.org/10.1080/00207450590958475.

Williams, Leanne M., Hermens, D.F., Thein, T., Clark, C.R., Cooper, N.J., Clarke, S.D., Lamb, C., Gordon, E., Kohn, M.R., 2010. Using brain-based cognitive measures to support clinical decisions in ADHD. Pediatr. Neurol. 42 (2), 118–126. https://doi.org/10.1016/j.pediatrneurol.2009.08.010.

Wu, Y.-T., Prina, A.M., Brayne, C., 2015. The association between community environment and cognitive function: a systematic review. Soc. Psychiatr. Psychiatr. Epidemiol. 50 (3), 351–362. https://doi.org/10.1007/s00127-014-0945-6.

Xiao, R., Wang, G., Wang, M., 2018. Transportation disadvantage and neighborhood sociodemographics: a composite indicator approach to examining social inequalities. Soc. Indicat. Res. 137 (1), 29–43. https://doi.org/10.1007/s11205-017-1616-2.

Zoellner, L.A., Feeny, N.C., Cochran, B., Pruitt, L., 2003. Treatment choice for PTSD. Behav. Res. Ther. 41 (8), 879–886. https://doi.org/10.1016/S0005-7967(02)00100-6.