#### **Working memory performance in adverse environments: Enhanced, impaired, or intact?**

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# Data Availability

All scripts and materials needed to reproduce the findings are available on the article’s Github repository (<https://github.com/stefanvermeent/liss-wm-profiles-2023/README.md>). We also include instructions on how to reproduce each step of our analyses. In this paper, we make use of data from the LISS panel (Longitudinal Internet studies for the Social Sciences) managed by the non-profit research institute Centerdata (Tilburg University, the Netherlands). All datasets are available in the LISS data archive. Researchers who want to access the data are required to sign a statement confirming that information about individual persons, households, etc., will not be released to others (Go to <https://statements.centerdata.nl> for more information).

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# Disclosures

We declare no conflicts of interest.

# Ethics Approval Statement

This study was approved by the Ethics Review Board of the Faculty of Social & Behavioural Sciences of Utrecht University (FETC20-490) and the Ethics committee for research in the Sciences and Life Sciences of the University of Amsterdam (FNWI-41\_2023).

# Proposal abstract

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# Working memory performance in adverse environments: Enhanced, impaired, or intact?

Living in adverse conditions, with prolonged exposure to intense stress, tends to have a substantial impact on cognitive functioning. A domain that seems to be particularly affected by adversity is working memory (WM), a system for mentally building, maintaining, and updating immediately relevant information (Oberauer et al., 2018). WM is associated with a host of social and cognitive abilities, such as mathematics ability (Peng & Fuchs, 2016), reading ability (Chiappe et al., 2000), learning (Cowan, 2014), general intelligence (Conway et al., 2003), and mentalizing (Mutter et al., 2006). Not surprisingly, then, deficits in WM have negative consequences for educational and professional outcomes (Ahmed et al., 2018; Alloway & Alloway, 2010; Guo et al., 2020; Spiegel et al., 2021). Although decades of research show that adversity is generally negatively associated with WM (Goodman et al., 2019), a small, emerging literature suggests that specific aspects of WM might be intact or even enhanced through developmental adaptations to adversity. So far, these literatures have tended to focus on related, but different aspects of WM, limiting a fuller integration. Here, we take a psychometric modeling approach to simultaneously examine potential decreases and enhancements in WM performance.

# Deficit-based and adaptation-based models

A large literature has shown negative associations between exposures to adversity and WM, potentially attributable to the enduring influence of stress on several key brain regions that support WM (Duval et al., 2017; Hanson et al., 2012). Although not always mentioned explicitly, much of this work has focused on WM capacity, or the ability to keep multiple pieces of information simultaneously available for further processing. For early-life adversity, this negative association is already present during childhood, and persists into adulthood (Bos et al., 2009; Evans & Schamberg, 2009; Farah et al., 2006; Goodman et al., 2019; Hackman et al., 2010; Noble et al., 2007; but see Nweze et al., 2021). Other studies have found a similar link between recent adverse experiences and lowered WM capacity in college student samples (Klein & Boals, 2001; Shields et al., 2019, 2017). The most often used tasks have been simple span tasks (repeating a string of stimuli of increasing length), complex span tasks (remembering a string of stimuli while being engaged by a secondary task), and *n*-back tasks (judging whether the current stimulus in a string is identical to the stimulus *n* steps ago) (Goodman et al., 2019). Performance on these tasks is assessed through the number of items that can be retained in WM, that is, its overall capacity (with the exception of *n*-back; for concerns about the construct validity of this task, see Frost et al., 2021; Kane et al., 2007). Other research has shown that recent life stress is negatively associated with WM capacity, but not the precision of representations in WM (Shields et al., 2019).

Although both early-life and recent adversity appear to lower WM capacity, a small set of studies suggest that exposure to adversity may leave intact, or even enhance, WM updating (i.e., the ability to rapidly replace old information in WM with new information) (Young et al., 2018, 2022). These findings exemplify an emerging, theoretical framework grounded in adaptation reasoning that is complementary to deficit frameworks (Ellis et al., 2017, 2022; Frankenhuis et al., 2020; Frankenhuis & Weerth, 2013). This adaptation framework assumes that developmental processes tailor an individual’s cognitive abilities to the unique challenges and opportunities posed by their environment. The link between adversity and cognitive abilities is further assumed to be specific; as different types of adversity (e.g., threat vs. deprivation) pose different challenges, they should (at least in part) shape different cognitive abilities. WM updating has been argued to be especially adaptive in environments that are unpredictable, which can be defined as random variation in harshness over space or time (Ellis et al., 2009). In such environments, WM updating allows people to maintain an up-to-date overview of the current state of the environment (Young et al., 2018). Improved WM updating performance has also been documented for threat exposure (Young et al., 2022), and unpredictability might particularly shape cognition in circumstances of high deprivation, such as lower-resource contexts like poverty (Li et al., 2018).

# Associations between WM capacity and updating

With deficit frameworks mainly focusing on WM capacity and adaptation frameworks on WM updating, we may wonder how these WM components are related to each other. Research to date has demonstrated substantial overlap between capacity and updating tasks using structural equation modeling (SEM). For example, correlations between latent capacity and updating factors can be high, to the extent that both complex span and updating paradigms are seen by some as valid measures of WM capacity (Wilhelm et al., 2013). In fact, some research suggests that the amount of updating-specific variance on typical updating tasks might be as low as 15% (Frischkorn et al., 2022). This overlap might stem from the fact that both WM updating and capacity tasks require maintaining information in WM for a short time (Ecker et al., 2010; Frischkorn et al., 2022; Oberauer et al., 2000; Schmiedek et al., 2009; Wilhelm et al., 2013).

Nevertheless, updating tasks might involve processes other than maintenance that set them apart from WM capacity tasks. Updating tasks require different combinations of retrieval (making information available for immediate processing), transformation (changing a prior value into a new one, e.g., by addition or subtraction), and substitution (replacing a prior value for a new value) (Ecker et al., 2010). Ecker et al. (2010) measured three indicators of WM capacity as well as eight versions of a WM updating task that required different combinations of retrieval, transformation, and substitution. They found positive correlations of around .50 between WM capacity with retrieval and transformation accuracy, whereas substitution accuracy was not correlated with WM capacity. Thus, the ability to accurately substitute old with new information—a key aspect of WM updating—seems to be independent from WM capacity.

These findings underscore the importance of accounting for WM capacity when assessing a person’s WM updating ability. This is especially important in the context of adversity research, as previous studies suggest that certain types of adverse conditions might have opposing effects on WM capacity and updating (e.g., Goodman et al., 2019; Young et al., 2018, 2022). Yet, to our knowledge, no previous research has analyzed both abilities within a single statistical model. This could lead us to underestimate—or altogether miss—ways in which adversity enhances WM components, with implications for basic and applied science. For basic science, it could bias inferences about WM abilities, especially when the negative association between adversity and WM capacity is stronger than the positive association with WM updating. For applied science, it could hide from view potential pathways to leverage people’s existing strengths in school or work contexts.

# Current study

In this study, we will estimate associations between three types of adversity exposure and latent estimates of WM capacity and updating. Specifically, we will measure exposure to two forms of harshness: *neighborhood threat* (perceived neighborhood safety, personal crime victimization), and *material deprivation* (perceived scarcity, income-to-needs). We further include a measure of unpredictability *unpredictability*, indexed as random variation in deprivation-induced harshness over time. Together, these adversity types capture key dimensions in contemporary models of adversity (threat vs. deprivation vs. unpredictability; Ellis et al., 2009, 2022; McLaughlin et al., 2019; McLaughlin & Sheridan, 2016). Although it would have also been theoretically interesting to look at unpredictability in neighborhood threat, our dataset does not include enough timepoints to compute such estimates. We will address three research questions. First, what is the association of adversity with WM capacity? Second, what is the association of adversity with WM updating *after* accounting for WM capacity? Third, are these two associations similar or different for neighborhood threat, material deprivation, and unpredictability?

Theoretically, we will evaluate evidence for deficit and adaptation frameworks. Figure 1 summarizes which combinations of lowered, enhanced, and intact WM capacity and updating performance would provide support for deficit and adaptation frameworks. Crucially, we assume that deficit and adaptation processes can operate simultaneously (Frankenhuis et al., 2020), meaning that we could find (lack of) support for both frameworks in the same model. A hypothesis generated within a deficit framework would be consistent with lowered performance on WM capacity or updating, but not with enhanced or intact performance. This follows from previous literature hypothesizing broad WM deficits (Farah et al., 2006; Sheridan et al., 2020). A hypothesis generated within an adaptation framework would be consistent with two different patterns. First, if performance on WM updating is enhanced. Second, if performance on WM updating is intact, but only in combination with lowered WM capacity performance. If both updating and capacity are intact, this would instead suggest that the WM system is unaffected by adversity (i.e., neither impairment nor adaptation processes have shaped WM).

Figure 1B depicts the theoretical possibilities in relation to deficit or adaptation frameworks (as formalized in Figure 1A) and how we hypothesize them to be linked to threat, material deprivation, and unpredictability. First, we expect that all three, and in particular material deprivation, will be associated with deficits in WM capacity, consistent with literature showing that deprivation is most strongly associated with cognitive deficits (Salhi et al., 2021; Sheridan et al., 2020). In this literature, most studies have focused on cognitive deprivation, which is not identical to material deprivation (as measured here). However, both are related to a person’s access to stimulating resources (e.g., formal education, books; Heppt et al. (2022)). Most research has focused on children, so it is unclear whether and how cognitive and material deprivation affects cognitive outcomes in adults.

In contrast, we expect adaptations in WM updating to be most strongly associated with unpredictability (Young et al., 2018, 2022), as well as with threat (in line with existing empirical findings; Young et al., 2022). In addition, we expect an interaction between unpredictability and mean levels of deprivation, such that WM updating shows the highest increase under conditions of high material deprivation *and* high unpredictability. Unpredictability is challenging to define, and has been measured in many different ways, ranging from number of residential changes, to perceived inconsistencies in household routines, to random variation in income (Ugarte & Hastings, 2023; Walasek et al., 2023; Young et al., 2020).

One issue is that timescales of unpredictability measures may not always align with those of the cognitive abilities that are assumed to be shaped by them. For example, while residential changes occur on timescales of months or years, WM updating constitutes a process unfolding on the timescale of seconds to minutes. However, we expect that our measure of unpredictability (random variation in perceived resource scarcity and income-to-needs based on yearly measures) is a proxy for everyday situations that require rapid updating of information in WM. For example, yearly fluctuations in material deprivation, especially for someone living close to the poverty line, could reflect many everyday instances in which the person needs to update information about their current financial state in order to meet basic needs (e.g., because of an unpredictable income, or unforeseen costs or debts, that constrain everyday decisions like how much to spend on groceries).

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| **Figure 1.** Overview of predictions derived from deficit and adaptation frameworks. Panel A depicts the most likely data patterns based on previous literature, and whether we would consider them consistent with deficit and adaptation frameworks (see the main text for more details). Panel B depicts an overview of the Structural Equation Model, including predictions for associations between different dimensions of adversity and WM components. All four manifest WM measures load on a latent WM capacity factor, reflecting the fact that people have to hold information active in WM on all tasks. WM updating is modeled as a latent factor capturing the residual variance in the updating task after accounting for variance related to WM capacity. |

# Methods

## Participants

We collected data in the Longitudinal Internet studies for the Social Sciences (LISS) panel (Scherpenzeel, 2011). The LISS panel is a representative probability sample of roughly 5,000 Dutch households (~7,500 individuals) drawn from the population register by Statistics Netherlands on an invite-only basis. Households without a computer or internet connection are provided with these facilities by LISS. Participants complete a yearly core battery of questionnaires about various aspects of their lives. In addition, participants can complete online questionnaires every month, which are more variable. The current study includes archived data as well as new data collected as part of a monthly data collection that took place between October 2nd and December 22nd, 2023. We signed a contract with LISS stipulating that we will receive access to the data only after Stage 1 acceptance of the Registered Report.

We based our power analysis on simulations reported by Kretzschmar & Gignac (2019), determining the required sample size to detect a small effect size ( = 0.1) with at least 90% power at = 0.05. Assuming a reliability of at least 0.7 (which is typical for WM tasks with a number of trials similar to ours; e.g., Wilhelm et al., 2013), we would require a sample size of N = 730. Anticipating some exclusions, we therefore decided to include 800 participants. Participants were eligible for inclusion if they 1) were currently between 18 and 55 years old, 2) had completed at least one wave of the ‘Conventional and computer crime victimization’ survey (<https://doi.org/10.17026/dans-zch-j8xt>) which ran between 2008 and 2018 at two-year intervals, and 3) had given permission to link their LISS data to government microdata (not relevant here). To ensure sufficient representation of people from lower socioeconomic backgrounds, half the total sample was sampled from participants who reported one or more of the following at least once in the three years: (1) a monthly income < €1,500, (2) HAVO or VWO as highest completed education (which are the two highest levels in Dutch secondary education), or (3) a score of 4 or lower on the ‘ladder of life’ (“If you imagine a ‘ladder of life’, where the first step represents the worst possible life, and the tenth (top) step the best possible life, on what step would you place yourself?”). Participants will be excluded if they (1) switched to and interacted with other browser tabls *during* one or more of the cognitive tasks, except when this happened in between tasks or during a scheduled break, (2)

## Measures

### Neighborhood threat

**Neighborhood crime.** We included four items from existing LISS data collected across six waves (<https://doi.org/10.17026/dans-zch-j8xt>), in which participants answered how often it happens that they 1) “avoid certain areas in your place of residence because you perceive them as unsafe”, 2) “do not respond to a call at the door because you feel that it is unsafe”, 3) “leave valuable items at home to avoid theft or robbery in the street?”, 4) “make a detour, by car or on foot, to avoid unsafe areas?” on a scale of 1 (“(Almost) never”), 2 (“Sometimes”), or 3 (“Often”). We will recode these items so that 0 indicates “(Almost) never”. We then sum the responses within each wave for which participants have data, and calculate an average across the waves.

In addition, we will use the Neighborhood Violence Scale (Frankenhuis et al., 2020; NVS; Frankenhuis & Bijlstra, 2018) which was included in the current study. The NVS includes seven items measuring perceived exposure to neighborhood violence (e.g., “Crime is common in the neighborhood where I live”; “Where I live, it is important to be able to defend yourself against physical harm”). Participants answered these questions on a scale of 1 (“Completely disagree”) to 7 (“Completely agree”).

**Crime victimization.** We used existing LISS data collected across six waves (<https://doi.org/10.17026/dans-zch-j8xt>), in which participants indicated whether they fell victim to eight types of crime over the two years prior to a particular wave. We included seven items concerning physical crime: 1) burglary or attempted burglary; 2) theft from their car; 3) theft of their wallet or purse, handbag, or other personal possession; 4) wreckage of their car or other private property; 5) intimidation by any other means; 6) maltreatment of such serious nature that it required medical attention; 7) maltreatment that did not require medical attention. For each type of crime that participants indicated having been exposed to, they also indicated the frequency. We will average the frequencies for each type of crime separately across waves for which participants have data.

**Overall composite.** To compute an overall measure of neighborhood threat exposure, we will submit the averages of each measure (the two measures of neighborhood crime and average frequencies of each crime exposure) to a Principal Component Analysis (PCA). We will extract a single factor score that explains the largest part of the variance. Higher scores will indicate higher levels of neighborhood threat.

### Material deprivation

**Perceived scarcity.** We will use a few items from LISS data that was collected on a yearly basis between 2007 and 2023 (<https://doi.org/10.57990/1gr4-bf42>) to index perceived scarcity. First, participants indicated how hard or easy it currently is to live off the income of their household, on a scale of 0 (very hard) to 10 (very easy). Second, participants were asked to choose which of the following best applied to their current situation: 1) “we are accumulating debt”; 2) “we are somewhat eating into savings”; 3) “we are just managing to make ends meet”; 4) “we have a little bit of money to spare”; 5) “we have a lot of money to spare”. Their response was reverse-coded, so that a higher score indicated a worse financial situation. Third, participants answered which of the following issues they were confronted with at present (0 = no, 1 = yes): 1) “having trouble making ends meet”; 2) unable to quickly replace things that break”; 3) “having to lend money for necessary expenditures”; 4) “running behind in paying rent/mortgage or general utilities”; 5) “debt collector/bailiff at the door in the last month”; 6) “received financial support from family or friends in the last month”. Fourth, participants answered whether their household expenditure was more than, equal to, or less than their household income over the last 12 months, not counting large investments (e.g., buying a house). We will dummy-code this variable, using expenditure lower than income as the reference category.

**Income-to-needs.** We will calculate a household income-to-needs ratio for each year using monthly self-reported net household income (<https://doi.org/10.57990/qn3k-as78>). First, we average monthly reported income across years for each participant. Then, we divide the average income per year by the *poverty threshold*, as determined by Statistics Netherlands (CBS) (Brakel et al., 2023). The poverty threshold changes across time to account for purchasing power. In addition, different thresholds are determined each year for different household compositions (single adult vs (married) couple and number of children (up to three)) by multiplying the threshold of a single-person household without children with a particular equivalence factor. As thresholds are only provided for households with up to three children, we will use the equivalence factor of a household with three children for households with more than three children. Likewise, we will use the equivalence factor of a household with a (married) couple for households with more than two adults that are not children.

**Overall composite.** Similar to neighborhood threat, we will use PCA to extract a single estimate of material deprivation measured by perceived scarcity and income-to-needs. In contrast to neighborhood threat, we will apply the PCA to the most recent data (2023) and use the resulting weights to compute material deprivation scores for previous years. This approach will allow us to compute both the mean level of material deprivation, as well as random variation in material deprivation over time. If a participant has partial data for a particular year, we will use multiple imputation to impute the value using the *mice* package (Buuren & Groothuis-Oudshoorn, 2011). We will not impute data for years where a participant has missings on all indicators. We will compute within-subject averages of material deprivation across all years for which participants data available.

### Unpredictability

**Overall composite.** Unpredictability will be based on the same PCA as used for material deprivation, involving the same indicators. we operationalize unpredictability as within-person variability in material deprivation over time (Ugarte & Hastings, 2023; Young et al., 2020). Specifically, we will compute unpredictability by dividing the within-subject standard deviation of material deprivation by the within-subject mean-level of material deprivation. Dividing by the mean accounts for the fact that the mean and standard deviation in income have been found to be strongly negatively correlated, indicating that people with lower incomes tend to experience less variability in income (Li et al., 2018; Young et al., n.d.). For that reason, the standard deviation alone has been called into question as a measure of adversity, as the same fluctuation in income can have a greater relative impact for people close to the poverty line than for people with high incomes.

### WM tasks

All materials and scripts for the cognitive tasks can be found at <https://github.com/StefanVermeent/liss_wm_profiles_2023/tree/master/materials>. Prior to collecting LISS data, we conducted a pilot study through Prolific in a Dutch sample of N = 100. The main goals of this pilot study were to collect participant feedback (e.g., difficulty of instructions, whether we included sufficient breaks) and to analyze performance and correlations between tasks. The results of this pilot study are described in more detail in the Supplemental Materials.

**Operation Span Task.** The Operation Span Task (Figure 2A) is a common measure of WM capacity (Conway et al., 2005; Wilhelm et al., 2013). In this task, participants alternated between a primary memorization task and a secondary processing task. On each trial, participant’s task was to memorize a sequence of letters in the correct order (from a set of 12 letters). Each letter was presented for 1,000 ms in the center of the screen. Next, participants saw a simple mathematical equation including the outcome. Their task was to indicate whether the outcome was correct or incorrect by pressing either the ‘a’ or ‘l’ key on their keyboard. The equations always contained one addition or subtraction, with numbers ranging between one and 10. Outcomes were always positive integers. On each trial, participants had to memorize between four and six letters, with each set size repeated three times. At the end of each sequence, all letters were presented in a 3X4 grid, and participants clicked the letters in the correct order.

Participants first practiced the letter task (three times), then the math task (eight times), and then the full task (three times). If they performed at or below chance, they had the opportunity to either repeat a part or advance to the next part. After practicing, participants completed 12 test trials.

**Rotation Span Task.** The Rotation Span Task (Figure 2B) was similar to the Operation Span Task and was adopted from Wilhelm et al. (2013). On each trial, participants’ task was to memorize the orientation of a sequence of arrows in the correct order. Arrows could take on eight different orientations, with steps of 45. Each arrow was presented for 1,000 ms in the center of the screen. Next, participants saw a capital ‘G’ or ‘F’ that was rotated at one of eight different orientations, with steps of 45. Their task was to indicate whether the letter was mirrored or not. On each trial, participants had to memorize between two and five arrows, with each set size repeated three times. At the end of each sequence, all arrows were presented simultaneously, and participants clicked the arrows in the correct order.

Participants first practiced the arrow task (three times), then the letter task (eight times), and then the full task (three times). If they performed at or below chance, they had the opportunity to either repeat a part or advance to the next part. After practicing, participants completed 12 test trials.

**Binding-Updating Task.** The Binding-Updating task (Figure 2C) was adopted from [XXX]. On each trial, participants saw a 3x3 grid, with a fixation cross in the central cell. After 1,000 ms, they were presented with a sequence of numbers (0-9) in random locations of the grid. Each new number was presented for 1,500 ms, after which it disappeared for 500 ms before the next number was presented. The participants’ task was to remember the last number they saw in each location. Memory set sizes (i.e., the number of unique locations in the grid) ranged between three and five. On half of the trials, only one number was presented in each location. These constituted the binding-only trials. On the other half of the trials, some letters were presented in the same location as previous numbers, requiring mentally replacing the old number with the new number. These constituted the updating trials. We used two, three, and four updating steps, each repeated in combination with the different set sizes. At the end of the trials, participants indicated which letter they saw last in each location in random order.

Participants first completed four practice trials. If they performed at or below chance, they had the opportunity to either repeat the practice trials or advance to the full task. After practicing, they completed 18 test trials. We will compute a binding score by calculating the overall accuracy (%) across trials with zero updating steps. We will compute an updating score by calculating the overall accuracy (%) across trials containing updating steps.

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| **Figure 2.** Overview of the working memory tasks. Panel A: Operation Span Task. Participants had to memorize letters in the correct order, while engaging in a secondary math task. Panel B: Rotation Span Task. Participants had to memorize the orientation of arrows, while judging whether letters were mirrored or normal in a secondary task. Panel C: Participants had to memorize numbers in the correct location in a 3x3 grid. On half of the trials, all numbers were presented in unique locations, only requiring binding the numbers to the correct position. On the other half, some numbers were presented in the same location as a previously presented number, requiring updating. Note that stimuli are not to scale. |

## Procedure

We received ethical approval from the first institutions ethical board. Upon starting the study, participants were informed that the study could only be completed on a laptop or desktop PC. Participants started with the WM tasks, which on average took between 20 and 25 minutes. The WM tasks were completed in fullscreen mode. If participants left fullscreen mode at any moment during the tasks, they saw instructions at the top of their screen that allowed them to return to fullscreen mode. the order of the WM tasks was counterbalanced, and participants had the opportunity to take breaks at regular intervals.

After the cognitive tasks, participants answered three questions about the environment in which they completed the WM tasks: 1) “How much noise was there in your environment during the memory tasks?”; 2) “Were you at any moment interrupted during the memory tasks?”; 3) “Did you at any moment during the memory tasks leave the computer?”. Next, they completed questionnaires about their future orientation (not considered here), personality (not considered here), past adversity exposure, and recent adversity exposure. Finally, they completed a standard set of evaluation questions asking about their experiences with the study, with the possibility to provide open-ended feedback. This part on average took 5 minutes. Participants received €7.50 for their participation through LISS. If participants experienced difficulties of any sort, they could contact the LISS helpdesk.

## Proposed analysis plan

### Data access

The working memory data and one of the neighborhood threat indices were collected through October-December 2023, prior to submitting the Stage 1 protocol. These data will only be made available to the first author after Stage 1 acceptance, as stipulated in a signed contract with LISS. During planning of the study, the first author received access to the LISS data archive and inspected three waves of the LISS data containing the items about neighborhood safety and crime exposure, as well as the three most recent monthly data collections containing basic demographic info. The reason was to discover how many people who completed the waves a few years back were still active in the panel (i.e., to see if we could reasonably create a link between these previous waves and newly collected data). All data access events were automatically detected and logged on the GitHub repository using the ‘projectlog’ R package (Vermeent, 2023). We took the following measures to prevent bias: 1) we randomly shuffled the participant IDs in each data set using ‘projectlog’, so that we were unable to link participant data between (waves of) studies; 2) we did not inspect any of the measures that will be part of our adversity composites; 3) we did not know which participants would be selected for the new LISS study; 4) the primary analyses will be based on composite measures that combine measures from these previous studies with data that were collected at a later timepoint.

### Primary analyses

See Figure 1B for an overview of the model specification. We will fit a single model containing all adversity measures using the *lavaan* package (Rosseel, 2012). Missing data will be handled using full information maximum likelihood (FIML). If participants are from the same household, this clustering within families will be accounted for using the *lavaan.survey* package (Oberski, 2014).

WM capacity will be estimated as a latent factor loading on all outcome measures. In addition, we will estimate WM updating as a latent factor capturing residual variance in the updating measure. Thus, this factor accounts for updating-specific variance after accounting for WM capacity. We will estimate the effect of each adversity type (dashed lines in Figure 1B) through regression analyses. Each association is controlled for: (1) age in years ; (2) the quadratic effect of age; (2) environmental noise (“How noisy was your environment during the memory tasks”, rated on a scale of 1 (very little noise) to 5 (a lot of noise)); (3) two items measuring interruptions (“Where you at any moment interrupted during the memory tasks?” and “Did you at any moment during the memory tasks leave your computer?”, rated as yes or no). Goodness of fit will be assessed using the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). CFI values > .90 and RMSEA values < .08 will be interpreted as acceptable model fit, and CFI values > .95 and RMSEA values ≤ .06 as good model fit.

We anticipate that we may have to optimize the model further in case of bad model fit, and will therefore estimate the model in two steps to prevent bias. First, we will construct the measurement model only, without including the adversity measures. This step will be carried out prior to accessing any of the adversity measures. Once we obtain at least acceptable model fit, we will access and add the adversity measures to the model. This procedure will be tracked and timestamped on the GitHub repository using the procedure outlined above. We will control for multiple testing using the false discovery rate (Benjamini & Hochberg, 1995; Cribbie, 2007). We will use two one-sided tests (TOST) equivalence testing to test whether small effects—which we define as standardized effects between -.10 and .10—are practically equivalent, which we will interpret as evidence for intact performance.

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