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Characterizing the role of unpredictability within different dimensions of early life adversity

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Abstract

Dimensional models of early life adversity highlight the distinct roles of deprivation and threat in shaping neurocognitive development and mental health. However, relatively little is known about the role of unpredictability within each dimension. We estimated both the average levels of, and the temporal unpredictability of deprivation and threat exposure during adolescence in a high-risk, longitudinal sample of 1354 youth (Pathways to Desistance study). We then related these estimates to later life psychological distress, and Antisocial and Borderline personality traits, and tested whether any effects are mediated by future orientation. High average levels of both deprivation and threat exposure were found to be associated with worse mental health on all three outcomes, but only the effects on Antisocial and Borderline personality traits were mediated by decreased future orientation, a pattern consistent with evolutionary models of psychopathology. Unpredictability in deprivation exposure proved to be associated with increased psychological distress and a higher number of Borderline traits, but with increased future orientation. There was some evidence of unpredictability in threat exposure buffering against the detrimental developmental effects of average threat levels. Our results suggest that the effects of unpredictability are distinct within different dimensions of early life adversity.

Keywords: deprivation; early life adversity; evolutionary psychopathology; threat; unpredictability

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Introduction

Childhood adversity refers to negative environmental experiences, such as poverty, neglect, or maltreatment, that require significant adaptation by a typical child (Frankenhuis & Amir, 2022; McLaughlin et al., 2019). A large body of research using the cumulative adversity approach has demonstrated the pervasive effects of early life adversity on mental and physical health (Evans et al., 2013; Grummitt et al., 2021). Developmental scholars have been increasingly highlighting the value of extending these important results by building more specific and mechanistic models of the effects of adversity factors (Berman et al., 2022; McLaughlin et al., 2019, 2021). So-called dimensional models of adversity and psychopathology propose that individual adversity types (such as physical or sexual abuse, emotional neglect, poverty, etc.) impact development through neither fully distinct, nor fully overlapping mechanisms. Instead, their effects on psychological and biological functions are best accounted for by a set of core dimensions (Ellis et al., 2022; McLaughlin et al., 2021).

One line of dimensional models, based on life history theory – a theoretical framework in evolutionary developmental biology (Stearns, 1992) – identifies "harshness" and "unpredictability" as the most important dimensions (Ellis et al., 2009). Harshness refers to extrinsic morbidity–mortality, which encompasses all external factors causing death and disability in a given population and that are beyond the individuals' control, while unpredictability refers to the rates at which harshness varies stochastically over time and space (Ellis et al., 2009). In harsh and/or unpredictable environments, organisms favor reproductive efforts and short-term goals, at the expense of somatic maintenance efforts and longer-term goals. This "fast" life history strategy – so named in opposition to a "slow" strategy whereby the organism would prioritize health and survival over immediate reproduction – is not only mediated by physiological mechanisms. Although this acceleration is only adaptive in certain contexts (de Vries et al., 2023), there is evidence consistent with this pattern from a wide array of species (Promislow & Harvey, 1990; Promislow, 1991). In humans, high levels of psychosocial adversity and temporal unpredictability in such adversity have also been shown to be associated with accelerated paces of life (Šaffa et al., 2019; Bulley & Pepper, 2017; Mell et al., 2018; Nettle, 2010), although the evidence is somewhat weaker in non-Western populations (Sear et al., 2019; Sear, 2020). Importantly, this "fast" life history strategy is also dependent on psychological traits such as impulsivity, risk-taking,

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and present orientation that facilitate access to biological goals (Del Giudice et al., 2015; Ellis et al., 2012). These traits can then predispose individuals to certain mental and physical health conditions, especially those that comprise the externalizing spectrum of psychopathology (e.g., Antisocial and Borderline Personality Disorders, substance abuse, the positive symptoms of Schizophrenia and some eating disorders) (Del Giudice & Haltigan, 2023). This might happen for multiple reasons, for example, because such traits are adaptive in the evolutionary sense of increasing fitness, but are associated with behaviors that are considered undesirable in the sociocultural context, or because such traits are developed as a result of early environmental cues, that end up being mismatched with the actual state of adult environments.

A parallel line of models, rooted in experience-driven neuroplasticity, instead focuses on the dimensions of "deprivation" and "threat" (Sheridan & McLaughlin, 2014). Deprivation is defined as the lack of expected environmental inputs, and threat is defined as physical harm or threat of harm. Once again, there is a large evidence base linking these dimensions to cognitive, affective and behavioral dysregulation (McLaughlin et al., 2019; Miller et al., 2018, 2021). Recent theoretical and empirical progress has integrated the Deprivation-Threat and Harshness-Unpredictability frameworks into a three-component model based on the assumption that threat and deprivation are best conceptualized as distinct sources of harshness, in the sense that both contribute to increasing disability and death in the population (Ellis et al., 2022; Usacheva et al., 2022). This model therefore identifies (i) Threat as a source of harshness capturing morbidity–mortality from harm imposed by other agents; (ii) Deprivation as a source of harshness capturing morbidity–mortality from insufficient environmental inputs; and (iii) Unpredictability as stochastic spatiotemporal variability in both Threat and Deprivation.

One major gap in our current understanding of the effects of these dimensions concerns the conceptualization and operationalization of unpredictability (Young et al., 2020). There are two sources of unpredictability in the environment. On the one hand, humans might have evolved to preferentially process certain discrete events that have served as reliable cues of environmental variability in the evolutionary past (e.g., disruptive family events). These events now serve as "ancestral cues" to estimate environmental unpredictability and to guide development. Research guided by this approach has tended to operationalize unpredictability by creating sum scores of exposure to disruptive events, hypothesized to be such ancestral cues (e.g., Belsky et al., 2012; Brumbach et al., 2009; Doom et al., 2016). On the other hand, the brain also might have the capacity to continuously monitor informative features of the current environment (e.g., harshness of physical discipline) and integrate these estimates to infer environmental unpredictability, with "statistical learning" mechanisms. Research guided by this approach has tended to operationalize unpredictability by quantifying the degree of random variability in trajectories of harshness exposure across time (e.g., Li et al., 2018; Li & Belsky, 2022; Zachrisson & Dearing, 2015).

Results using both approaches have been generally consistent with idea that unpredictability contributes to the development of "fast" life history strategies, and related mental health outcomes. It has been linked to more unrestricted sociosexuality (Belsky et al., 2012; Brumbach et al., 2009; Simpson et al., 2012; Szepsenwol et al., 2017), greater risk-taking (Belsky et al., 2012; Simpson et al., 2012; Wu et al., 2020), and more externalizing problems and substance use (Doom et al., 2016; Martinez et al., 2022). There is also some evidence linking unpredictability with internalizing problems (Glynn et al., 2018; Wu, 2024). Results regarding the interaction of unpredictability and harshness have been far less consistent. Li and Belsky (2022) identify multiple possible patterns, with each of them having some empirical support in the literature: (a) A dual-risk pattern would mean that unpredictability amplifies the negative effects of harshness, with worse outcomes for children exposed to high harshness and high unpredictability. This is what is found by Doom et al. (2016). (b) A dual-benefit pattern would mean that low unpredictability amplifies the positive effects of low harshness, with the best outcomes for children exposed to low harshness and low unpredictability. This is consistent with the results of Simpson et al. (2012). (c) A buffering pattern would mean that the negative consequences of harshness are attenuated in the absence of unpredictability. This is what Cohen and Wills (1985) found. (d) A pattern in which the combination of high harshness with low unpredictability leads to the most problematic developmental outcomes. This is observed by Li et al. (2018). Moreover, while it is theoretically assumed that unpredictability is a feature of deprivation and threat (i.e., each dimension has its own pattern of variability, potentially distinct from each other), studies have tended to operationalize it as a separate exposure on its own. Therefore, we know very little about the way mean levels of deprivation and threat and their unpredictability interact to shape development and contribute to the emergence of psychopathology.

In this work, we start to fill this gap by separately estimating average levels of adolescent deprivation and threat exposure, as well as their temporal unpredictability, using residuals from random effects models on the same set of indicators, in a sample of more than 1300 youth. We first investigate the agreement between our proposed residual based metric to other unpredictability metrics. We then relate these scores to later mental health outcomes of Borderline and Antisocial personality features, and overall psychological distress. We also investigate whether the effects are mediated by future orientation, as more present-oriented decision-making has been repeatedly highlighted as an important psychological component of "fast" life history strategies (Copping et al., 2014; Farkas et al., 2021; Pepper & Nettle, 2017). Our predictions were guided by the evolutionary psychopathology framework of Del Giudice (2018), proposing that while independent clusters, both fast spectrum conditions (such as Borderline and Antisocial personality disorder) and distress conditions (such as depression and anxiety) are more likely to develop following early life adversity. However, as distress conditions do not reflect "fast" life histories, they should not be strongly linked to more present orientation. With respect to the specific effects of deprivation and threat and their unpredictability, the current evidence base does not allow strong hypotheses to be made. Putting it all together, we expected (i) that average and unpredictable deprivation and threat will be associated with more present orientation and worse outcomes on all three of our mental health measures and (ii) that present orientation will be associated with more Borderline and Antisocial traits, but not with higher overall psychological distress. We were agnostic regarding the effects of average × unpredictability interactions.

Methods

Participants

Data was drawn from the Pathways to Desistance Study, a United States longitudinal study of primarily male juvenile offenders in

Phoenix, Arizona and Philadelphia, Pennsylvania (Schubert et al., 2004). Youth were eligible for enrollment if they were between 14 and 17 years of age and had been convicted of a felony or a similarly serious nonfelony offense (e.g., a misdemeanor weapons offense, misdemeanor sexual assault). Enrollment into the study occurred between November, 2000 and January, 2003. The proportion of male youth found guilty of a drug charge was capped at 15% to avoid an over-representation of drug offenders. All females who met the age and crime criteria were also approached for enrollment, as were youth being considered for trial in the adult system. Eighty percent of approached youth agreed to participate. The total sample consists of 1354 participants.

Participants completed an initial baseline interview and were then reinterviewed a total of 10 times. Every 6 months for the first 6 assessments, and yearly for the remaining 4. Data for the current study was drawn from the baseline interview, and the follow-up interviews at 6, 12, 18, 24, 30, 36, and 72 months after baseline. Demographic information is presented in Table 1. Most of the sample was male, identified as Black, with parental education levels corresponding to High school diploma or less. Mean age at the Baseline interview was 16 years. The ratio of respondents from the two study sites was relatively balanced, with slightly more participants recruited at the Philadelphia site. Around half of all interviews were conducted at the participant's home. Retention rates were high, with 87% of participants completing the 72 months follow-up interview.

Participant assent and parent or guardian consent were obtained for youth under age 18. All participants were consented as an adult when they reached 18. Computer assisted interviews were conducted in either a facility, the juvenile's home, or a mutually agreed-upon location in the community by trained interviewers. Participants were reminded during each interview, that the investigators were prohibited from disclosing any personally identifiable information to anyone outside the research staff. All recruitment and assessment procedures were approved by the Institutional Review Boards (IRBs) of the participating universities. Participants were paid $50 for their participation in the baseline interview, $65 at 6 months, $75 at 12 months, $100 at 18 months, $115 at 24 months, $130 at 30 months, and $150 at 36 months. All data accessed by us for the current study was fully anonymized.

Table 1. Sample descriptive statistics

	M (SD)	*N* (%)
Age at Baseline (years)	16 (1.14)	
Study site		
Philadelphia		700 (51.70%)
Phoenix		654 (48.30%)
Interview location		
At participant's home		5035 (50.42%)
At the placement		3580 (35.85%)
Somewhere else		1371 (13.73%)
Gender		
Male		1170 (86.41%)
Female		184 (13.59%)
Ethnicity		
White		274 (20.24%)
Black		561 (41.43%)
Hispanic		454 (33.53%)
Other		65 (4.80%)
Maternal education		
Some grad or prof school/prof or grad school		11 (0.86%)
College graduate		50 (3.89%)
Business or trade school/some college/grad of 2–yr college		222 (17.29%)
High school diploma		414 (32.24%)
Some high school		434 (33.80%)
Grade school or less		153 (11.92%)
Paternal education		
Some grad or prof school/prof or grad school		12 (1.31%)
College graduate		35 (3.83%)
Business or trade school/some college/grad of 2–yr college		119 (13.03%)
High school diploma		388 (42.50%)
Some high school		226 (24.75%)
Grade school or less		133 (14.57%)
Retention at 6 month follow–up		1253 (92.54%)
Retention at 12 month follow–up		1253 (92.54%)
Retention at 18 month follow–up		1213 (89.59%)
Retention at 24 month follow–up		1223 (90.33%)
Retention at 30 month follow–up		1226 (90.55%)
Retention at 36 month follow–up		1229 (90.77%)
Retention at 72 month follow–up		1175 (86.78%)

Calculated from the full sample, comprising all participants of the Pathways study ($N = 1354$).

Measures

Our measurements can be divided into four sets: early life adversity, serving as the primary independent variables of interest; future orientation, serving as a mediator; mental health, serving as the primary outcome variables of interest; and covariates.

Early life adversity

Our aim was to capture youths' level of exposure to deprivation and threat, as well as the unpredictability of these exposures during the study period. We were guided by previous research in our operationalization of these constructs. Our conception of the dimensions of deprivation, threat and unpredictability followed the recent integrative model of Ellis et al. (2022). This model defines threat as experiences that confer the risk of physical and psychological harm, deprivation as experiences that reflect insufficient environmental input, and unpredictability as spatio-temporal variability in deprivation and threat. We operationalized average levels of deprivation and threat exposure using sum scores of average values on a set of indicators during the study period, and operationalized the unpredictability of deprivation and threat using sum scores of random temporal variability of the same set of indicators during the study period (Li & Belsky, 2022). Thus, we created four composite scores in total: Deprivation average, Deprivation unpredictability, Threat average, and Threat unpredictability. For all the early life adversity indicators, we used the

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data from the Baseline, and the 6, 12, 18, 24, 30, and 36 month follow-up assessments. Below, we summarize all chosen measures, and report their psychometric properties provided by the investigators of the Pathways dataset.

We selected our indicators in the following way. Firstly, we inspected and listed all 66 measures listed in the Pathways documentation (https://www.pathwaysstudy.pitt.edu/codebook/measures.html), plus the Money and Living calendars. We then classified these measures, and kept the ones that belonged to one of four pre-specified categories: (a) potential indicators of adversity; (b) potential mental health measures, specifically ones that are clearly linked to F-type, S-type, or D-type conditions in the framework of Del Giudice & Haltigan (2023); (c) potential proxies of life-history related traits, specifically linked to time perspective or impulsivity; (d) potential confounding variables necessary to be included as adjustment variables in our analyses. This resulted in 39 variables. From this, we then further excluded variables that: (i) had large amounts (>50%) of missing values due to the measure being taken only by a subset of participants, e.g., variables relating to institutional climate for participants residing at an institution during interview; (ii) were only available from collateral informants with no self-reported data, e.g., Disruptive Behaviour Disorder variable; (iii) were not available at relevant timepoints, e.g., domestic violence exposure being only assessed at baseline; (iv) did not have available data with enough detail for our analysis, e.g., the CIDI scale only providing binary variables indicating meeting or not meeting diagnostic criteria, instead of continuous symptom scores; (v) were adversity indicators but not clearly definable as deprivation or threat, based on our working definitions of deprivation and threat as written below, e.g., friendship quality. After this, we were left with two candidate measures for life-history related traits (Psychosocial Maturity Inventory, Future Outlook Inventory) and F-type disorders (PAI, Substance use), between which we selected the one that had better psychometric properties based on available data, resulting in the final set of measures detailed below. Finally, we wanted clear temporal separation between what variables correspond to causes and consequences in our conceptual and eventual statistical model, therefore we retained longitudinal data of adversity variables at Baseline and the 6, 12, 18, 24, 30, and 36 month follow-up assessments, and for our outcome variables at the 36 month follow-up assessment only.

Deprivation

Deprivation was measured using five indicators of *Caring adults*, *Maternal warmth*, *Social capital*, *Neighbourhood physical disorder*, and *Unstructured socializing*. What ties these indicators together is that they are indicative of family and neighborhood environments characterized by relatively lower levels of social and cognitive input (Berman et al., 2022; Ellis et al., 2022; McLaughlin et al., 2021).

Caring adults was measured by asking youth to identify the total number of supportive adults in their environment across a range of eight domains: adults you admire and want to be like, adults you could talk to if you needed information or advice about something, adults you could talk to about trouble at home, adults you would tell about an award or if you did something well, adults with whom you can talk about important decisions, adults you can depend on for help, adults you feel comfortable talking about problems with, and special adults who care about your feelings. We used the total number of adults across the eight domains, and reverse scored this indicator by subtracting values from 0, so that higher values indicated a smaller number of caring adults. The measure had excellent psychometric properties during both the baseline and follow-up interviews, reliability and CFA fit indices at baseline: Cronbach alpha = .78; NFI = .98, NNFI = .99, CFI = .99, RMSEA = 04; reliabilities at follow-up: 6 month Cronbach alpha = .84; 12 month Cronbach alpha = .87; 18 month Cronbach alpha = .89; 24 month Cronbach alpha = .90.

Maternal warmth was measured with an adaptation of the Quality of Parental Relationships Inventory (Conger et al., 1994). Items from the measure tap parental warmth (e.g., "How often does your mother let you know she really cares about you?") and parental hostility (e.g., "How often does your mother get angry at you?"). We used the subscale reflecting maternal warmth, and reverse coded the indicator so that higher scores indicate a less supportive and nurturing relationship with the youth's mother. A four-factor model fit to the overall scale resulted in acceptable fit: NFI = .78, NNFI = .82, CFI = .83, RMSEA = .06. The maternal warmth subscale specifically had the following CFA goodness of fit at baseline: NFI = .95, NNFI = .94, CFI = .95, RMSEA = .08. It also had excellent reliability, baseline Cronbach alpha = .92; 6 month Cronbach alpha = .93; 12 month Cronbach alpha = .92; 18 month Cronbach alpha = .93; 24 month Cronbach alpha = .93.

Social capital was measured with the Social Capital Inventory (Nagin & Paternoster, 1994). This scale captures the connectedness an adolescent feels to their community, along three dimensions of intergenerational closure (e.g., "How many of the parents of your friends know your parents?"), social integration (e.g., "How many of your teachers do your parents know by name?"), and perceived opportunity for work (e.g., "Employers around here often hire young people from this neighbourhood?"). Total scores on the combined Closure and Integration subscale provided by the Pathways investigators were used. This scale had adequate psychometric properties: Cronbach alpha = .74, CFA fit indices RMR = .059, GFI = .954, RMSEA = .084. This indicator was reverse coded, so that higher scores indicate a lower degree of perceived community connectedness.

Neighborhood physical disorder was measured by an adaptation of a neighborhood conditions measure by Sampson and Raudenbush (1999). Items from the self-report measure tap physical disorder (e.g., "cigarettes on the street or in the gutters," "graffiti or tags"), and social disorder (e.g., "adults fighting or arguing loudly," "people using needles or syringes to take drugs") of the neighborhood. We used the physical disorder subscale, which is the mean of the 12 physical disorder items. Higher scores indicate a greater degree of physical disorder within the community. This scale had excellent reliabilities: baseline Cronbach alpha = .91; 6 month Cronbach alpha = .94; 12 month Cronbach alpha = .94; 18 month Cronbach alpha = .93; 24 month Cronbach alpha = .94.

Unstructured socializing was measured by items drawn from the Monitoring the Future Questionnaire (Osgood et al., 1996). The four items tap into unstructured activities with peers, that happen in the absence of an authority figure (e.g., "How often did you get together with friends informally?"). There is a crucial difference between the original coding of these items, and ours. Namely, that in Osgood et al. (1996), the authors investigated the relationship between unsupervised socializing and drug use and delinquency, based on the idea that less supervision in these activities allows for more dangerous or criminal behavior. Whereas, in our framework, we consider *the lack of opportunities* for unstructured socializing to be indicative of *greater social deprivation*. As such, a total score of the mean of the four items was utilized, and reverse coded, so that higher scores indicate less unstructured socializing. This scale had low, but acceptable levels of reliability: baseline Cronbach alpha = .62; 6 month Cronbach alpha = .73; 12 month Cronbach alpha = .70; 18 month Cronbach alpha = .70; 24 month Cronbach alpha = .68.

Threat

Threat was measured using five indicators of *Exposure to violence*, *Maternal hostility*, *Peer delinquent behavior*, *Peer delinquent influence*, and *Neighbourhood social disorder*. What ties these indicators together is that they are indicative of family and neighborhood environments characterized by a high degree of violence, crime and threatening situations (Berman et al., 2022; Ellis et al., 2022; McLaughlin et al., 2021).

Exposure to violence was measured by an adaptation of the Exposure to Violence Inventory (Selner-O'Hagan et al., 1998). Items tap into multiple types of violence that the youth either experienced directly (i.e., Victim – 6 items, e.g., "Have you been chased where you thought you might be seriously hurt in the past month?") or observed (i.e., Witnessed – 7 items, e.g., "Have you seen someone else being raped, an attempt made to rape someone or any other type of sexual attack in the past month?"). In addition to these items about experiences with violent incidents, four questions inquire about the youth's exposure to death (e.g. has anyone close to you tried to kill him/her self in the past month, has anyone close to you died in the past month, have you found a dead body in the past month, have you tried to kill yourself in the past month). Finally, one open-ended item assesses involvement in other types of situations which could have led to death or serious injury. In total, this scale inquires about 18 types of situations. We used the total sum score, reflecting the total number of violent situations that the youth either experienced or witnessed. Higher scores indicate a greater exposure to violence. This scale had low, but acceptable levels of reliability: baseline Cronbach alpha = .67; 6 month Cronbach alpha = .75; 12 month Cronbach alpha = .74; 18 month Cronbach alpha = .75; 24 month Cronbach alpha = .75. We note that this scale includes items assessing exposure to self-harm and suicide, which might inflate its association with mental health outcomes. However, given the large number and variety of items included in our overall threat composite, it is unlikely that this single item would significantly inflate associations. Indeed, as seen in the results below, the association between threat and Antisocial traits was even higher than with Borderline traits, even though the former show a much weaker (although not absent, see Verona et al., 2001) association with suicide risk. This scale also includes items assessing sexual assault/rape exposure. Sexual assault and rape incur harm to the victims and are often accompanied by additional physical violence. For female victims, sexual assault and rape is significantly linked with a dysregulation of the reproductive physiology (medically explained missing menstrual periods, and medically unexplained dysmenorrhea, menstrual irregularity) and a decreased sexual activity (less sexual desire, more pain during intercourse, lack of sexual pleasure) (Golding, 1996). For these reasons, sexual assault and rape can be said to threaten two fundamental biological goals, i.e., survival and reproduction. In addition, sexual assault and rape are generally considered as prototypical examples of threating and violent experiences (Chen et al., 2010; Domino et al., 2020; Dworkin et al., 2017; Nickerson et al., 2013; Siegel et al., 1990), which warrant their inclusion in our composite.

Maternal hostility was measured with an adaptation of the Quality of Parental Relationships Inventory (Conger et al., 1994). Items from the measure tap parental warmth (e.g., "How often does your mother let you know she really cares about you?") and parental hostility (e.g., "How often does your mother get angry at you?"). We used the subscale reflecting maternal hostility, and reverse coded the indicator so that higher scores indicate a more hostile relationship with the youth's mother. A four-factor model fit to the overall scale resulted in acceptable fit: NFI = .78, NNFI = .82, CFI = .83, RMSEA = .06. The maternal warmth subscale specifically had the following CFI goodness of fit at baseline: NFI = .73, NNFI = .69, CFI = .74, RMSEA = .09. It also had good reliability, baseline Cronbach alpha = .85; 6 month Cronbach alpha = .80; 12 month Cronbach alpha = .82; 18 month Cronbach alpha = .79; 24 month Cronbach alpha = .82.

Peer delinquent behavior and *Peer delinquent influence* were measured by a subset of items from the Rochester Youth Study (Thornberry et al., 1994). These items assess the degree of antisocial activity among the youth's peers, along two dimensions: Antisocial behavior (e.g., "During the recall period how many of your friends have sold drugs?") and Antisocial influence (e.g., "During the recall period how many of your friends have suggested that you should sell drugs?"). The scale contains 19 items in total. We used the Antisocial behavior score, which is the mean rating of the prevalence of friends who engage in the 12 behaviors listed in this section and the Antisocial influence score, which is the mean rating of the prevalence of friends who encourage the youth to engage in the seven items listed in this section. Higher scores indicate a greater degree of peer antisocial behavior and influence. Both scales had acceptable CFA model fits, Peer Delinquency-Antisocial behavior: NFI = .93, NNFI = .92, CFI = .94, RMSEA = .09; Peer Delinquency-Antisocial influence: NFI = .95, NNFI = .93, CFI = .96, RMSEA = .07. Their reliabilities were also good, Peer Delinquency-Antisocial behavior: baseline Cronbach alpha = .92; 6 months Cronbach alpha = .89; 12 months Cronbach alpha = .89; 18 months Cronbach alpha = .89; 24 months Cronbach alpha = .91; 30 months Cronbach alpha = .90; 36 months Cronbach alpha = .88; 48 months Cronbach alpha = .88; 60 months Cronbach alpha = .89; 72 months Cronbach alpha = .88. 84 months Cronbach alpha = .87; Peer Delinquency-Antisocial influence: baseline Cronbach alpha = .89; 6 months Cronbach alpha = .93; 12 months Cronbach alpha = .94; 18 months Cronbach alpha = .94; 24 months Cronbach alpha = .94; 30 months Cronbach alpha = .93; 36 months Cronbach alpha = .93; 48 months Cronbach alpha = .94; 60 months Cronbach alpha = .94; 72 months Cronbach alpha = .94; 84 months Cronbach alpha = .93.

Neighborhood social disorder was measured by an adaptation of a neighborhood conditions measure by Sampson and Raudenbush (1999). Items from the self-report measure tap physical disorder (e.g., "cigarettes on the street or in the gutters," "graffiti or tags"), and social disorder (e.g., "adults fighting or arguing loudly," "people using needles or syringes to take drugs") of the neighborhood. We used the social disorder subscale, which is the mean of the 9 social disorder items. Higher scores indicate a greater degree of social disorder within the community. This scale had excellent reliabilities: baseline Cronbach alpha = .87; 6 month Cronbach alpha = .92; 12 month Cronbach alpha = .92; 18 month Cronbach alpha = .92; 24 month Cronbach alpha = .92.

Mediators

Future orientation was measured by the Future Outlook Inventory, developed for the Pathways to Desistance study, using items from the Life Orientation Task (Scheier & Carver, 1985), the Zimbardo Time Perspective Scale (Zimbardo & Boyd, 1999), and the Consideration of Future Consequences Scale (Strathman et al., 1994). The inventory contains 15 items asking participants to rank from 1 to 4 (1 = Never True to 4 = Always True) the degree to

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which each statement reflects how they usually are (e.g., I will keep working at difficult, boring tasks if I know they will help me get ahead later). Higher scores indicate a greater degree of future consideration and planning. We used the data from the 72 months follow-up assessment. A one factor CFA at baseline resulted in the following fit indices: NFI = .96, NNFI = .96; CFI = .97, RMSEA = .03. The scale also had acceptable reliabilities: baseline Cronbach alpha = .68; 6 month Cronbach alpha = .73; 12 month Cronbach alpha = .70; 18 month Cronbach alpha = .72; 24 month Cronbach alpha = .69

Mental health

Antisocial traits and *Borderline traits* were both measured by the associated clinical scales of the Personality Assessment Inventory (PAI, Morey, 1991). The Borderline Features items focus on attributes indicative of a borderline personality, including unstable and fluctuating interpersonal relations, impulsivity, affective lability and instability, and uncontrolled anger. Subscales are: affective instability, identify problems, negative relationships and self-harm. The Antisocial Features items focus on a history of illegal acts and authority problems, egocentrism, lack of empathy and loyalty, instability, and excitement-seeking. Subscales are: antisocial behaviors, egocentricity, and stimulus-seeking. We used the total raw Antisocial and Borderline subscale scores, reflecting the sum of all associated items. Higher scores are indicative of more Antisocial and Borderline personality features. We used the data from the 72 month follow-up assessment. Reliability information for these scales was not provided by the investigators of the Pathways dataset, but Boyle and Lennon (1994) found good internal consistency for both scales: Borderline Cronbach alpha = .88; Antisocial Cronbach alpha = .85.

Psychological distress was measured by the Brief Symptom Inventory (BSI, Derogatis & Melisaratos, 1983). The BSI is a 53-item self-report inventory in which participants rate the extent to which they have been bothered (0 =”not at all” to 4=”extremely”) in the past week by various symptoms. We used the global severity index, which is the mean score of all items. We used the data from the 72 month follow-up assessment as the primary outcome measure. The global severity index had excellent reliability: 6 months Cronbach alpha = .95; 12 months Cronbach alpha = .96; 18 months Cronbach alpha = .96; 24 months Cronbach alpha = .96; 30 months Cronbach alpha = .96; 36 months Cronbach alpha = .96; 48 months Cronbach alpha = .96; 60 months Cronbach alpha = .96; 72 months Cronbach alpha = .96; 84 months Cronbach alpha = .96.

Covariates

Gender was measured as participants self-reported gender at Baseline, and coded as Male (0) or Female (1).

Ethnicity was measured by participants self-reported ethnicity as baseline, and was recoded into 2 categories of White (0), and non-White (1), as members of minority racial and ethnic groups likely experience an overall higher level of environmental adversity (Pascoe & Smart Richman, 2009; Williams et al., 2019), making it a potential confounding factor.

Site refers to the study site location, that is, the geographic site where the subject is located. It was coded as either Philadelphia (0) or Phoenix (1).

Age refers to participants age at Baseline (in years), calculated as interview date minus the participant’s date of birth truncated to a whole number.

It was important to control for preexisting internalizing and externalizing problem behaviors, to make sure any results we uncover during the study period are not due to their confounding effects. To this end we made use of Early onset problem behaviors (proxy of primarily externalizing behaviors before age 11) and the BSI psychological distress scores at Baseline (proxy of primarily internalizing behaviors at recruitment).

Early onset of behavioral problems was measured by a series of five questions that assess whether the participant got in trouble for cheating, disturbing class, being drunk/stoned, stealing, or fighting, before the age of 11. The score is simply the count of the number of early onset problems that were endorsed.

Psychological distress at Baseline was measured by the global psychological distress scale of the BSI, as described above.

Missing data

Little’s test (Little, 1988) indicated that the data are not missing completely at random, $\chi^2(238) = 491$, $p < .001$. However, pairwise comparisons of missingness patterns indicated that missingness in our outcome variables was systematically related to our explanatory variables, such that missing at random (MAR) could still be supported (Supplementary tables S12, S13, S14). We thus handled missing data using Full Information Maximum Likelihood (FIML), which is appropriate for cases of MAR and outperforms other approaches, such as listwise deletion (Baraldi & Enders, 2010; Enders & Bandalos, 2001). Thus, our sample consisted of all 1354 participants of the Pathways dataset. Fraction of missing values for primary variables are presented in Supplementary Table S11.

Data analytic plan

Our analytic plan consisted of two stages. In the first stage, we used linear mixed models (LMMs) to create individual trajectories of adversity exposure for each variable and used these to derive estimates of both typical levels of deprivation and threat exposure, and temporal variability in deprivation and threat exposure. In the second stage, we constructed a path analytic model to investigate the associations of these average and unpredictability adversity composite scores with later life mental health outcomes, as well as the mediating effect of future orientation. We now detail these stages in turn.

In order to derive indices of average and unpredictable adversity, we adapted the longitudinal modeling approach of Li and Belsky (Li et al., 2018; Li & Belsky, 2022), which itself is based on earlier work by Hoffman (2007). This involved fitting a series of LMMs for each adversity indicator, with both a fixed effect of time, as well as subject-specific random intercept and slopes. Time was a mean-centered variable, with 7 levels, reflecting the Baseline (−3), and the 6 (−2), 12 (−1), 18 (0), 24 (1), 30 (2), and 36 (3) month follow-up assessments. These models thus resulted in predicted trajectories for each adversity indicator, for each individual. The estimated intercepts of these models served to represent typical levels of exposure to that adversity factor for each individual. The root mean squared error of the individual level models served to represent temporal unpredictability in exposure to that adversity factor across the studied period. The strength of this approach is that it allows us to separate systematic, and thus predictable variability from random variability. This is an important point, as most theoretical frameworks for the role of unpredictability in development, including the evolutionary developmental approach we adopt, concern the effects of primarily random variability (Ellis et al., 2009; Evans et al., 2005; Young et al., 2020). Furthermore, this approach also allows for a straightforward way of handling missing data at the indicator level, as both model-predicted intercepts and residuals can be calculated even for subjects with missing data on some timepoints, without any need for specific missing data approaches.

After these average and unpredictability scores were calculated for each indicator, they were then z-scored in the whole sample to equalize scale and summed to create specific composite scores for deprivation and threat. Thus, average scores on the *Caring adults*, *Maternal warmth*, *Social capital*, *Neighbourhood physical disorder*, and *Unstructured socializing* indicators were summed into a Deprivation average composite score, whereas unpredictability scores on these same indicators were summed into a Deprivation unpredictability composite score. In the same manner, average scores on the *Exposure to violence*, *Maternal hostility*, *Peer delinquent behavior*, *Peer delinquent influence*, and *Neighbourhood social disorder* indicators were summed into a Threat average composite score, whereas unpredictability scores on these same indicators were summed into a Threat unpredictability composite score. Finally, expanding on the methodology earlier work (Li et al., 2018; Li & Belsky, 2022), Deprivation average × Deprivation unpredictability and Threat average × Threat unpredictability interactions terms were also calculated by multiplying the respective average and unpredictability variables. As a result, we were able to approximate individual exposure to multiple dimensions of adversity and separate the effects of mean levels of exposure from temporal unpredictability in exposure, as well as their interaction. In order to keep our model simple, and the lack of previous empirical demonstration of cross dimensional interactions, we decided not to add them into the model. Details on the models are provided in Supplementary Tables S1 to S10, and trajectories of individual indicators are plotted in Supplementary Figures S1–S10. We also computed a set of other unpredictability metrics and combined them with the same sum of *z*-scores approach. This included the standard deviation, the entropy, and the first order autocorrelation, inspired by Walasek et al. (2024), as well as a score that reflected the mean percentage change between timepoints, suggested by a reviewer. We investigated the agreement between these various metrics, as well as the similarity between their associations with outcomes by bivariate correlations.

We then related these six adversity composite scores (4 main effects + 2 interaction terms) to later mental health and mediator variables. Specifically, we created a path analytic, mediation model, in which the six adversity composites had direct effects on the three mental health outcomes (Antisocial traits, Borderline traits, Psychological distress), as well as indirect effects through Future orientation. Control variables of Early onset problem behaviors, Baseline psychological distress, Baseline age, Ethnicity, Sex, and Site were also incorporated into the model by regressing them on each variable. Covariances between the three mental health variables were also specified. This resulted in a saturated model. The model was fit using Robust Maximum Likelihood estimation (MLR estimator) and missing data was handled with FIML. We also perform sensitivity analyses with two alternative models. A first alternative model with listwise deletion of participants with missing values, instead of FIML; and a second alternative model with bootstrapped standard errors and standard ML estimation, instead of MLR.

All pre-processing, analysis and visualization was carried out in *R* version 4.2.3 (R Core Team, 2021), with the help of the *tidyverse* (Wickham et al., 2019), *ggplot2* (Wickham, 2016), *afex* (Singmann et al., 2023), *lavaan* (Rosseel, 2012), and *psych* (Revelle, 2022) packages. All p values reported are two-tailed, with alpha set to .05. Effect sizes are reported as standardized betas. No outliers were removed. As we only interpret the magnitudes and the overall patterns of correlations to determine the agreement between unpredictability metrics and their functional consequences, and draw no inference regarding any individual bivariate correlation, we do not correct these correlation matrices for multiple comparisons.

All pre-processed data and code necessary to reproduce all results in the paper are available on the OSF framework (https://osf.io/src3u/). The raw data that support the findings of this study are similarly available after the appropriate steps from the Pathways to Desistance study website (https://www.pathwaysstudy.pitt.edu/index.html). This study was not pre-registered.

Results

Unpredictability metrics

Our primary metric of unpredictability was a LMM residual based score (based on Li et al., 2018 and Li & Belsky, 2022), which captures stochastic temporal variability of individual adversity trajectories around the overall group level linear trend. In addition to this, we also computed multiple unpredictability metrics within the deprivation and threat dimensions, including the standard deviation, the first order autocorrelation, the entropy (based on Walasek et al., 2024), and a percentage change score. Bivariate correlations among these metrics are presented in Figures 1a,b, and between these metrics and our outcomes in Figure 1c, and their distributions are plotted in Supplementary Figure S11. Within both deprivation and threat, the highest agreements were found between our model residual score, the standard deviation and the percentage change score, first order autocorrelation had weaker associations with the other metrics. Surprisingly, entropy showed negative correlations with other unpredictability metrics. In a similar vein, bivariate correlations of the metrics with our outcome variables suggested that the model residual score, standard deviation, and percentage change score share similar associations with future orientation and mental health. Whereas the first order autocorrelation seemed the least related to all outcomes and entropy again showing associations in the opposing direction. All of this suggests that our proposed random effects model residual score, intended to measure stochastic temporal variability captures similar unpredictability types as other previously proposed measures. On the other hand, first order autocorrelation and entropy seemed to capture entirely independent sources of variability, even though, similarly to our model residual score, it is intended to capture unpredictable variability. This is likely due to our relatively small number of datapoints, making the estimation of autocorrelation and entropy inaccurate. Based on these patterns, we decided to use our model residual score as our primary unpredictability metric, and to ease readability, we henceforth refer to it as Threat unpredictability and Deprivation unpredictability.

Path analysis

We fit a path analytic, mediation model, that related composite scores reflecting adolescent deprivation and threat exposure to later life future orientation, and mental health outcomes. Importantly, we created separate terms for average adversity exposure levels, unpredictability in exposure levels, and the interaction between the two. Correlations between primary variables are presented in Table 2, and histograms showing their

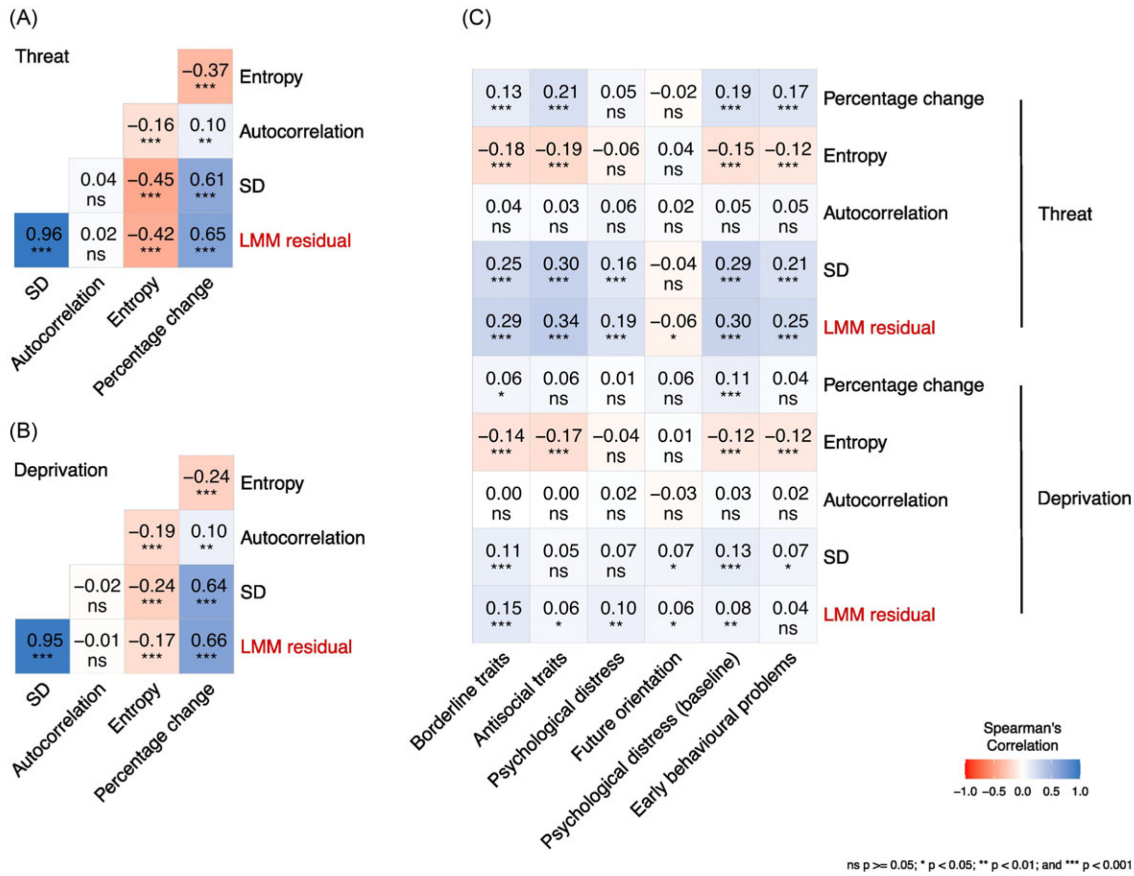

Figure 1. Bivariate Spearman's correlations of unpredictability metrics. (*a*) Correlations between multiple unpredictability metrics of the threat dimension. (***b***) Correlations between multiple unpredictability metrics of the deprivation dimension. (***c***) Correlations of multiple unpredictability metrics of both dimensions and outcomes. In all figures, p values are uncorrected for multiple comparisons. Our candidate linear mixed model residual based metric, that is used in the path analysis are highlighted in red.

distribution are presented in Supplementary Figure S12. To aid the clarity of the presentation of the results, we refrain from quoting the statistics in the main text. Parameter estimates are reported in Table 3, and a simplified graphical representation of the model's results is presented in Figure 2. The model was saturated, therefore standard goodness of fit indices are not available. R^2 metrics indicate that the model explained 26% of variance in Antisocial traits, 22% of variance in Borderline traits, and 13% of variance in Psychological distress. The three mental health outcomes had moderate to strong positive covariances. Given the large correlation between the Threat unpredictability threat and Threat average scores, we tested the impact of multicollinearity on our estimates, by calculating VIFs from a regression model corresponding to the prediction of Future orientation from our set of adversity variables. This indicated that while the Threat average and Threat unpredictability variables do indeed have the highest VIF values, they are still only 2.29 and 2.73, respectively, much below the usually recommended cutoff of 10 (Kutner et al., 2004; Myers, 1990).

We also performed two sensitivity analyses. A first alternative model has the same specification as our main model, but is fit with listwise deletion of participants with missing values, instead of FIML. This model allows us to detect which effects are highly dependent on our missing data handling method, however, due to the greatly reduced sample also has lower statistical power. A second alternative model also has the same specification as our main model, but is fit with bootstrapped standard errors and standard ML estimation, instead of MLR. This model allows us to obtain estimates of parameters and confidence intervals without relying on the assumption of normality, and investigate the precision of these estimates.

Direct effects of adversity dimensions on psychopathology

Results indicated that Threat average had significant, positive direct effects on all three of our mental health outcomes, and Deprivation unpredictability had positive direct effects on Borderline traits, and Psychological distress, with Threat average being associated with generally larger effect sizes (Table 3 and Figure 2). The interaction terms were not significant. This means that exposure to highly variable levels of deprivation (independently of its average level) and high average levels of threat (independently of its variability) during adolescence, both contribute to a higher number of Borderline and Antisocial personality features, and a greater degree of general psychological distress, later in life. Surprisingly, Threat unpredictability was found to negatively predict Psychological distress.

Direct effects of adversity dimensions on future orientation

Threat average and Deprivation average were also significantly negatively associated with Future orientation, indicating that high average levels of exposure to both dimensions of adversity is associated with a more present-oriented outlook (Table 3 and Figure 2). Interestingly, Deprivation unpredictability was positively associated with Future orientation, suggesting that contrary

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Table 2. Bivariate Spearman's correlations between primary variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Deprivation Avg	–	.10***	– .03	.17***	.15***	– .08**	– .14***	.06	.13***	.09*	.12***	.02
2. Deprivation Unp		–	.02	.06*	.37***	.01	.06*	.06*	.15***	.10**	.08**	.04
3. Deprivation Avg × Unp			–	– .09***	– .03	.09**	– .01	– .06	– .05	– .06	– .02	– .02
4. Threat Avg				–	.73***	– .06*	– .12***	.42***	.35***	.29***	.34***	.30***
5. Threat Unp					–	– .06*	– .06*	.34***	.29***	.19***	.30***	.25***
6. Threat Avg × Unp						–	.01	.00	– .03	– .01	– .04	– .01
7. Future orientation							–	– .28***	– .24***	– .05	– .03	– .11***
8. PAI Antisocial								–	.61***	.27***	.19***	.25***
9. PAI Borderline									–	.45***	.32***	.14***
10. BSI total score										–	.30***	.11**
11. BSI total score Baseline											–	.14***
12. Early onset behav probs												–

P values are uncorrected for multiple comparisons.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

to average levels, a greater degree of variability in deprivation exposure might be associated with more, and not less future oriented thinking. While not reaching our set level of statistical significance, we observed a small effect of the Threat unpredictability × Threat average interaction, on future orientation. As the nature of such interactive effects is an unresolved question in the literature, we performed a simple slopes analysis to investigate which pattern the interaction effects observed here match, at least qualitatively. These revealed effects consistent with the buffering pattern, whereby high levels of threat were associated with the strongest negative effects on development (more present orientation), while coupled with low unpredictability (Supplementary Figure S13).

Direct effects of future orientation on psychopathology

Future orientation was significantly negatively associated with Borderline and Antisocial traits, but not with Psychological distress, indicating that a more present-oriented outlook is associated with a higher number of Borderline and Antisocial personality features, but not with general psychological distress (Table 3 and Figure 2).

Indirect effects of adversity dimensions on psychopathology through future orientation

We finally tested the indirect effects of the adversity dimensions on psychopathology, routed through future orientation, that were suggested by the path estimates (Figure 2). Specifically, we estimated the indirect effect of Deprivation average, Deprivation unpredictability, and Threat average on Antisocial and Borderline traits (Table 3). Deprivation average had a significant, positive indirect effect on both Antisocial ($b = 0.115$, 95% CI = [0.054, 0.176], $p < .001$) and Borderline traits ($b = 0.126$, 95% CI = [0.059, 0.176], $p < .001$). Threat average also had a significant, positive indirect effect on both Antisocial ($b = 0.068$, 95% CI = [0.006, 0.129], $p = .031$) and Borderline traits ($b = 0.075$, 95% CI = [0.008, 0.141], $p = .028$). The indirect effect of Deprivation unpredictability in association with greater future orientation, and thereby, lower Antisocial ($b = -0.066$, 95% CI = [−0.126, −0.007], $p = .029$) and Borderline traits (b = −0.073, 95% CI = [−0.139, −0.008], $p = .029$) also proved statistically significant.

Sensitivity analyses

Parameter estimates for the model proved relatively robust in a sensitivity analysis with listwise deletion of missing values (Supplementary Table S16). There were two important differences however: the link between Deprivation unpredictability and Future orientation turned non-significant, which in turn rendered the indirect effects of Deprivation unpredictability non-significant as well; and the direct effect of Deprivation unpredictability on Antisocial and Borderline traits turned significant. This suggests, that the estimates of these effects might be biased by our handling of missing data. However, it also has to be noted that this model had substantially smaller sample size ($N = 736$, instead of $N = 1354$ for the main model), which means it was more likely to be underpowered.

Parameters were entirely robust in a second alternative model with bootstrapped standard errors, and standard ML estimation (Supplementary Table S17). Both parameter estimates themselves and their confidence intervals were extremely similar compared to the main model. This suggests that, our main model does not suffer from a significant bias from violation of distributional assumptions.

Discussion

The present paper examined the effect of exposure to multiple dimensions of environmental adversity during adolescence, on later life Antisocial and Borderline personality traits, and psychological distress, as well as the mediating role of future orientation. Importantly, we distinguished between typical levels of adversity exposure, and variability in adversity exposure. All of this allowed for a fine-grained level of analysis. Results were mostly consistent with our hypotheses. High average levels of both deprivation (defined as mortality-morbidity risk from lack of environmental input and nurture) and threat (defined as mortality-morbidity risk from physical and psychological harm) were related to more present orientation. Present orientation, coupled with impulsivity, risk-taking, and steeper discount rates has been

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Table 3. Parameter estimates of the path analytic mediation model

Outcome	Predictor	b (SE b)	95% CI	β	z
Future orientation	**Deprivation Avg**	**− 0.028 (0.007)**	**[− 0.041, −0.015]**	**− .136**	**− 4.228**
	Deprivation Unp	**0.016 (0.007)**	**[0.002, 0.031]**	**.078**	**2.271**
	Deprivation Avg × Unp	− 0.001 (0.002)	[− 0.005, 0.003]	− .017	− 0.573
	Threat Avg	**− 0.017 (0.007)**	**[− 0.031, −0.002]**	**− .108**	**− 2.294**
	Threat Unp	0.001 (0.009)	[− 0.017, 0.018]	.003	0.062
	Threat Avg × Unp	0.002 (0.001)	[0.000, 0.005]	.059	1.681
Antisocial traits	Deprivation Avg	− 0.135 (0.109)	[− 0.348, 0.079]	− .034	− 1.238
	Deprivation Unp	0.175 (0.119)	[− 0.059, 0.409]	.044	1.465
	Deprivation Avg × Unp	0.007 (0.039)	[− 0.069, 0.083]	.006	0.189
	Threat Avg	**0.968 (0.129)**	**[0.716, 1.220]**	**.331**	**7.534**
	Threat Unp	0.139 (0.148)	[− 0.151, 0.429]	.043	0.941
	Threat Avg × Unp	− 0.005 (0.027)	[− 0.058, 0.048]	− .006	− 0.185
	Future orientation	**− 4.052 (0.584)**	**[− 5.198, −2.907]**	**− .214**	**− 6.934**
Indirect effects	**Deprivation Avg –> Future**	**0.115 (0.031)**	**[0.054, 0.176]**	**.029**	**3.687**
	Deprivation Unp –> Future	**− 0.066 (0.030)**	**[− 0.126, −0.007]**	**− .017**	**− 2.177**
	Threat Avg –> Future	**0.068 (0.031)**	**[0.006, 0.129]**	**.023**	**2.153**
Borderline traits	Deprivation Avg	0.101 (0.128)	[− 0.150, 0.352]	.025	0.790
	Deprivation Unp	**0.527 (0.127)**	**[0.278, 0.776]**	**.129**	**4.146**
	Deprivation Avg × Unp	0.012 (0.037)	[− 0.061, 0.084]	.009	0.317
	Threat Avg	**0.815 (0.135)**	**[0.550, 1.080]**	**.272**	**6.032**
	Threat Unp	− 0.149 (0.156)	[− 0.455, 0.158]	− .045	− 0.952
	Threat Avg × Unp	− 0.016 (0.028)	[− 0.070, 0.039]	− .019	− 0.563
	Future orientation	**− 4.463 (0.592)**	**[− 5.623, −3.303]**	**− .230**	**− 7.541**
Indirect effects	**Deprivation Avg –> Future**	**0.126 (0.034)**	**[0.059, 0.193]**	**.031**	**3.705**
	Deprivation Unp –> Future	**− 0.073 (0.033)**	**[− 0.139, −0.008]**	**− .018**	**− 2.189**
	Threat Avg –> Future	**0.075 (0.034)**	**[0.008, 0.141]**	**.025**	**2.198**
Psychological distress	Deprivation Avg	0.008 (0.006)	[− 0.004, 0.020]	.046	1.325
	Deprivation Unp	**0.015 (0.007)**	**[0.001, 0.030]**	**.088**	**2.143**
	Deprivation Avg × Unp	0.001 (0.002)	[− 0.003, 0.005]	.018	0.509
	Threat Avg	**0.036 (0.008)**	**[0.021, 0.051]**	**.281**	**4.669**
	Threat Unp	**− 0.016 (0.008)**	**[− 0.032, −0.001]**	**− .115**	**− 2.035**
	Threat Avg × Unp	0.000 (0.001)	[− 0.003, 0.003]	.005	0.128
	Future orientation	− 0.040 (0.029)	[− 0.097, 0.018]	− .047	− 1.345

Statistically significant effects are highlighted in bold. Selected indirect effects that are suggested by the individual parameter estimates are also tested and included in the table. Effects of covariates are omitted for clarity. Full list of parameters is available in the .Rdata file provided in the supplementary materials.

robustly linked to early life adversity, and is an important component of life history-inspired models of development (Copping et al., 2014; Farkas et al., 2021; Hill et al., 2008; Lee et al., 2018; Martinez et al., 2022; Wu et al., 2020). A more present-oriented decision-making style, along with a lower perceived sense of control is a core component of what Pepper and Nettle (2017) called the behavioral constellation of deprivation, and has also been highlighted as an important mediator of socioeconomic status effects on decision-making by Sheehy-Skeffington (2020). In these theoretical accounts, such decision-making reflects a contextually appropriate response to adverse conditions, that lower the certainty of being able to collect and benefit from delayed rewards. In another, not mutually exclusive model, Mell et al. (2021) argued that discounting can also reflect the costs of waiting, in the sense of losing out on potential gains in biological and social capital during the waiting period. Our results are consistent with either mechanism. It is also important to note, that temporal impulsivity is only an adaptive strategy under certain conditions, for example, when organisms are close to critical thresholds, resources are predictable, or interruptions are common (Fenneman et al., 2022; Fenneman & Frankenhuis, 2020). Given this, it is intriguing that whereas average levels of deprivation were associated with more present orientation, unpredictability in deprivation (corresponding with low levels of resource predictability) was associated with

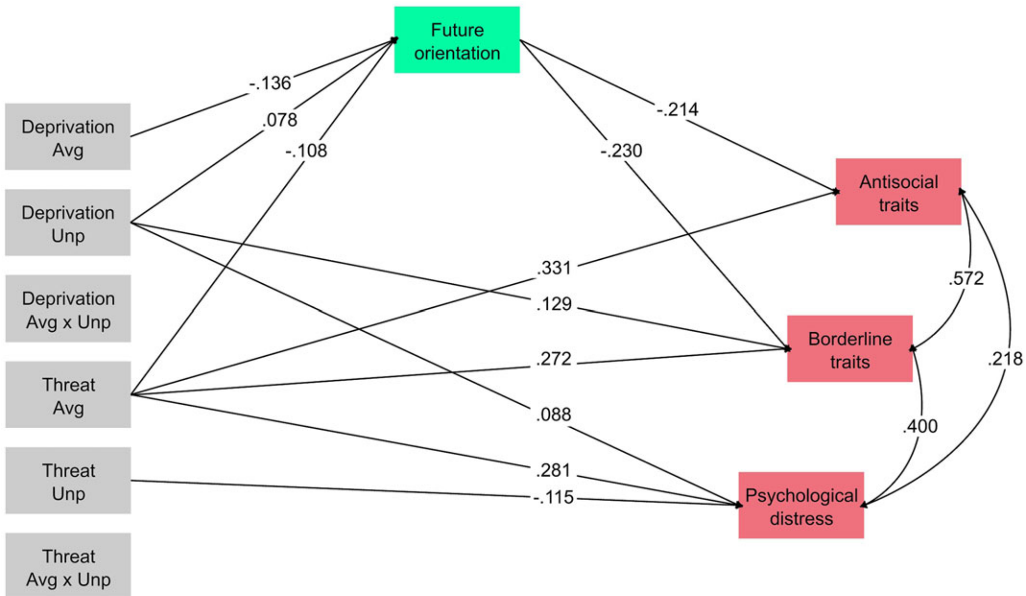

Figure 2. Simplified representation of the path analytic mediation model. Indicators and standardized parameter estimates. Statistically significant regression paths and covariances are represented by single and double headed arrows, respectively.

more future orientation. We did not observe a direct effect of average deprivation on any of the mental health outcomes. The lack of a direct deprivation effect on mental health is not surprising, given that it is usually more strongly associated with cognitive and linguistic outcomes, which stand in contrast of the more direct link of threat with emotional processing and mental health (McLaughlin et al., 2019; Miller et al., 2018, 2021). However, our results do suggest that deprivation can have an impact on mental health indirectly through more present orientation, and perhaps through the induction of psychosocial acceleration more broadly. This possibly important indirect link remains to be further explored.

The pattern of associations of present orientation with the mental health outcomes is also entirely in line with our hypotheses based on evolutionary approaches to psychopathology. Notably, in the model of Del Giudice (Del Giudice, 2018; Del Giudice & Haltigan, 2023), the taxonomic space of psychopathology is oriented along two, largely orthogonal axes of fast-slow life history strategy, and prolonged defense activation. Fast spectrum disorders comprise primarily externalizing conditions, such as Antisocial, Borderline and Narcissistic personality disorder, Schizophrenia spectrum disorders and some eating disorders. On the opposing end, Slow spectrum disorders comprise primarily subtypes of Attention Deficit Hyperactivity Disorder, Obsessive Compulsive Disorder and Autism spectrum disorders, as well as Obsessive Compulsive Personality Disorder. Finally, a third cluster is formed by defense activation type disorders, which comprise primarily internalizing conditions, including Depression, Post Traumatic Stress Disorder, Phobias and Generalized anxiety. While both fast spectrum and defense activation disorders are proposed to be more prevalent in dangerous and unpredictable environments, the mechanisms of such effects are somewhat different. Risk for fast spectrum conditions reflects an adaptive developmental response to adversity in the form of "fast" life history strategies, which as explained above, likely includes a psychological component of present-oriented decision-making. Risk for defense activation type conditions instead reflects the upregulation of adaptive defense mechanisms to intense and/or prolonged exposure to stress and is therefore relatively unrelated to broader life history strategies and future outlook. This line of reasoning would thus predict that while adversity should be associated with worse outcomes on all three measures, only the effect on fast spectrum traits should be mediated by present orientation. If we interpret Antisocial and Borderline personality features (as measured by the PAI) as markers of Fast spectrum symptoms, and general psychological distress (as measured by the BSI) as markers of defense activation type symptoms, this is exactly what we find.

The associations of unpredictability proved more complex. On the one hand, unpredictability in deprivation had positive direct effects on mental health outcomes, dovetailing a large body of previous findings, highlighting unpredictability as a major risk factor for "problematic" child development, above and beyond the effect of harshness (Brumbach et al., 2009; Doom et al., 2016; Glynn et al., 2018; Li et al., 2018; Li & Belsky, 2022; Simpson et al., 2012; Szepsenwol et al., 2017; Wu, 2024). One way in which our findings extend these earlier results is by suggesting that it is unpredictability in the dimension of deprivation that might be responsible for these associations. In our study, a high and stable level of danger, and inconsistency in resource availability and stimulation have emerged as the strongest drivers of mental health problems. However, in addition to these main effects, unpredictability in deprivation had a small, positive association with future orientation, i.e., in the opposing direction to the effect of average deprivation and threat. Similarly, unpredictability in threat had a negative effect on general psychological distress. Finally, while not reaching our set level of statistical significance, an interaction was observed between average and unpredictable threat on future orientation. This interaction seemed to suggest a buffering pattern, whereby high typical levels of threat had the strongest effect, when it was coupled with low unpredictability. These results are not entirely unexpected, as multiple studies have revealed similar interactions between harshness and unpredictability on developmental outcomes (Li et al., 2018; Li & Belsky, 2022). Li and Belsky (2022) interpret these effects in light of Bayesian models of plasticity, proposing that environmental unpredictability effectively lowers the reliability of cues, that organisms use to guide development (Frankenhuis & Panchanathan, 2011; Stamps &

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Frankenhuis, 2016). All else being equal, a stable high level of adversity offers stronger evidence for future environmental adversity, than a variable level of adversity with the same mean. This reasoning also echoes findings from human reinforcement learning and decision-making, highlighting that certain kinds of uncertainty should downregulate learning rates, and that humans indeed behave in this way (Lee et al., 2023; Piray & Daw, 2021; Story et al., 2023). These effects argue in favor of the statistical learning framework for unpredictability, proposing that individuals track the level of unpredictability in their environment across time and update their internal models accordingly (Young et al., 2020). Under this conceptualization one could imagine low variability leading to more imprecision in the estimation of adversity, and by virtue of that, less strong or delayed developmental adaptation. Nevertheless, this reasoning is difficult to reconcile with the detrimental main effects of unpredictability, when modeled from indicators such as parental and residential transitions, that consistently emerge in the literature, even in the absence of harshness effects. If unpredictability operated solely through a reduction of cue reliability, then it should not be associated with aspects of psychosocial acceleration on its own, when not paired with high average levels of harshness. Another possible explanation lies in the potential confounding of income unpredictability (the primary measure in the studies of Li et al. (2018) and Li & Belsky (2022)) by income level, as families with low income do not have much income that could vary. The relatively high reported correlations between their harshness and unpredictability variables ($r = -.66$, and $r = -.45$) as well as between our Average threat and Unpredictable threat scores ($r = .70$) lends credibility to this explanation. Future work with more diverse indicators, a fine temporal resolution, and formal modeling will be indispensable in understanding these effects (Frankenhuis et al., 2019). Similarly, while not the focus of this study, testing cross dimensional interactions between deprivation and threat is another important avenue for future research.

The notable strengths of our work have to be balanced against a number of limitations. While our primary aim was to capture the effects of nonshared environments, phenotypic variability in all constructs we investigated has notable genetic components (Niv et al., 2012; Reichborn-Kjennerud et al., 2015; Richardson et al., 2023; Zheng et al., 2022). Future work with genetically informative designs will be necessary to tease apart environmental and genetic influences, and their interactions. Secondly, while we believe our operationalization of unpredictability to be one of the strengths of our work, it also comes with limitations. Our composite scores likely gloss over important differences in the timescale of variability and type of unpredictability that different individuals encountered. As not all kinds of unpredictability are expected to have the same effects on learning and development, this imprecision will be important to address in future studies (Young et al., 2020). In a similar vein, we focused on the statistical learning approach to conceptualize unpredictability and were unable to assess how this source of signal interacted with ancestral cues. The recent study of Li et al. (2023) highlighted important differences in the mechanisms that mediate the effects of these different sources of information. Thirdly, while our bootstrapped alternative model (Supplementary Table S17) yielded entirely converging results to our main model, the other alternative model with listwise deletion of participants with missing data (Supplementary Table S16) suggested that our estimates of the effects of Deprivation unpredictability might be biased by our missing data handling (FIML). Therefore, our uncovered associations require additional support and tests using samples with more complete datasets. Finally, the nature of our sample necessarily limits the generalizability of our findings. As it has been designed as a cohort to understand juvenile offending, the Pathways study is a necessarily non-representative sample of youth, with predominantly male offender participants from highly adverse backgrounds. This precluded any investigation of sex differences and leaves open the question of whether the associations we uncovered hold in lower-risk populations. In addition, while our large, rich, and longitudinal dataset was ideally posed for investigating variability in multiple adversity factors, it has to be noted that the number of datapoints per individual is much lower than what would be desirable for the accurate calculation of more complex unpredictability metrics, such as the autocorrelation and entropy. This is especially important, given the surprising negative correlation of entropy with other unpredictability metrics and our mental health outcomes. It is intriguing that Walasek et al. (2024) also observe a similar effect, and that multiple recent studies have drawn attention to the potentially important differences between different timescales and different degrees of predictability of variability (Farkas et al., 2024; Munakata et al., 2023; Ugarte & Hastings, 2023; Young et al., 2020). The timing of adversity exposure that we have considered here is also much later than the sensitive periods during which early life adversity is generally thought to mark a child's development (Lussier et al., 2023; Simpson et al., 2012). Even though our effects are adjusted for preexisting internalizing and externalizing behaviors and psychological distress, the proximity in time of our various measurements does not allow us to draw strong conclusions about whether these effects stem from external predictive adaptive responses. Nevertheless, due to environmental continuity adolescent experiences likely correlate with early life ones. For example, in a longitudinal study, Simpson et al. (2012) report a correlation of $r = .67$ between early (ages 0–5) and late (ages 6–16) harshness and a correlation of $r = .42$ between early (ages 0–5) and late (ages 6–16) unpredictability. In addition, psychological and biological processes that translate environmental adversity to developmental changes likely do not stop fully after initial sensitive periods and continue to operate throughout the lifecourse, albeit with possibly reduced strength. For example, even adversity experienced during adulthood has considerable impact on mental and physical health (Hajat et al., 2020; Liu et al., 2023), and there is plenty of evidence suggesting that stress induced epigenetic changes are not restricted to early life (Doherty & Roth, 2016).

Notwithstanding these important limitations, we believe our study contributes to a growing understanding of the complex effects of multiple dimensions of early life environments on development and mental health. By disentangling typical levels of exposure, and variability in exposure, separately in the dimensions of deprivation and threat, we were able to highlight important differences in their developmental sequalae. Our results suggest that while high stable levels of danger, and variable levels of resource availability increase fast spectrum and distress symptoms, unpredictability has more complex associations, possibly reflecting its effects on cue reliability. Our approach highlights both the value of evolutionary developmental frameworks for understanding psychopathology (Del Giudice & Ellis, 2016), and the need for a greater degree of precision in our conceptualization of early life adversity (McLaughlin et al., 2021).

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