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Capturing Environmental Dimensions of Adversity and Resources in the Context of Poverty Across Infancy Through Early Adolescence: A Moderated Nonlinear Factor Model

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Income, education, and cumulative-risk indices likely obscure meaningful heterogeneity in the mechanisms through which poverty impacts child outcomes. This study draws from contemporary theory to specify multiple dimensions of poverty-related adversity and resources, with the aim of better capturing these nuances. Using data from the Family Life Project (*N* = 1,292), we leveraged moderated nonlinear factor analysis (Bauer, 2017) to establish group- and longitudinally invariant environmental measures from infancy to early adolescence. Results indicated three latent factors—material deprivation, psychosocial threat, and sociocognitive resources—were distinct from each other and from family income. Each was largely invariant across site, racial group, and development and showed convergent and discriminant relations with age-twelve criterion measures. Implications for ensuring socioculturally valid measurements of poverty are discussed.

Children growing up in poverty have a greater likelihood of experiencing a litany of adverse exposures ranging from resource scarcity to domestic and neighborhood violence (Evans, 2004). While many children growing up with material and psychosocial disadvantage flourish, others are placed at risk for early socioemotional and cognitive difficulties (Blair & Raver, 2012; Yoshikawa, Aber, & Beardslee, 2012). Identifying the mechanisms underlying these associations is central to strengthening community, school, and family supports for resilience and for developing targeted intervention and policy efforts.

Historically, income, maternal education, and other sociodemographic indicators have been widely used as proxies of poverty-related adversity. However, there is growing concern that these broad indicators likely obscure meaningful heterogeneity in mechanisms by which poverty impacts child outcomes (Duncan & Magnuson, 2003). This has underscored the need for measures that capture individual differences in experiences in the context of poverty that account for the wide range in severity, timing, and type of exposure that may be driving its impacts.

An equally pressing concern is that these common indicators of poverty may not have the same meaning across time or across racial-ethnic groups, leading to empirical imprecision and conclusions that do not adequately characterize the experience of any sociocultural group (Borsboom, 2006). This consideration is especially important given that children and families of color are disproportionately represented among the poor due to pervasive structural racial and social inequalities (Jiang & Koball, 2016; Raver & Blair, 2020). The intersections of race and class can be seen in the vast income and wealth racial disparities that exist: even when controlling for education level, White household income is

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twice the size and net worth is 13 times the size of African American households in the United States (Parker, Horowitz, & Mahl, 2016). Because traditional poverty indicators like income are so intertwined with these racial disparities, more direct measures capturing resource scarcity and other proximal stressors may be more useful in its ability to represent the mechanistic pathway by which low-income impacts child outcomes (Gershoff, Aber, Raver, & Lennon, 2007; Parker et al., 2016). Indeed, among more racially and ethnically diverse samples, measured indicators of parents' subjective experience of hardship have been shown to make up to a fourfold increase in explained variance in predicting family level outcomes compared to household income alone (Hurwich-Reiss, Watamura, & Raver, 2019).

Reducing racial, social, and developmental bias in our measures is a major goal of developmental science. Towards this end, rigorous methods testing and adjusting for possible bias should be considered alongside substantively relevant developmental questions among diverse populations. In this study, we draw from contemporary theoretical models of adversity and leverage recent advances in latent variable modeling to develop more nuanced representations of the constraints and supports experienced by families struggling with economic adversity.

Beyond Income: Capturing Environmental Heterogeneity in the Context of Poverty

Two differing theoretical and empirical frameworks guide our approach to measuring dimensions of poverty-related adversity and resources in this study. First, by focusing on families' resources, we adopt an integrative, strengths-based approach by examining the considerable heterogeneity in children's experiences that exist above and beyond their place on the income distribution (Frankenhuis, Young, & Ellis, 2020; Hostinar & Miller, 2019). Such an approach highlights experiences in the context of poverty that are both more empirically precise and less stigmatizing or marginalizing (Shafir, 2017; Syed, Santos, Yoo, & Juang, 2018). Many families struggling with the uncertainty and strain of not having enough money to meet material needs are nonetheless able to create environments that are emotionally secure, affirming, and safe (Frankenhuis & Nettle, 2019). Clarifying these individual and family differences is central to understanding both risk and resilience in children's development across the socioeconomic spectrum.

Capturing the range of exposures associated with childhood poverty is a significant challenge, but clarifying certain domains of experience has promise to yield significant empirical benefits. To illustrate the value of considering multiple poverty-relevant contextual factors as predictors of specific developmental adaptations, we draw from the dimensional model of adversity and psychopathology (DMAP; McLaughlin & Sheridan, 2016). DMAP builds largely from adversity research over the last 20 years, which incorporates a wide range of scientific methods such as observational human and experimental animal neuroscientific models. Through those new methods, we have come to better understand that deprivation (operationalized as insufficient resources) and being exposed to conditions that are threatening have both distinct biological and neurocognitive sequelae that allow for adaptation to a given set of environmental demands. For example, studies of sensory deprivation (e.g., dark rearing; Wiesel & Hubel, 1965) and threat learning (e.g., repetitive foot shock; Raineki, Cortés, Belnoue, & Sullivan, 2012) demonstrate unique associations with cognitive neural development (Huttenlocher, de Courten, Garey, & Van der Loos, 1982) and stress responsivity outcomes, respectively (Brunson, Eghbal-Ahmadi, Bender, Chen, & Baram, 2001). Evidence from humans also suggests that deprivation and threat may exert distinct effects on neurodevelopment, which help to provide malleable targets for intervention and prevention (e.g., McLaughlin et al., 2016; Rosen, Sheridan, Sambrook, Meltzoff, & McLaughlin, 2018). Although many DMAP studies have used low-income as an index of deprivation, studies leveraging large data sets are increasingly taking a more individual difference approach that considers home, school, and neighborhood contexts of poverty in their measurement (Ellwood-Lowe, Whitfield-Gabrieli, & Bunge, 2020; Rosen, Amso, & McLaughlin, 2019). While there are many poverty-related environmental dimensions that could be examined, we focus this study on three representative constructs inspired by the DMAP—namely, material deprivation, sociocognitive resources, and psychosocial threat.

Measurement Invariance: Making Apples-to-Apples Comparisons

Critically, the validity and ultimate utility of measures tapping environmental exposures hinge on the extent to which these measures reflect common substantive and quantitative scales across groups and developmental time—broadly termed, *measurement invariance* (MI; Meredith, 1993; Widaman, Ferrer, & Conger, 2010). When the underlying meaning or scale of a measured construct differs across groups or development—that is, when a measure is *non*invariant—it undermines one's ability to interpret group or developmental differences because measurement differences are inherently confounded with substantive differences (Flake & Fried, 2019). In simple terms, it becomes unclear whether one is comparing apples to apples or to oranges.

At the item level, noninvariance is often referred to as differential item functioning (DIF), and there are times when we might well expect DIF across groups or development. For instance, a scale item for sociocognitive resources might include and item like, "has a toy appropriate for grasping or mouthing." Developmentally, one would expect this item to be endorsed far more often in a study of 6-month-olds, than during a longitudinal follow-up three years later, when such toys are no longer as developmentally meaningful. However, all other things being equal, if this item's contribution to the construct is weighted equally over time —which is done implicitly in any summary score that fails to adjust the weight explicitly—one would erroneously conclude that sociocognitive resources decreased across early childhood. An analog extends to group differences. As a purely illustrative example, affluent families in the US likely have many of such conventional infant toys while families in poverty may have fewer conventional toys, yet other nonconventional items *that fulfill the same developmental purpose*. If this were the case, then a typical summary score would suggest lower levels of sociocognitive resources for the low-income family, despite the fact that the true latent construct is identical across groups. As such, the cost of DIF can be high—spurious conclusions driven by measurement artifacts rather than true differences in the outcome of interest (Borsboom, 2006; Millsap, 1998).

Traditional approaches to testing and adjusting for DIF include Multiple Groups analysis (MGA; Henseler, Ringle, & Sinkovics, 2009) and Multiple Indicators, Multiple Causes (MIMIC) modeling (Jöreskog & Goldberger, 1975). Each approach has both strengths and weaknesses. For instance, MGA allows one to model heterogeneity in most of the parameters of typical psychometric interest to applied researchers (e.g., factor loadings; item intercepts; factor (co)variances, item residual (co)variances; factor means). In so doing, they allow one to maintain a common latent scale across groups (i.e., apples to apples comparison), while also accounting at least partially for group differences in: (a) the extent to which an *item* is representative of higher versus lower levels of the *latent* construct (i.e., item difficulty), (b) the magnitude of the linear (continuous item) or nonlinear (categorical item) relation between the latent construct and the item (i.e., item discrimination), and (c) the stochastic properties of both the construct and the items (see Table S1). However, in practical terms, the MGA approach quickly becomes intractable as the number of groups increases. MGA is also difficult to apply to continuous moderators—like age—without devising often arbitrary age-groupings. Traditional MIMIC models are useful for such continuous moderators, yet typically limit one's invariance adjustment to item difficulty (see Bauer, 2017). Combined, these limitations are particularly problematic for longitudinal studies of diverse populations, in which measurement noninvariance may exist simultaneously between groups (e.g., racial and gender category groups) and developmental time (Curran et al., 2014).

Fortunately, recent psychometric innovations (e.g., Approximate MI; Alignment; Muthén & Asparouhov, 2014; see Davidov, Muthen, & Schmidt, 2018 for review) have greatly improved the detection of and adjustment for DIF. In this study, we leverage a novel methodological approach to DIF testing that is particularly well-suited for unbalanced longitudinal data collected from a sociodemographically diverse population—moderated nonlinear factor analysis (MNLFA; Bauer, 2017; Bauer & Hussong, 2009; Curran et al., 2014). Conceptually, MNLFA combines the best aspects of MGA and MIMIC into a single approach. Like MGA, MNLFA allows one to adjust for DIF across all parameters of typical psychometric interest (e.g., measurement intercepts, factor loadings, factor (co)-variances). However, like MIMIC models, MNLFA allows one to readily extend these tests to multiple, simultaneous moderators—either continuous or categorical.

The Present Study

In this study, we leverage these recent methodological advances to address three key aims. Our first aim was to apply recent theoretical models of environmental adversity to a large sample of children living in predominately low-income rural communities. We used three widely used measures: (a) The Economic Strain Questionnaire (ES; Conger, Ge, Elder, Lorenz, & Simons, 1994) to measure distal sources of material deprivation; (b) the Home Observation for Measurement of the Environment (HOME; Bradley & Caldwell, 1984), to measure more proximal sources of sociocognitive resources, and (c) the Conflict Tactics Scale (CTS; Straus & Gelles, 1990) to measure psychosocial threat in the form of intimate partner violence, both verbal and physical.

Our second aim was to test the extent to which the proposed measures are commensurable across key demographic covariates and developmental time. Due to the ways in which measures of poverty are deeply confounded with structural racial inequalities, we anticipated racial group membership to contribute to both measurement artifact and latent mean differences in measures of poverty-related adversity. We anticipated similar effects with respect to age for the HOME given children's increasing independence away from caregivers (Larson, Richards, Moneta, Holmbeck, & Duckett, 1996). We had no a priori hypotheses for gender category group membership, and thus considered potential gender differences as exploratory. Our third aim was to investigate the utility of using MNLFA above and beyond raw mean scores. To do this, we used multi-level growth curve analyses to examine differences between raw-score- and MNLFA-derived estimates, with respect to developmental change and group differences. We also examined the relationship between cognitive and behavioral child outcomes and MNLFA-derived estimates to investigate the predictive utility of MNLFA scores. Based on the DMAP framework, we hypothesized that: (a) higher levels of psychosocial threat would be more positively correlated with greater behavioral problems but less so with cognitive performance, while (b) lower sociocognitive resources and greater material deprivation would show comparatively stronger relations with children's cognitive performance than with their behavioral problems. Lastly, we expected that income would be more strongly related to material deprivation and sociocognitive resources than to psychosocial threat.

Method

Participants

The Family Life Project (FLP) was designed to study families in two of the four major geographical regions of the United States with high poverty rates (Dill, 1999). Three counties in eastern North Carolina (NC) and three counties in central Pennsylvania (PA) were selected to be indicative of the Black South and Appalachia, respectively. The FLP adopted a developmental epidemiological design in which sampling procedures were employed to recruit a representative sample of 1,292 children whose families resided in one of the six counties at the time of the target child's birth. Families were oversampled for low-income status in both states, and families identifying as African American were oversampled in NC (African American families were not oversampled in PA because African Americans made up < 5% of the population of the target communities). On average, families manage with an income 190% of the federal poverty threshold. For a comprehensive description of the sampling plan and recruitment procedures, see Vernon-Feagans et al. (2013).

Families were seen in 2- to 3-hr home visits when children were approximately 6 months, and 1, 2, 3, 5, 7, and 12 years of age. During the visits, the primary caregiver (in 99% of cases the mother), completed questionnaires concerning family demographics, income, economic hardship, family conflict, and child behavior. Trained home visitors completed a series of measures related to the home environment. At the 12-year visit, children completed computerized tasks measuring aspects of self-regulation. Overall, 49% children in this sample were identified by their parents as female, 42% were identified by their parents as African American, and 58% reside in NC. Demographics for missing and nonmissing cases were very similar at each time point; information on demographics, missingness, and retention rates over time can be found in Table S2).

Measures

Material Deprivation

Economic need and material sufficiency were reported by the primary caregiver across all time points using the six-item Economic Strain Questionnaire (Conger et al., 1994). Two items assess economic need (the extent to which the family has difficulty paying bills and runs out of money each month) and four items assess economic sufficiency (the extent to which the family feels it is able to adequately meet its needs for housing, clothing, food, and medical care). Scores were rated on a Likert-type scale (range 1–5). Higher scores indicated that families reported experiencing greater material deprivation.

Sociocognitive Resources

Home visitors reported on the presence of parent responsiveness and opportunities for cognitive resources at each of the seven home visits using the HOME scale (Bradley & Caldwell, 1984). All items were scored such that a 1 on any one item indicated the presence of a given resource and a zero indicated an absence. Three versions of the HOME were used to ask developmentally appropriate questions over the seven time points; one item was common across every time point, eight items were unique to one time point, and all other items were administered on at least two time points.

The HOME is intended to measure many aspects of a child's home environment. For this study, we conducted a content analysis of the HOME items and selected an initial set of 61 items that were deemed substantively relevant to sociocognitive resources—namely, items pertaining to developmentally appropriate learning materials and parent-child interactions that help to scaffold children's learning (Rosen et al., 2019). Specifically, we surveyed items corresponding to the responsivity, mom/child behaviors, and the learning and language materials/resources subscales established elsewhere (Bradley, 1994; Bradley & Caldwell, 1984). We then retained items that demonstrated reasonable variation (≥ 10% with either 0 or 1). This resulted in a final list of 29 items included in the models (see Table 1).

Psychosocial Threat: Exposure to Intimate Partner Violence

Primary caregivers reported on their own and their partners' use of verbal aggression and physical aggression during the past 12 months (CTS—Couple Form R; Straus & Gelles, 1990) across all time points. The CTS was collected if the primary caregiver reported that she was married or had a partner at that time point (70%–82% of the sample; see Table S1). Items assess the frequency with which the respondent and the partner used verbal acts that emotionally or psychologically hurt the other party (e.g., "How often has he insulted or swore at you?") as well as the frequency with which physical force was used as a means of resolving the conflict (e.g., "How often has he pushed, grabbed, or shoved you?"). Items ranged from 0 = never to 6 = more than 20 times in the past year. However, due to low base rates and skew of the response distribution, item responses were collapsed and recoded as 0 = never, 1 = 1–5 times, 2 = 6 or more times. To capture overall exposure, irrespective of which partner was the perpetrator, we then took the highest of the two scores as the indicator for the measurement models. We removed seven items pertaining to physical violence, given low base-rates (< 10%); the remaining nine items were retained in the measurement models (Table 1).

Moderator/Invariance Variables

Child age was measured as chronological age, continuously scaled in years and centered at the mean age at the 6-month visit. Study site (NC = 1, PA = 0), racial group membership (1 = Black, 0 = White), and gender group membership (1 = Female, 0 = Male) were also included as moderators.

Criterion Variables

Executive function. Child performance on the Hearts and Flowers Task (HF; Diamond, Barnett, Thomas, & Munro, 2007) measured at the age 12 visit was used to examine convergent validity in the cognitive domain via executive function (EF). Participants are instructed to respond by pressing the designated key on the same side of the stimulus when the stimulus is a heart and on the opposite side when the stimulus is a flower. There are three conditions: (a) congruent, where only one rule applies (press the key on the same side as the heart), (b) incongruent, where participants must remember another rule (press the key on the opposite side that the flower appears), and (c) mixed, where congruent and incongruent trials are intermixed. The task included a total of 57 test trials across three blocks (12 hearts-only, 12 flowers-only, and 33 mixed). Stimulus display and response window duration were 750 ms, preceded by a 500 ms fixation cross and 500 ms blank screen. Participants who were < 60% accurate on congruent only trials were removed (n = 38) from analyses. EF for this study was indexed by accuracy and reaction time on mixed trials.

Behavioral problems. Parent-reported behavioral problems on the Strengths and Difficulties Questionnaire (SDQ; Goodman, 2001) measured at the age 12 visit were used to examine convergent validity in the affective domain. Primary caregivers reported the degree to which items were not true, somewhat true, and certainly true for their children. While multiple subscales are created from this measure, we used the behavioral problems total score, which represents the mean response across all 25

Table 1
List of Items for Each Environmental Exposure and Time Points at Which Each Item Was Available

	0.6 years	1.5 years	2 years	3 years	5 years	7 years	12 years
Material deprivation							
How difficult is it for you to pay your family's bills each month	X	X	X	X	X	X	X
Generally, at the end of each month, do you end up with. . .	X	X	X	X	X	X	X
My family has enough money to afford the kind of home we need. Do you. . .	X	X	X	X	X	X	X
We have enough money to afford the kind of clothing we need. Do you. . .	X	X	X	X	X	X	X
We have enough money to afford the kind of food we need. Do you. . .	X	X	X	X	X	X	X
We have enough money to afford the kind of medical care we need. Do you. . .	X	X	X	X	X	X	X
Sociocognitive resources							
Caregiver initiates verbal interchanges with visitor	X	X	X			X	X
Caregiver spontaneously praises child, at least twice	X	X	X	X	X	X	X
Caregiver kisses or caresses child, at least once	X	X	X	X	X		
At least 10 books are present	X	X	X	X		X	X
Muscle activity toys or equipment	X	X	X				
Caregiver provides toys for child to play with during visit	X	X	X				
Learning facilitators—mobile, table and chair, high chair, play pen	X	X	X				
Complex eye-hand coordination toys	X	X	X				
Toys for literature and music	X	X	X				
Caregiver holds child close 10–15 min per day				X	X		
CD player or tape recorder and 5 or more children's CDs or tapes are available to the child					X		X
10 or more books for adults are visible in the home				X	X		
Caregiver regularly buys or receives 1 or more magazines				X	X		
Fairly regular/predictable daily family schedule						X	X
Caregiver sometimes yields to child's fears or rituals						X	X
Caregiver uses term of endearment for child when discussing child						X	X
Child has access to musical instrument						X	X
Child has near access to 2 pieces playground equipment						X	X
Caregiver use complete sentences/long words to talk w/ visitor						X	X
House has at least 2 pictures or art on walls						X	X
Family provides lessons/memberships for child's talents						X	X
Child is encouraged to learn shapes				X			
Two or more toys which teach colors, size, and shape are available to the child				X			
Three or more puzzles are available to the child				X			
Two or more games which help teach numbers are available to the child				X			
Caregiver introduces visitor to child					X		
Child's art work is displayed in some visible place in the home					X		
Child is encouraged to learn to read a few words					X		
TV is used judiciously					X		
Psychosocial threat							
Insulted or swore at him/her/you	X	X	X	X	X	X	X
Sulked or refused to talk about an issue	X	X	X	X	X	X	X
Stomped out of the room or house or yard	X	X	X	X	X	X	X

Table 1
Continued

	0.6 years	1.5 years	2 years	3 years	5 years	7 years	12 years
Cried	X	X	X	X	X	X	X
Did or said something to spite him/her/you	X	X	X	X	X	X	X
Threatened to hit or throw something at him/her/you	X	X	X	X	X	X	X
Threw or smashed or hit or kicked something	X	X	X	X	X	X	X
Threw something at him/her/you	X	X	X	X	X	X	X
Pushed, Grabbed, or shoved him/her/you	X	X	X	X	X	X	X

items. This score ranges from zero to two, with higher values reflecting more behavior problems.

Income. Income-to-needs ratios (INR) for each time point were calculated as the family's reported total household income for a given year divided by the federal poverty threshold for that year, adjusted for the number of persons in the home.

Analytic Plan

Study Aim 1: Apply Recent Theoretical Models of Environmental Adversity for the Context of Poverty

The ES, HOME, and CTS questionnaires were chosen to represent environmental measures of material deprivation, sociocognitive resources, and psychosocial threat, respectively. In addition to their substantive alignment with the DMAP dimensions, these measures were also collected across all seven time points in the FLP sample, affording subsequent testing for longitudinal MI. A series of descriptive and graphical examinations of the data were used for initial item screening. To test configural invariance we fitted separate common-factor, longitudinal CFA models for each of the constructs in Mplus (see Van de Schoot, Lugtig, & Hox, 2012). For each, we constrained all latent factor means and variances to zero and one, respectively, to identify the model, and all other parameters were freely estimated over time. We then consulted the fit indices, parameter estimates, and modification indices for evidence of heterogeneous factor structures.

Study Aim 2: Model DIF Across Site, Gender and Racial Group Membership, and Developmental Time

Based on the models generated in Aim 1, we conducted MNLFA for each construct, using a slightly altered version of the automated MNLFA (aMNLFA; Gottfredson et al., 2019) package available for the R statistical analysis platform (Cole, Gottfredson, Giordano, & Janssen, 2018). Specifically, the MNLFA proceeded by, first, generating a calibration sample from the larger longitudinal sample by taking a single longitudinal observation from each case. This rendered the calibration sample functionally cross-sectional and, in so doing, removed the dependencies inherent to longitudinal data. This calibration sample was used in all subsequent analyses, with the exception of the final estimation model when the full longitudinal data set was used.

In a second step, the latent factors and variances were regressed on the covariates. Although these structural relations do not speak directly to DIF, per se, they need to be accounted for to accurately assess DIF in the indicator loadings and intercepts. As noted in the following section, these relations also contribute important information to the factor scores extracted from these models. Because we expected growth rates in our environmental constructs to vary across children (i.e., random effects), as well as systematically across the levels of the covariates (i.e., fixed effects), we examined these structural relations using mixed models, as discussed under our third aim.

Actual DIF testing begins in the third step. Specifically, because a model testing DIF simultaneously across all loadings and indicator intercepts would be under-identified, MNLFA adopts a two-step process: (a) DIF for the indicator loadings and intercepts are first tested individually for each indicator, with the remaining indicators constrained to invariance (i.e., no DIF). Then (b) the indicators deemed to be invariant (i.e., no DIF) in the first step are constrained to invariance in the second step, in order to identify a model in which DIF is tested simultaneously across the remaining indicators. Given multiple testing, this second step adopts Benjamini–Hochberg corrections to adjust for inflated type I error rates. All models were fitted to the data using a robust maximum likelihood estimator and a logit (binary) or cumulative logit (ordinal) link function.

Lastly, the parameter estimates from this final calibration-sample model are applied as model constraints in a model fitted to data from the entire sample. Individual- and time-specific factor scores (expected *a posteriori* estimates) are then extracted from this final model. As such, these factor scores represent an individual's estimated DIF-adjusted level of the construct, given his/her age, gender group membership, racial group membership, and research site. For a detailed description of these steps in the aMNLFA statistical package, see Gottfredson et al. (2019).

Study Aim 3: Compare Empirical Differences Between Raw-Score- and MNLFA-Based Estimates With Respect to Developmental Change, Group Differences, and Predictive Utility

To evaluate the advantages of the MNLFA scores, mean proportion scores of ES, HOME, and CTS were calculated at each time point and graphically compared against factor scores. We also fitted a series of mixed linear models (Lmer package in R 3.3.1; Kuznetsova, Brockhoff, & Christensen, 2017), to test the extent to which the random and systematic differences in the growth of each of these constructs differed across the factor- versus raw-score scales. Specifically, we first specified a series of growth models to establish the optimal growth function and (co)variance structure for the given construct (see Singer & Willett, 2002). We subsequently tested the extent to which growth in each construct varied as a function site and race. Model comparisons were conducted using likelihood ratio tests and second-order Akaike information criteria (AIC).

To test convergent validity and predictive utility, partial correlations (controlling for covariates retained in final MNLFA models) between the raw and MNLFA scores and three theoretically relevant constructs of interest were examined: (a) EF indexed by accuracy and reaction time on mixed HF blocks, (b) behavioral problems indexed by the total problems subscale on the SDQ, and (c) poverty as indexed by INR.

Results

Study Aim 1: Apply Recent Theoretical Models of Environmental Adversity for the Context of Poverty

Preliminary longitudinal CFAs with each construct suggested longitudinal configural invariance, such that model fit, the model parameters, and the modification indices for each construct suggested homogeneity in the respective factor structures over time. Specifically, although statistically significant χ^2 values indicated imperfect fit—common with large samples—fit indices were within common thresholds (ES: $\chi^2 = 1{,}858.17$, $df = 665$, $p < .001$, comparative fit index [CFI] = .94, root mean square error of approximation [RMSEA] = .038; HOME: $\chi^2 = 4{,}396.77$, $df = 2{,}254$, $p < .001$, CFI = .89, RMSEA = .028; CTS: $\chi^2 = 3{,}677.43$, $df = 1{,}687$, $p < .001$, CFI = .96, RMSEA = .031), and the modification indices did not suggest regions of strain suggestive of a heterogeneous factor structure over time. Rank-order stability in the constructs ranged from .10 to .79 (ES: .10-.22; HOME: .30–.55; CTS: .36–.79).

Study Aim 2: Model DIF Across Site, Gender and Racial Group Membership, and Developmental Time

Material Deprivation

DIF testing via MNLFA indicated that the common-factor model for parent-reported material deprivation (indexed via ES questionnaire) was invariant across gender and racial group membership, site, and age (Figure S1). Accounting for false-discovery rate, the factor variances, factor loadings, and indicator intercepts were statistically indistinguishable across levels of the moderators.

Sociocognitive Resources

The MNLFA results indicated that the common items across time in the HOME data were largely invariant, with the exception of three items tapping caregiver responsivity ("*Caregiver kisses or caresses child at least once*") and learning materials ("*Presence of learning facilitators—table and chair, high chair, play pen*" and "*CD player or tape recorder and 5 or more children's CDs or tapes are available to the child*"). Specifically, caregiver responsivity ($B = -.651$, $p < .001$) and learning facilitators ($B = -1.135$, $p < .001$) tended to be endorsed less as children aged, whereas materials requiring a CD player tended to be endorsed more as children aged ($B = .159$, $p < .001$). All longitudinal DIF effects were on the intercepts only (i.e., partial scalar non-invariance). All other parameters were invariant across age, gender group membership, racial group membership, and site (Figure S2). Accounting for false-discovery rate, the factor variances, factor loadings, and indicator intercepts were statistically indistinguishable across levels of the moderators.

Psychosocial Threat

The MNLFA for the CTS data indicated no evidence of DIF for the items tapping exposure to intimate partner violence. All other parameters were invariant across age, gender, and racial group membership, and site (Figure S3).

Study Aim 3: Comparison of MNLFA-Derived Factor Scores and Raw-Variable Composites

Although our MNLFA models tested and adjusted for fixed effects for age, site, and racial group on the latent factors, the MNLFA approach precluded our abilities to test random variation in growth or systematic differences in growth as a function of the covariates (i.e., cross-level interactions; see Figure S4 for raw individual growth trajectories). To address these questions and subsequently compare these estimates across the MNLFA factor scores and raw-variable composites, we fitted a series of nested mixed linear models to both the MNLFA factor scores and the raw-variable composites—first, establishing plausible growth functions and covariance structures and then testing individual differences in these growth rates as a function of site, and racial group (see Singer & Willett, 2002). Because gender category did not show up as a meaningful moderator in the MNLFA or subsequent analyses, we do not discuss it further.

Model comparisons were based on likelihood ratio tests and second-order AIC comparisons, where statistically nonsignificant fixed and random effects were constrained to zero for parsimony (Table 2). As the MNLFA factor scores and raw-variable composites are on different scales, the parameter estimates cannot be compared directly. We, thus, provide descriptive comparisons of the model-implied growth functions and standardized effect sizes, in lieu of inferential comparisons. All standardized estimates are scaled on the square root of the unconditional variance for the given measure (i.e., factor score vs. raw composite), based on the most relevant level of analysis (i.e., between-person inferences are scaled on between-person variation and within-person inferences are scaled on within-person variation).

As expected, the correlations between the MNLFA factor scores and the raw variable composites were very strong (material deprivation: $r = .96$; sociocognitive resources: $r = .74$; psychosocial threat: $r = .97$). However, the MNLFA scores demonstrated much larger individual variability than did the raw scores. This is exemplified, for instance, by the range of MNLFA scores available for every individual who had the lowest score on the raw-variable composite (Figure 1). Despite these differences in variation, the two scales manifested in very similar substantive conclusions with respect to random and systematic differences in growth. For example, irrespective of scale type, families tended to show statistically significant and substantively similar quadratic declines in *material deprivation* over time. For both the factor scores and the raw-variable composites, the magnitudes of the instantaneous linear slopes were strongest at 6 months ($B_{\text{mnlfa}} = -.057$, $p < .001$; $B_{\text{raw}} = -.037$, $p < .001$) and leveled off at similar rates across childhood ($B_{\text{mnlfa}} = .003$, $p < .001$; $B_{\text{raw}} = .002$, $p < .001$). Indeed, the estimated points of inflection for these curves were quite similar across the measures (MNLFA = 10 years; raw = 9.75 years). Scaling on their respective unconditional within-person variances, these inflection points represent an approximate $-.39$ and $-.34$, standard deviation decrease in material deprivation from families' average 6-month levels. Similarly, regardless of scale type, there was evidence that African American families tended to show higher levels of material deprivation ($B_{\text{mnlfa}} = .419$, $p < .001$; $B_{\text{raw}} = .235$, $p < .001$). These relations were statistically constant over time for both the MNLFA and raw-variable composite scores, and corresponded to standardized effect sizes of $d = .64$ and $d = .48$, respectively. No site differences were evident in material deprivation.

There were also some noteworthy differences across the MNLFA factor score and raw-variable composites. For example, despite the fact that there was little indication of DIF in the loadings or the indicator intercepts for our measure of *psychosocial threat*, simply treating threat as a reflective latent factor led to different substantive conclusions compared with those derived from the raw-variable composite. Specifically, with the raw-variable composite, we found that, on average, families tended to show statistically significant quadratic decay in psychosocial threat across childhood ($B_{\text{raw\_lin}} = -.053$, $p < .001$; $B_{\text{raw\_quad}} = .003$, $p < .001$) and comparatively higher levels of reported threat in PA ($B_{\text{raw}} = -.134$, $p < .001$) and among African American families ($B_{\text{raw}} = .092$, $p < .001$; $d = .44$) at the 6-month wave (Figure 2). Neither research site nor racial group membership was predictive of changes in psychosocial threat.

Identical tests with the MNLFA factor scores indicated similar racial group disparities at 6 months ($B_{\text{mnlfa}} = .304$, $p < .001$; $d = .47$), as well as a similar overall quadratic functional form as

Table 2

Baseline and Final Growth Models for MNLFA (Left) and Raw Mean Scores (Right) for Each Measure Making Up the Material Deprivation, Sociocognitive Resources, and Psychosocial Threat Dimensions

	MNLFA scores						Raw mean scores					
	Baseline models			Final models			Baseline models			Final models		
	ES	HOME	CTS	ES	HOME	CTS	ES	HOME	CTS	ES	HOME	CTS
Fixed effects												
(Intercept)	0.043 (.028)	0.073 (.021)***	0.042 (.034)	0.044 (.028)	0.082 (.021)***	−0.013 (.038)	2.192 (.015)***	0.770 (.004)***	0.636 (.010)***	2.169 (.002)***	0.860 (.006)***	0.791 (.016)***
Age	−0.057 (.007)***	0.476 (.007)***	−0.138 (.007)***	−0.057 (.007)***	0.476 (.007)***	−0.118 (.010)***				−0.037 (.005)***	−0.023 (.002)***	−0.053 (.003)***
Site (North Carolina)			−0.301 (.052)***			−0.198 (.063)**						−0.134 (.002)**
Race (Black)	0.419 (.040)***	−.970 (.028)***	0.283 (.052)***	0.419 (.040)***	−0.992 (.027)***	0.304 (.064)***				0.235 (.030)***	−0.206 (.009)***	0.092 (.024)***
Interactions												
Age × Age	0.003 (.000)***	−0.027 (.000)***	0.007 (.001)***	0.003 (.000)***	−0.027 (.001)***	0.006 (.001)***				0.002 (.000)***	0.002 (.000)***	0.003 (.000)***
Age × Site						−0.055 (.018)**						
Age × Race						0.018 (.019)					0.040 (.004)***	
Age^2 × Site						0.003 (.001)*						
Age^2 × Race						−0.003 (.001)*					−0.003 (.000)***	
Random effects												
(Intercept)	0.389	0.148	0.403	0.424	0.158	0.501	0.237	0.015	0.094	0.260	0.013	0.127
Age				0.003	3.28 e-04	0.003				0.002	1.85 e-05	0.001
Age × Age					5.57 e-06						4.99 e-09	
Residual	0.493	0.461	0.397	0.449	0.457	0.346	0.260	0.034	0.095	0.232	0.032	0.077
AIC	18,395.6	16,809.6	13,524.8	18,290.7	16,789.5	13,347.6	13,671.5	−2,597.6	4,942.7	13,393.4	−3,164.7	4,261.5
Log likelihood	−9,191.8	−8,398.8	−6,755.4	−9,137.4	−8,383.7	−6,660.8	−6,832.7	1,301.8	−2,468.4	−6,688.7	1,595.3	2,121.7

Note. baseline models for the moderated nonlinear factor analysis (MNLFA) scores are conditional on the variables included in the final MNLFA scoring models, as mean impacts are embedded in the estimation of the final MNLFA scores. ES = Economic Strain Questionnaire; HOME = Home Observation for Measurement of the Environment; CTS = Conflict Tactics Scale; AIC = Akaike information criteria.

**p* < .05. ***p* < .01. ****p* < .001.

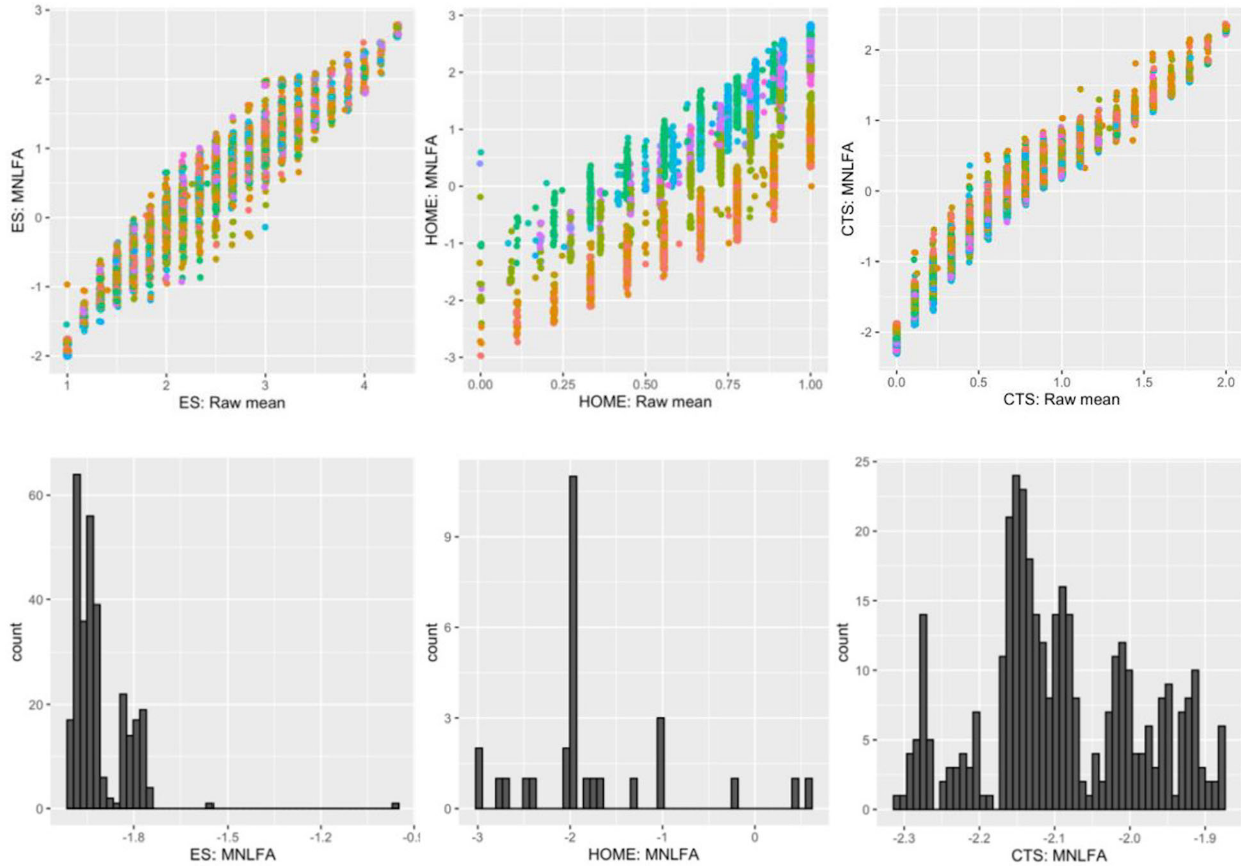

Figure 1. Graphs illustrating enhanced individual variability from MNLFA scores. Top panel: Scatterplot of MNLFA scores against corresponding raw mean scores colored by age (rounded for better plotting). Bottom panel: The complete distribution of MNLFA scores associated with the lowest mean score on each of the measures (ES: mean = 1; HOME: mean = 0; CTS: mean = 0). MNLFA = moderated nonlinear factor analysis; ES = Economic Strain Questionnaire; HOME = Home Observation for Measurement of the Environment; CTS = Conflict Tactics Scale.

those established with the raw-variable composite. However, the results using the MNLFA factor scores showed systematic differences in families' trajectories of psychosocial threat, as a function race. Specifically, the MNLFA-derived data indicated that, although African American families showed higher levels of psychosocial threat at 6 months, they also showed more rapid quadratic declines. By the age-12 wave, these growth differences led to a substantial decrease in the racial group disparity observed at the 6-month wave (i.e., $d_{age6mo} = -.47$ to $d_{age12} = -.18$).

The MNLFA-derived data also showed differences with respect to site. Recall that the results from the raw-variable composite indicated that PA families tended have higher levels of psychosocial threat that were stable over time ($d = .44$). The results from the MNLFA-derived data, in contrast, indicated that 6-month psychosocial threat was more pronounced for *NC* families ($B_{mnlfa} = -.198$; $p < .001$; $d = -.31$) and largely limited to early infancy (Figure 2).

Differences in families' trajectories of *sociocognitive resources* (via HOME scale) also differed between the MNLFA factor scores and the raw-variable composites. Based on the raw-variable composite, on average, African American families tended to have fewer sociocognitive resources than White families at the 6-month assessment ($B_{raw} = -.206$, $p < .001$; $d = -1.68$) and to largely maintain these lower levels through the age-12 assessment (Figure 2). In addition to starting with more sociocognitive resources, on average, the raw-variable data suggested that White families tended to show stronger declines ($B_{raw\_linear} = .040$, $p < .001$; $B_{raw\_quad} = -.003$, $p < .001$) in their sociocognitive resources from 6-months to approximately age 6 (inflection = 5.75 years). As a function of these varying trajectories, the 6-month disparity between racial groups was comparatively smaller

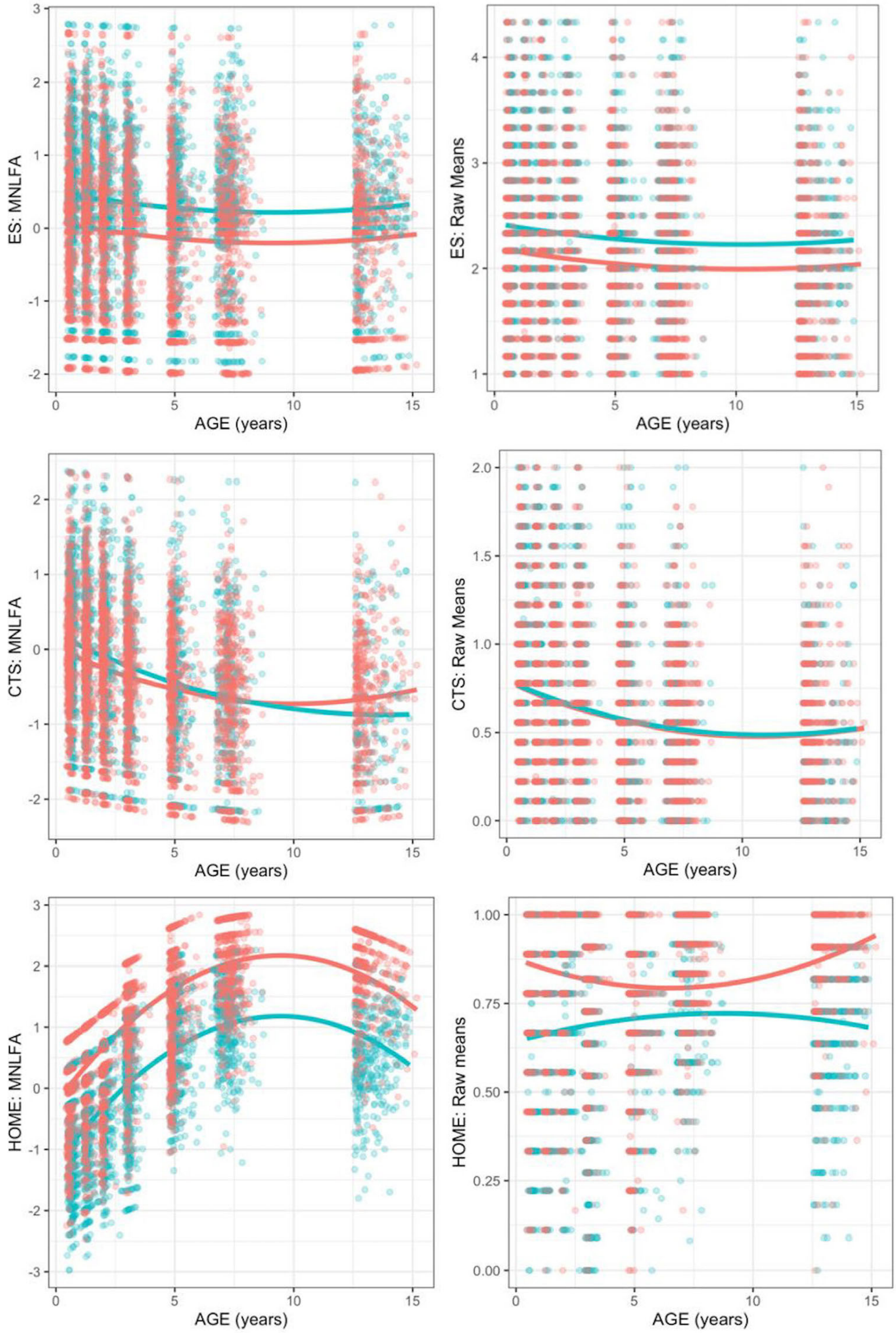

Figure 2. Group trajectory estimates from mixed effects models for MNLFA scores (left panel) and raw mean scores (right panel). Colored lines indicate the predicted change curves for African American (blue) and White (red) children, superimposed on the raw data points. MNLFA = moderated nonlinear factor analysis; ES = Economic Strain Questionnaire; HOME = Home Observation for Measurement of the Environment; CTS = Conflict Tactics Scale.

when it reached its smallest point at approximately the age of 6.5 (d = .59)—though, still nontrivial in absolute terms.

In contrast, the results using MNLFA-derived data showed some noteworthy differences. Similar to the raw-variable composite results, there was evidence

Table 3

Partial Correlations Between Material Deprivation, Sociocognitive Resources, Psychosocial Threat, and Theoretically Relevant Outcomes (Accounting for Covariates Retained in Respective Final Moderated Nonlinear Factor Analysis [MNLFA] Models)

	MNLFA scores			Raw means		
	1	2	3	1	2	3
1. Material deprivation						
2. Sociocognitive resources	−.13***			−.11***		
3. Psychosocial threat	.19***	−.10***		.23***	−.05***	
4. H&F mixed block: % accuracy	−.08***	.13***	.02	−.08***	.14***	.02
5. H&F mixed block: latency	−.01	.01	−.02	−.01	.01	−.03
6. Behavioral problems	.23***	−.15***	.17***	.24***	−.15***	.17***
7. Income-to-needs ratio	−.33***	.22***	−.05***	−.33***	.23***	−.06***

***$p < .001$.

of a large disparity between racial groups in sociocognitive resources at 6 months ($B_{\text{mnlfa}} = -.992$, $p < .001$; $d = -1.81$ Unlike the raw-variable composite results, though, the statistically nonsignificant interactions with linear and quadratic age indicated that the 6-month disparity in sociocognitive resources was rather stable over time.

Relations With Criterion Measures

To provide a sense of construct validity for the newly formed constructs, we examined partial correlations between the respective mean factor score values (over time) and a number of criterion variables, adjusting for racial group and age (and site for the CTS; Table 3). First, we examined associations between our environmental factors (i.e., material deprivation, sociocognitive resources, and psychosocial threat). As expected, the factor scores were only modestly correlated with each other ($r = -.13$ to .19), suggesting that the material deprivation, sociocognitive resources, and psychosocial threat constructs are largely distinct. As expected, material deprivation and sociocognitive resources were moderately associated with family INR ($r = -.33$ and .22, respectively), whereas psychosocial threat showed only a weak relation with INR ($r = -.05$). We also examined potential overlap in factor score distributions using typical INR cutoffs. Among families with an INR at or below 1, 38% fell above the total sample mean for sociocognitive resources and 55% fell below the total sample mean for psychosocial threat exposure (Figure 3). These descriptive findings highlight the large proportion

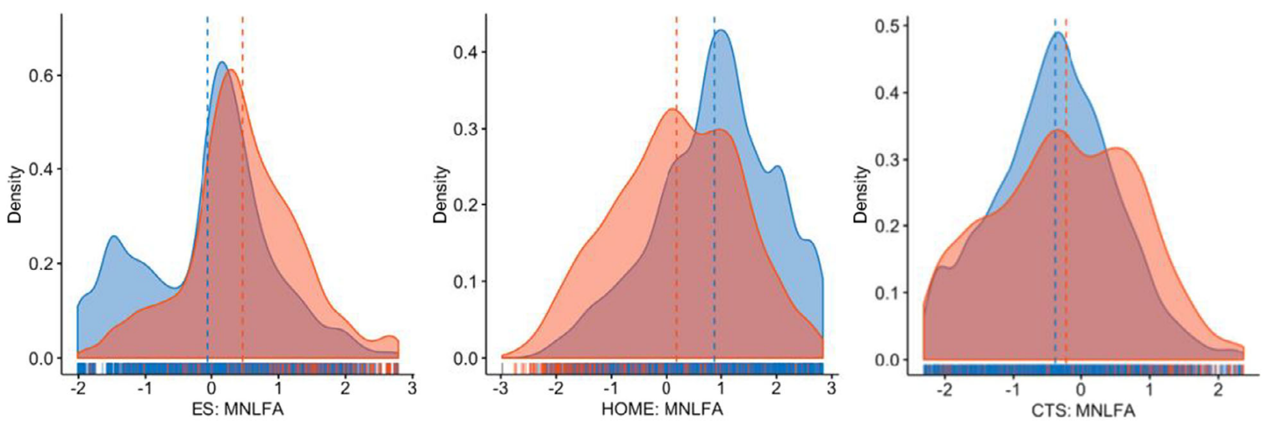

Figure 3. Density plots for MNLFA-derived scores. Red distributions represent families that fall at or below an income-to-needs ratio of 1 (i.e., 100% of the federal poverty threshold) and blue represent those above 1. Overlap between low- and higher-income groups highlights what it lost when grouping families by income cutoffs. MNLFA = moderated nonlinear factor analysis; ES = Economic Strain Questionnaire; HOME = Home Observation for Measurement of the Environment; CTS = Conflict Tactics Scale.

of families providing sociocognitively supportive and safe environments despite financial hardship—nuance that would have been obscured if making group comparisons by income.

Next, we examined the (adjusted) associations between these latent factor scores and the age-12 child outcomes. Across the board, these relations were rather modest. As expected, psychosocial threat was comparatively more strongly correlated with children's behavior problems ($r = .17$, $p < .001$) than either measure of EF ($r_{\text{correct}} = .02$, $r_{\text{latency}} = -.02$; Fisher's $z = 3.85$, $p < .001$, and $z = 4.87$, $p < .001$, respectively). However, contrary to our hypotheses, the remaining environmental measures were rather diffusely correlated across the cognitive and social outcomes. Sociocognitive resources were modestly associated with fewer behavior problems ($r = -.15$, $p < .001$) and better EF accuracy ($r = .13$, $p < .001$). Material deprivation was somewhat more strongly correlated with worse behavior ($r = .23$, $p < .001$) problems and lower EF accuracy ($r = -.08$, $p < .001$). Correlations between the raw mean scores and criterion variables were largely similar to MNLFA scores (Table 3).

Discussion

This study sought to test for group and longitudinal MI among environmental dimensions of adversity and resources in a population-based sample of children and families, the majority of whom reported living on low incomes relative to the U.S. national poverty line. This study answers calls to employ less biased and more rigorous statistical methods to measure children's environmental exposures in the context of poverty across developmental time, beyond traditional indicators such as income or cumulative risk. To this end, we applied and expanded current models of adversity by generating three distinct latent dimensions of environmental exposures across seven time points that spanned child age 6 months–12 years.

Findings for Aim 1

Our first aim was to test the extent to which theoretically informed constructs outlined in the DMAP framework (McLaughlin & Sheridan, 2016) would be supported empirically in sample of children and families growing up in low-income, rural contexts. On average, children in our sample were in households managing with an income of 190% of the federal poverty threshold, with 30% managing at or below 100% of the threshold (i.e., income-to-needs ≤ 1). While many DMAP studies categorize such income poverty as deprivation, we sought to create a more nuanced measurement model that captures the full range of variation in a family's level of both distal and proximal resources. A series of CFA models resulted in an uncorrelated three-factor model representing three distinct—albeit moderately related—dimensions of material deprivation (indexed as a perceived lack of financial resources) and sociocognitive resources (indexed as amount of social and cognitive resources in the home), as well as a dimension of psychosocial threat (indexed as exposure to intimate partner violence).

Findings for Aim 2: Models Examining DIF Across Site, Gender and Racial Group Membership, and Developmental Time

In line with our second aim, we examined the extent to which our derived constructs were commensurate across child demographic covariates using Bauer and Curran's MNLFA approach (Bauer, 2017; Gottfredson et al., 2019). By and large, we found that group and developmental differences in the meaning of the scales (i.e., noninvariance) were minimal. Some scales were more invariant than others, however. Our measures of material deprivation and psychosocial threat showed no evidence of DIF, irrespective of age, gender group membership, racial group membership, or site. This was a notable finding, given that rigorous analytical procedures suggested that the items on these two measures mean the same thing across key demographic covariates. Sociocognitive resources, as measured using partially overlapping versions of the HOME (Bradley & Caldwell, 1984) over time, however, showed some longitudinal DIF. Part of this was unavoidable, given discontinuities in the items included in versions of the HOME intended for different age bands. However, there was also some evidence of DIF for common items—specifically three items tapping caregiver responsivity and learning materials, suggesting that certain aspects of sociocognitive resources in the home are more or less likely to be endorsed as children get older. This is in line with developmental work showing increasing independence and time spent outside of the home as children transition into adolescence (Larson et al., 1996). Crucially, MNLFA scores adjust for DIF and therefore generate more empirically accurate estimates in subsequent modeling.

Findings for Aim 3: Disparities Between Racial Groups

At the latent construct level, average racial group (as determined by families who self-identified as members of a particular race category) differences were found across all three constructs. On average, African American children in our sample experienced more material deprivation, fewer sociocognitive resources, and more psychosocial threat than White children. We speculate that these differences presumably reflect larger systemic inequalities and longstanding racial income disparities stemming from historical forms of racial segregation. Even in this predominantly low-income sample, on average, the income of White families was nearly twice that of African American families (mean income-to-needs: 2.39 and 1.26, respectively). Such macro-level forms of social stratification have been argued to influence group-level variation in families' values and behaviors, resulting in a uniquely adaptive culture that better meets the specific contextual demands faced by a given group (Coll et al., 1996). In addition to the challenges of parenting in poverty (Magnuson & Duncan, 2002), families of color additionally experience a host of stressors related to discrimination and bias (e.g., police brutality, lower quality healthcare) that undoubtedly exert cascading effects on resource scarcity and caregivers' well-being (Raver & Blair, 2020). While direct examination of these individual- and structural-level forms of racial and class inequalities is beyond the scope of this article, our findings underscore the need for applying an intersectional framework in future work (Syed & Ajayi, 2018).

Findings for Aim 3: Heterogeneity in Exposure to Adversities

A significant contribution of our derived measurement model is best revealed in descriptive findings highlighting the ways different children whose families reported very similar incomes nonetheless experienced a wide array of differing types of stressors and resources. Overall, many children in our sample experienced high levels of material deprivation across time, yet a relatively smaller proportion experienced low levels of sociocognitive resources over time and even fewer were exposed to intimate partner violence (Figure 3). The three derived factors were also minimally to moderately related to each other; in other words, these forms of poverty-related adversity do not always occur together. Income-to-needs was only moderately correlated with our latent constructs, underscoring the ways that many families in our sample are providing a safe and cognitively stimulating home environment despite economic hardship, and this nuance in individual differences is a nontrivial improvement from comparisons made by income alone. Taken together, our findings provide support for growing consensus in the field to move towards adaptation-based models that account for the entire spectrum of variation in experiences that children in poverty are exposed to (Frankenhuis & Nettle, 2019; Hostinar & Miller, 2019). Doing so affords a greater understanding of the ways families are able to maintain high levels of resilience in the face of economic adversity.

Findings for Aim 3: Criterion Validity

Although individual differences in children's experiences and resources in the context of poverty were clear, how such exposures are related to specific adaptive outcomes across multiple domains remains somewhat unclear. As hypothesized, psychosocial threat—as indexed by inter-partner violence—was modestly associated with heightened levels of behavior problems, yet was unrelated to children's cognitive outcomes. Thus, there was potentially some evidence of developmental specificity, even if the effect size was modest in absolute terms. While the cognitive measure we used tapped executive functioning skills specifically, the behavioral problems scale had some limitations. First, there was shared rater bias in the psychosocial threat measure and the child behavior problems scale. Second, behavior problems tapping both internalizing and externalizing may have been too broad, and a more emotionally salient task (e.g., fear conditioning) at this age may be necessary to better disentangle the effects of these dimensions on domain-specific outcomes (McLaughlin et al., 2016; Raver, Blair, Garrett-Peters, & Family Life Project Investigators, 2015). Contrary to our hypotheses that material deprivation and sociocognitive resources would be more strongly associated with cognitive than with affective outcomes, the modest to moderate relations were rather largely diffuse across these outcomes. This may be because material and financial resources likely increase exposure to conditions that pose a threat to the child (e.g., being forced to live in higher crime neighborhoods in order to afford rent), which may explain why the material deprivation factor was comparatively more strongly related to our affective outcome. Nonetheless, the degree to which children had access to sociocognitive resources in the home was more strongly related to EF compared to the other two latent factors. However, these relations were small in magnitude, perhaps because such resources matter more at earlier stages of cognitive development, which we were unable to examine in this study. Despite this, the specificity of these relations aligns with prior literature suggesting that compared to threat, access to developmentally appropriate learning materials and a variety of scaffolded experiences with caregivers shapes individual differences in cognitive outcomes (e.g., Rosen, Amso, & McLaughlin).

Value Added: Comparison of MNLFA-Derived Factor Scores and Raw-Variable Composites

Why use MNLFA scores in research examining the developmental effects of poverty-related environmental exposures, as opposed to raw-item sums? With regard to methodological benefits, MNLFA scores are continuously and normally distributed, and demonstrate a large increase in individual variability due to the ways in which this approach incorporates unique information on individual differences (i.e., scores adjust for which items were endorsed at each time point and by whom). Moreover, in contrast to raw-item proportion scores, variation in the type and severity of items are accounted for using item-level weighting —which may be one of the reasons we found large differences in developmental trajectories for the HOME measure, for example. Such increased variation also increases statistical power and thus increases the ability to accurately detect a true effect. Lastly, the flexibility of this approach is undeniable. This is illustrated by its ability to incorporate multiple longitudinal measures with a substantial amount of nonoverlap which can be leveraged for large-scale multi-site developmental data—enhancing generalizability and external validity (Curran, Cole, Giordano, et al., 2018). In addition, MNLFA scores can be used in subsequent secondary models and have been shown to produce less biased estimates compared to CFA scores (Curran, Cole, Bauer, Cole, Bauer, Rothenberg, & Hussong, 2018).

On a substantive level, these scores empirically disentangle race and age, minimizing bias and thus permitting more developmentally and socioculturally appropriate conclusions about the effects of poverty-related exposures on child adaptive outcomes. This is reflected in our observed differences in growth trajectories between the scoring approaches, which resulted in substantively different conclusions. Specifically, growth patterns for MNLFA scores for sociocognitive resources were nearly opposite of the raw mean scores. We also found differences with respect to racial disparities between the two scoring approaches. Raw mean scores for psychosocial threat suggested race differences were constant over time, whereas the MNLFA scores suggested these differences become smaller over time. The opposite pattern was true for sociocognitive resources. For studies with policy or clinical implications, careful measurement work ensures our conclusions are driven by substantive differences on a given construct rather than by measurement artifacts. This is essential to avoid wasting tax-payer dollars, individuals' time, and in extreme circumstances, the risk of contributing to racial oppression. While we found minimal evidence for DIF in this study, this may not always be the case in studies representing more diverse populations. Accurate measurement of our constructs also have important theoretical implications. Since MNLFA scores permit apples-to-apples comparisons, developmental researchers can more accurately and rigorously examine the role of timing and sensitive periods, while simultaneously accounting for heterogeneity in dose and severity of environmental exposures. Such analyses using the current MNLFA-derived scores are currently underway from our research team.

Strengths, Limitations, and Conclusions

This study has notable strengths including the use of a large, diverse sample of children in low-income contexts, tests of longitudinal MI across seven time points, and the use of multiple measures that better illustrate the multidimensional nature of poverty-related adversity. However, there were a number of limitations. First, the measures included in this analysis represent only three poverty-relevant contextual factors. While this was a limitation of available data across the seven time points, additional factors such as racial discrimination, social support, and neighborhood safety should be examined in future studies. Second, because the CTS measure was only collected among caregivers with partners who rarely (if ever) reported experiencing more severe forms of intimate partner violence, findings related to psychosocial threat exposure are not generalizable to single-parent households or households that may be experiencing severe domestic violence. Third, the HOME measure provides a very rough and inadequate proxy for the many vibrant ways that families engage their children in cognitively stimulating and emotionally supportive practices. Furthermore, we were limited to home visitor- and parent-reported measures as child-reported measures were not collected until much later. Using mixed methods approaches to capture children's subjective lived experiences as they mature into adolescence is another important future direction for understanding how both external and internal resources in the context of poverty shape developmental adaptations. Finally, to the extent that sample characteristics including the nonurban and predominantly low-income regions in which our sample resides, the generalizability of our findings is an important question that can best be addressed through further analyses of data sets with similar types of variables to those analyzed here.

As researchers seek to examine the ways in which the type and timing of poverty influence neurodevelopmental mechanisms among diverse groups of children, care must be taken to ensure chosen measures are reliable and socioculturally valid. Our field is facing long overdue calls to action to address the grave harms and barriers that families and children face in coping with the toxic convergence of racism and social and economic inequality. Without sound methods, we cannot be confident in interpreting our substantive results, and novel methods do not advance the field unless appropriately applied to substantively meaningful questions. Here we highlight an innovative measurement approach that revealed three distinct environmental exposures in the context of poverty —providing tangible targets for the creation of individualized interventions as our nation works to ameliorate income poverty and structural racial, social, and economic inequalities. In sum, careful consideration of the statistical validity of poverty-related constructs will result in more trustworthy conclusions and therefore more informative policies and programs aimed to enable children to thrive.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Figure S1. MNLFA Final Model Output for the Material Deprivation Latent Factor (Eta)

Figure S2. Final MNLFA Model for the Sociocognitive Resources Latent Factor (Eta)

Figure S3. Final MNLFA Model for the Psychosocial Threat Latent Factor (Eta)

Figure S4. Random Subset of n = 75 Illustrating Raw, Individual Growth Trajectories for MNLFA Scores (Left Panel) and Raw Means (Right Panel)

Table S1. Cross-Walk Between Invariance/Equivalence Testing Terminology in the Context of CFA With Continuous Observed Items and CFA/2-Parameter IRT With Binary Items, Respectively

Table S2. Sociodemographic Descriptives, Attrition, and Missingness Over Time