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://stefanvermeent.github.io/liss_wm_profiles_2023/). We also include
instructions on how to reproduce each step of our analyses, as well as simulated data to ensure
computational reproducibility. 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).

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

Decades of research have shown that adversity tends to be associated with lower working memory (WM) performance. This literature has mainly focused on impairments in the capacity to hold information available in WM for further processing. However, some recent adaptation-based studies suggest that certain types of adversity can leave intact, or even enhance, the ability to rapidly update information in WM. One key challenge is that WM capacity and updating tasks tend to covary. This is likely due to the fact that both types of tasks require the creation and maintenance of bindings in WM; links between mental representations of information in WM. To estimate the associations between adversity and different processes in WM, we need to isolate variance in performance related to WM capacity from variance in performance related to updating ability. In this Registered Report, we combine archived and newly collected data in the Dutch Longitudinal Internet studies for the Social Sciences (LISS) panel, which includes a representative sample of the Dutch adult population. Participants completed three WM tasks: two complex span tasks and a task measuring both binding and updating of information. In addition, we will estimate participants' exposure to neighborhood threat, material deprivation, and unpredictability. Using structural equation modeling, we will estimate associations between the three types of adversity and latent estimates of WM capacity and updating. These findings will advance our theoretical understanding of how adversity is associated with WM, which will aid interventions aimed at alleviating performance difficulties and leveraging areas of strength.

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Living in adverse conditions, with prolonged exposure to intense stress, tends to have a profound and enduring impact on cognitive functioning (Farah et al., 2006; Sheridan et al., 2022; Sheridan & McLaughlin, 2014). Although adversity can be described in many ways, we follow contemporary models focusing on threat, deprivation, and unpredictability as key dimensions of adversity (Ellis et al., 2009, 2022; McLaughlin et al., 2021; McLaughlin & Sheridan, 2016). A domain that seems to be particularly affected by adversity is working memory (WM). WM is a system for mentally building, maintaining, and updating immediately relevant information (Oberauer et al., 2018). Performance on WM tasks is associated with a host of social and cognitive abilities, such as math (Peng & Fuchs, 2016), reading (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 both educational and professional outcomes (Ahmed et al., 2018; Alloway & Alloway, 2010; Guo et al., 2020; Spiegel et al., 2021). Decades of research show that adversity is generally negatively associated with performance on WM tasks (Goodman et al., 2019). However, emerging evidence suggests that specific aspects of WM might remain intact or even be enhanced through developmental adaptations to adversity. So far, the literature has tended to focus on related, but different aspects of WM in isolation, limiting a fuller integration. Here, we take a psychometric modeling approach to simultaneously examine potential decreases and enhancements in two WM components: capacity and updating.

Deficit-based and adaptation-based models

A large literature has shown negative associations between exposures to adversity and performance on WM tasks (Farah et al., 2006; Sheridan et al., 2022; Sheridan & McLaughlin,

2014). These associations may be potentially attributable to the enduring influence of stress on

several key brain regions that support WM (Duval et al., 2017; Hanson et al., 2012). 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). Studies with college students have found a link between both

recent and lifetime experiences of stressful major life events (discrete negative events that have a

clear onset and offset, unlike chronic adversity) with lowered WM capacity (Klein & Boals,

2001; Shields et al., 2019, 2017).

The most common tasks used to examine the negative association between adversity and

WM are 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

participants can retain in WM, that is, their 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).

Although both early-life and recent adversity appear to be negatively associated with

WM capacity, a small set of studies suggest that exposure to adversity may leave intact, or even

enhance, the ability to update items in WM in adolescents (Young et al., 2022) and adults

(Young et al., 2018). Updating is defined as the ability to rapidly replace old information in WM

with new information. The finding that updating may be left intact or even enhanced after

exposure to adversity exemplifies emerging theoretical frameworks grounded in adaptive

reasoning that are complementary to deficit frameworks (Ellis et al., 2017, 2022; Frankenhuis et al., 2020; Frankenhuis & Weerth, 2013).

Adaptation-based theories assume 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 cognitive abilities in different ways. For example, with regards to executive functioning, some previous studies have found that children and adults with more exposure to unpredictability (characterized by random variation in adversity exposure over space or time) and threat tend to be better at rapidly shifting their attention between tasks (Fields et al., 2021; Mittal et al., 2015; Steudte-Schmiedgen et al., 2014; Young et al., 2022; but see Nweze et al., 2021). WM updating may be especially adaptive in unpredictable environments. WM updating allows people to maintain an up-to-date overview of the (changing) current state of the environment (Young et al., 2018). Additionally, improved WM updating performance has also been documented for threat exposure (Young et al., 2022). An enhanced WM updating ability could facilitate keeping track of and integrating signals that may potentially signal acutely threatening situations.

Associations between WM capacity and updating

With deficit theories focusing on WM capacity and adaptation-based theories on WM updating, we may wonder how capacity and updating are related to each other. Performance on tasks measuring WM capacity and updating tend to be substantially correlated (in the range of .20-.50; Frischkorn et al., 2022; Löffler et al., 2022). This overlap appears to stem from shared demands of both types of tasks, in particular the need to create and maintain arbitrary bindings (Gruszka & Nęcka, 2017; Oberauer, 2009; Wilhelm et al., 2013). The term *binding* refers to the

process of mapping memory items to specific positions in WM (e.g., serial, spatial, or temporal positions, depending on the task) (Oberauer, 2009, 2019). For example, on most WM tasks, correct recall of memory items depends on remembering them in their correct serial position, or in relation to the location where they were presented.

The centrality of binding in WM is supported by theoretical models of WM and by empirical work showing that (latent) WM capacity is strongly related to the ability to maintain bindings (Oberauer et al., 2000; Oberauer, 2005, 2009, 2019; Wilhelm et al., 2013). The number of bindings a person can create and maintain in WM might be the main limiting factor in WM capacity, as maintaining several bindings at the same time will increasingly lead to interference between them (Gruszka & Nęcka, 2017; Oberauer, 2009; Wilhelm et al., 2013). This upper limit on WM capacity also affects performance on WM updating tasks. That is, updating items in WM requires not just dissolving old bindings and creating new ones, but also maintaining bindings of items that should not be updated. Thus, the overlap in performance on WM updating and capacity tasks likely stems from the need in both types of tasks to create and maintain bindings in WM (Ecker et al., 2010; Frischkorn et al., 2022; Oberauer et al., 2000; Schmiedek et al., 2009; Wilhelm et al., 2013).

Nevertheless, WM updating tasks additionally require the updating of established bindings, which sets them apart from WM capacity tasks (Ecker et al., 2010; Frischkorn et al., 2022). Different 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) included three measures of WM capacity as well as eight versions of a WM updating measure that required different combinations of retrieval, transformation, and

substitution. After accounting for overall updating accuracy (which was positively correlated with WM capacity), they found positive correlations of around .50 between WM capacity with latent estimates of retrieval and transformation accuracy, but not with a latent estimate of substitution accuracy. Thus, when the ability to accurately substitute old with new information—a key aspect of WM updating—is sufficiently isolated from WM capacity using latent modeling, capacity and updating seem to be independent components of WM.

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 to (1) an underestimation of the extent to which adversity undermines WM capacity, and (2) underestimation of the extent to which adversity can enhance WM updating. This, in turn, has implications for basic and applied science. For basic science, it could bias inferences about individual differences in performance on WM tasks, 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 latent estimates of WM capacity and updating with three types of adversity: threat, deprivation, and unpredictability. Together, these adversity types capture key dimensions in contemporary models of adversity (Ellis et al., 2009, 2022; McLaughlin et al., 2021; McLaughlin & Sheridan, 2016). Threat refers to experiences

involving the potential for harm imposed by others. We focus on perceived neighborhood violence, the extent to which an individual reports having been exposed to acts of violence in their neighborhood. Deprivation refers to having a low level of resources. We focus on perceived material deprivation, a (perceived) lack of access to material resources. Unpredictability refers to variation in material deprivation over time. This definition is inspired by, but deviates from the harshness-unpredictability framework, in which unpredictability is defined as stochastic variation in harshness (age-specific rates in morbidity and mortality) over space and time (Ellis et al., 2009, 2022). We will not calculate unpredictability in neighborhood threat given that participants have at most six timepoints, and often as few as one or two, which is insufficient to calculate variation over time (Walasek et al., 2024).

We will address three research questions. First, what is the association between adversity and WM capacity? Second, what is the association between adversity and WM updating *after* accounting for WM capacity? Third, are the directions and strengths of these associations similar or different for neighborhood threat, material deprivation, and unpredictability?

We will evaluate evidence for deficit- and adaptation-based frameworks (see Figure 1A for a visual summary, and Appendix 1 for the study design plan). Crucially, as deficit and adaptation processes can operate in concert (Frankenhuis et al., 2020), we could find support (or lack thereof) for both frameworks in the same model. We distinguish between three between-person data patterns: (1) lowered performance, (2) enhanced performance, and (3) intact performance. We define lowered performance as a statistically significant negative association between a type of adversity and WM capacity or updating (irrespective of effect size). We define enhanced performance as a statistically significant positive association between a type of adversity and WM capacity or updating (irrespective of effect size). We define intact

performance as an association between a type of adversity and WM capacity or updating that has

a standardized effect smaller than 0.1 *and* larger than -0.1—even if the effect is statistically

different from zero—which we will test using Two One-Sided T-Tests (TOST) equivalence

testing (see the 'Primary analyses' section; Lakens et al., 2018).

Deficit frameworks predict a negative association between all three types of adversity and

WM capacity as well as WM updating. This follows from the hypothesis that adversity leads to

broad WM deficits (Farah et al., 2006; Sheridan et al., 2020). Deficit frameworks are partially

supported if we find negative associations with only one (or two) types of adversity.

Within adaptation-based frameworks, theories make two predictions. First, if adaptive

processes enhance WM updating and there are no impairment processes operating, we can expect

a positive association between adversity and WM updating. Second, if, adaptive processes

operate in concert with general impairment processes, we can expect intact WM updating in

combination with lowered WM capacity. If neither impairment nor adaptative processes are

operating, we can expect both WM updating and capacity to be intact.

We also have two expectations based on prior studies. First, we expect the association

between material deprivation and WM capacity to be more negative than the associations with

unpredictability and neighborhood threat. This follows from findings showing that cognitive

abilities are more negatively associated with cognitive deprivation than threat (Salhi et al., 2021;

Sheridan et al., 2020). Although cognitive and material deprivation are distinct types of

deprivation, they tend to be correlated, and are both associated with limited access to resources

that stimulate cognitive development and functioning (Bradley et al., 2001; Lurie et al., 2024;

Rosen et al., 2019). Therefore, we expect that their associations with WM will have comparable

effect sizes. Second, researchers have hypothesized that WM updating is particularly adaptive in

unpredictable and threatening environments, as it facilitates keeping track of unpredictable

changes and sudden threats. Therefore, we expect WM updating to be associated with

unpredictability and neighborhood threat, but not with material deprivation (Young et al., 2018;

but see Young et al., 2022).
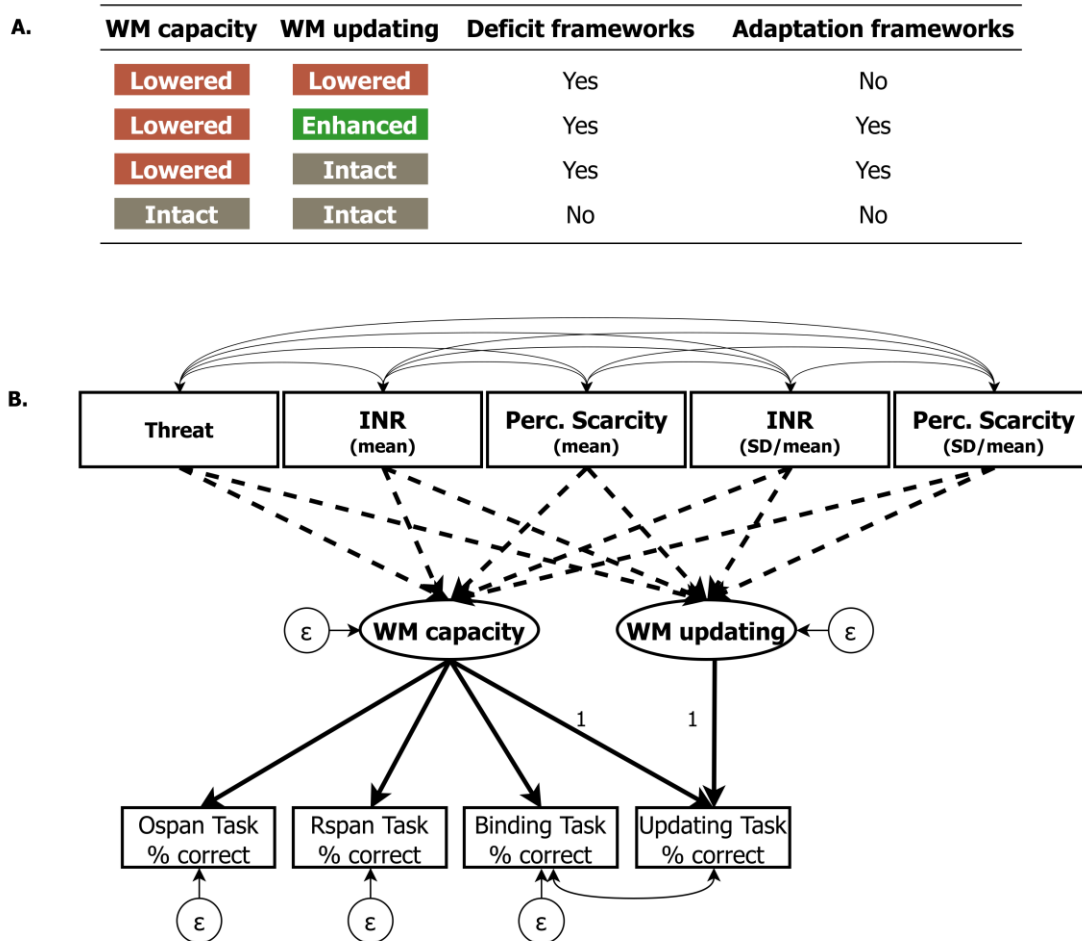
Figure 1. Overview of predictions derived from deficit and adaptation frameworks. Panel A depicts the most likely between-person data patterns based on previous literature, and whether we would consider them consistent with deficit and adaptation frameworks (see the main text for more details). Panel B depicts an overview of the Structural Equation Model. Ellipses represent latent variables, rectangles represent manifest variables, and circles represent residual variances. Unidirectional solid lines represent factor loadings, bidirectional solid lines represent covariances, and dashed lines represent regression paths. 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. We fix the loading of WM capacity on the Binding Task to 1, reflecting the idea that the ability to create and maintain bindings is the main limiting factor in WM capacity (Gruszka & Nęcka, 2017; Oberauer, 2009; Wilhelm et al., 2013). WM updating is modeled as a latent factor capturing the residual variance in the updating task after accounting for variance related to WM capacity. INR = income-to-needs ratio; Perc. Scarcity = perceived scarcity; SD = standard deviation.

Methods

Participants

Our study will include 800 participant who were randomly sampled from 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. Each year, participants complete the same core battery of questionnaires about—among other topics—their financial situation in the past year. In addition, participants can complete additional online questionnaires every month, with variable content. The current study integrates two data sources. First, our sample of 800 participants participated in a new LISS study between October 2023 and February 2024 (hereafter referred to as 'newly collected data'), in which we included a measure of neighborhood threat and multiple measures of working memory. Second, we will access data that were previously collected in LISS (hereafter referred to as 'the LISS archive'). See Figure 2 for a visual overview of the data sources and their measurement timepoints. We signed a contract with LISS stipulating that we will receive access to the newly collected data only after Stage 1 acceptance of this Registered Report.
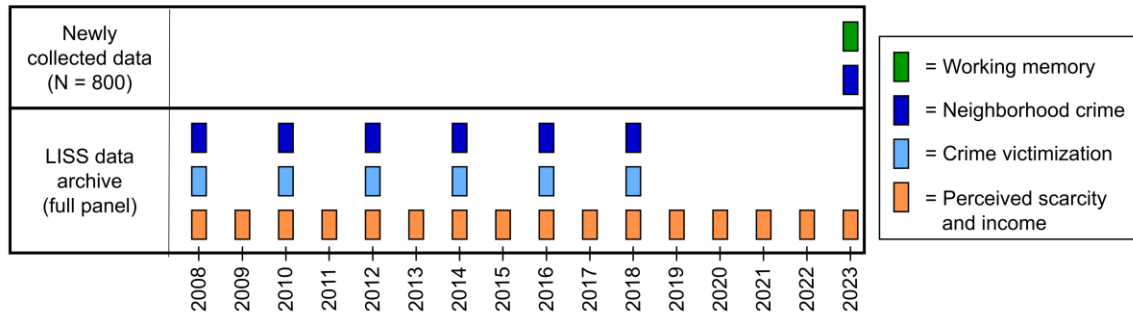
Figure 2.. Overview of the different data sources used in this study. We distinguish between measures taken from the LISS data archive and measures that were newly collected in our own study between October 2023 and February 2024. Perceived scarcity and income were collected yearly in the full panel from 2008 – 2023. Neighborhood crime and crime victimization were collected across six waves between 2008 and 2018. In the newly collected data, we collected data on a measure of neighborhood threat and multiple measures of working memory. Note that participants may not have data across all timepoints of the archived studies because they joined the LISS panel more recently or because they did not participate in each wave.

We based our power analysis on simulations reported by Kretzschmar & Gignac (2019),

determining the required sample size to detect a small effect size ($\beta = 0.1$) with at least 90%

power at $\alpha = 0.05$. 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 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 an archived longitudinal LISS study containing measures that we use to

operationalize crime neighborhood threat (see below), 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 tabs *during* one or more of the cognitive tasks, (2) did not perform above

chance level.

Measures

Neighborhood threat

  Perceived neighborhood crime. We included four items from the LISS archive 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 implemented the Neighborhood Violence Scale (Frankenhuis et al., 2020;

NVS; Frankenhuis & Bijlstra, 2018) in the newly collected data. 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"). We will compute an average of the seven items.

  Crime victimization. We used data from the LISS archive collected across six waves

(same dataset as above), in which participants indicated whether they fell victim to eight types of

crime over the two years prior to a particular wave (0 = no, 1 = yes). We included seven items

concerning exposure to 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.

We compute a variety score by summing the exposures to *unique* types of crime across all

waves. Thus, if a participants reports exposure to the same type of crime on separate waves, this

will count as one exposure in the total score (Sweeten, 2012).

Neighborhood threat composite. We will first compute an average across time for each

measure separately (i.e., the two measures of neighborhood crime and the measure of crime

victimization). If all correlations between averaged measures are equal to or larger than .60 (i.e.,

indicating a "strong" correlation), then we will compute a uniformly weighted average. If the

correlation is lower than .60, we will apply Principal Component Analysis (PCA) to the averaged

measures and extract only the first principal component score.

Material deprivation

We will measure material deprivation with two separate indicators: perceived scarcity

and the income-to-needs ratio.

Perceived scarcity (mean). We will use a few items from the LISS archive that were

collected on a yearly basis between 2008 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 from 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". Responses will be reverse-coded, so that higher scores indicate 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".

We will first compute the average across time for each item separately, and examine correlation between the item averages. We will follow the same guidelines as with neighborhood threat to determine if we will compute a uniformly weighted average or extract the first principal component using PCA.

Income-to-needs (mean). We will calculate an income-to-needs ratio for each year using monthly self-reported net household income from the LISS archive (https://doi.org/10.57990/qn3k-as78). Zero values in household income will be set to missing, as these could either indicate the lack of an income or an unwillingness to disclose the income. If monthly household income is missing (or zero) for an entire year for a participant, we will use, if available, the yearly net household income they reported in the LISS archive (https://doi.org/10.57990/1gr4-bf42), dividing it by 12 to obtain a monthly estimate. First, we will divide the average income per year by the *poverty threshold*, as determined by Statistics Netherlands (CBS) (Brakel et al., 2023; CBS, personal communication, December 15, 2023). As thresholds are only provided for households with up to three children, we will apply the threshold of a household with three children to households with more than three children. Likewise, we will apply the threshold of a household with two adults for households that contain

three or more adults. Second, we will calculate the average within-person income-to-needs ratio

for each year by averaging across the monthly income-to-needs estimates. We will reverse code

the yearly income-to-needs ratio so that higher scores indicate more deprivation.

Unpredictability

Perceived scarcity (SD/mean). This measure is based on the same items as outlined

above (see Perceived scarcity (mean)). We will compute unpredictability over time in perceived

scarcity using the coefficient of variation, which is the within-person standard deviation across

years divided by the mean (Key et al., 2017; Liu et al., 2022; Ugarte & Hastings, 2023; Walasek

et al., 2024; Young et al., 2020). 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.

To compute an overall measure of unpredictability in perceived scarcity, we will follow

the same procedure as with mean perceived scarcity, but based on the coefficient of variation.

Income-to-needs (SD/mean). Similar to perceived scarcity, we will compute

unpredictability over time in the income-to-needs ratio using the coefficient of variation.

WM tasks

The WM tasks were all part of the newly collected data. All materials and scripts for the

cognitive tasks can be found at

https://stefanvermeent.github.io/liss_wm_profiles_2023/materials/README.html. Prior to

collecting LISS data, we conducted a pilot study among in a Dutch sample (*N* = 100) through

Prolific Academic. 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

https://stefanvermeent.github.io/liss_wm_profiles_2023/supplement/README.html.

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 alternate

between a primary memorization task and a secondary processing task. On each trial, the task is

to memorize a sequence of letters in the correct order (from a set of 12 letters). Each letter is

presented for 1,000 ms in the center of the screen. Next, participants see a simple mathematical

equation including the outcome. Their task is to indicate whether the outcome is correct or

incorrect by pressing either the 'a' or 'l' key on their keyboard. The equations always contain

one addition or subtraction, with numbers ranging between one and 10. Outcomes are always

positive integers. On each trial, participants have to memorize between four and six letters, with

each set size repeated three times. At the end of each sequence, all letters are presented in a 3×4

grid, and participants click the letters in the correct order.

Participants first practice the letter task (three times), then the math task (eight times),

and then the full task (three times). If they perform at or below chance, they have the opportunity

to either repeat a part or advance to the next part. After practicing, participants complete 9 test

trials, with a total of 45 recall items and 45 math items. We will compute an operation span score

by calculating the proportion of letters recalled in the correct sequential position across trials
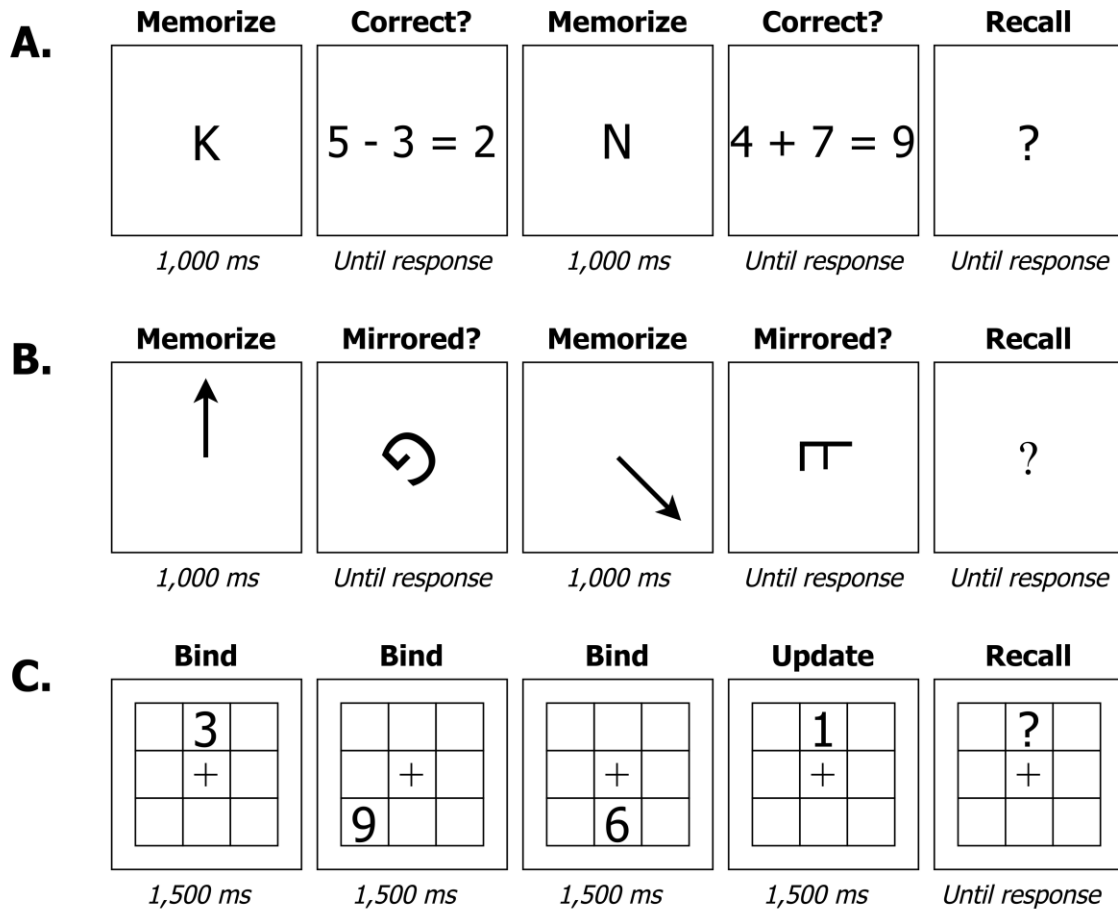
(Conway et al., 2005).

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

Participants first practice the arrow task (three times), then the letter task (eight times), and then the full task (three times). If they perform at or below chance, they have the opportunity to either repeat a part or to advance to the next part. After practicing, participants complete 12 test trials, with a total of 45 recall items and 45 letter items. We will compute a rotation span score by calculating the proportion of arrows recalled in the correct sequential position across trials (Conway et al., 2005).

Binding-Updating Task. The Binding-Updating task (Figure 2C) is adopted from Wilhelm et al. (2013). On each trial, participants see a 3×3 grid, with a fixation cross in the central cell. After 1,000 ms, they are presented with a sequence of numbers (0-9) in random locations of the grid. Each new number is presented for 1,500 ms, after which it disappears for 500 ms before the next number is presented. The task is to remember the last number they see in each location. Memory set sizes (i.e., the number of unique locations in the grid) ranges between three and five. On half of the trials, only one number is presented in each location. These constitute the binding trials. On the other half of the trials, some letters are presented in the same

location as previous numbers, requiring mentally replacing the old number with the new number. These constitute the updating trials. We use two, three, and four updating steps, each repeated in combination with the different set sizes. At the end of the trials, participants indicate which letter they saw last in each location in random order.

Participants first complete four practice trials. If they perform at or below chance, they have the opportunity to either repeat the practice trials or to advance to the actual task. After practicing, they complete 18 test trials, of which nine are binding-only (24 recall items in total) and nine are updating trials (24 recall items in total). We will compute a binding score by calculating the overall recall accuracy (%) across trials with zero updating steps. We will compute an updating score by calculating the overall recall accuracy (%) across trials with one or more updating steps.

A.

Memorize	Correct?	Memorize	Correct?	Recall
K	5 - 3 = 2	N	4 + 7 = 9	?
1,000 ms	*Until response*	*1,000 ms*	*Until response*	*Until response*

B.

Memorize	Mirrored?	Memorize	Mirrored?	Recall
↑	↺	↘	⊓	?
1,000 ms	*Until response*	*1,000 ms*	*Until response*	*Until response*

C.

Bind	Bind	Bind	Update	Recall
3 / +	+ / 9	+ / 6	1 / +	? / +
1,500 ms	*1,500 ms*	*1,500 ms*	*1,500 ms*	*Until response*

Figure 3. Overview of the working memory tasks. Panel A: Operation Span Task. Participants memorized letters in the correct order, while engaging in a secondary math task. Panel B: Rotation Span Task. Participants memorized the orientation of arrows, while judging whether letters were mirrored or normal in a secondary task. Panel C: Participants memorized numbers in the correct location in a 3×3 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: stimuli are not to scale.

Procedure

We received ethical approval from the first author's institutional ethical board. Upon starting the study, participants were informed that the study could only be completed on a laptop or desktop PC. If they attempted to start the study on a tablet or smartphone, they were unable to advance and prompted to switch to a suitable device. 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 accessed 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 purpose was to ascertain the number of individuals who had finished the

previous waves in the LISS data archive and were presently still participating in the panel (i.e., to

see if we could reasonably create a link between the LISS data archive 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 the *projectlog* R

package, so that we were unable to link participant data between (waves of) studies in the LISS

data archive; 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 newly collected

data; 4) the primary analyses will be based on composite measures that combine measures from

the LISS data archive with measures from the newly collected data.

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* R package (Rosseel, 2012). We will use

robust maximum likelihood estimation in case any variable is non-normally distributed. 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*

R 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 will be 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 (Hu &

Bentler, 1999).

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 of WM, 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).

To statistically test whether small effects are practically equivalent to zero—suggesting

intact performance—we will use Two One-Sided T-tests (TOST) equivalence testing (Lakens et

al., 2018), using -0.1 and 0.1 as equivalence bounds. TOST equivalence testing allows us to

conclude intact performance based on a significant effect, rather than erroneously interpreting a

non-significant effect as evidence for the absence of an effect. We consider any effect that falls

within this region to reflect practical equivalence, that is, a between-person difference in

performance that is practically equivalent to zero. TOST provides two *p*-values, one testing

against the upper bound and one testing against the lower bound; we will report only the largest

of the two *p*-values.

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    person?

Appendix I: Study Design Plan

Table S2. Study design plan.

Research question	Hypotheses	Sampling plan	Analysis plan	Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
1. what is the association between adversity and WM capacity?	Deficit frameworks predict a negative association between all three types of adversity and WM capacity as well as WM updating. This follows from the hypothesis that adversity leads to broad WM deficits. Deficit frameworks are partially supported if we find negative associations with only one (or two) types of adversity.	We are collecting data of 800 participants in the Dutch Longitudinal Internet studies for the Social Sciences (LISS) panel. First, we will use data that were previously collected in LISS. Second, we will use new data that we collected ourselves in LISS. Data collection started on October 2nd and is expected to be completed in February 2024. We signed a contract with LISS stipulating that we will receive access to the data only after Stage 1 acceptance of this Registered Report.

To ensure sufficient representation of people from lower socioeconomic backgrounds, roughly half the total sample will be sampled from | We will fit a single structural equation model (SEM) containing all adversity measures. We will use robust maximum likelihood estimation in case any variable is non-normally distributed. 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.

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. We will estimate the effect of each adversity type | We based our power analysis on simulations reported by Kretzschmar ad Gignac (2019), determining the required sample size to detect a small effect size ($\beta = 0.1$) with at least 90% power at $\alpha = 0.05$. 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 exclusions, we decided to include 800 participants. | Contrary to predictions of deficit perspectives, we might find that all associations between adversity and WM capacity are either practically equivalent or positive. This would suggest that WM capacity is either unaffected or even enhanced by adversity.

If we find both a non-significant association and practical non-equivalence, we will conclude that our data neither support nor refute either framework.

Contrary to predictions of adaptation-based perspectives, we might find that the association between adversity and WM updating is negative. This would suggest that WM updating is impaired by | Theoretically, our analyses directly compare evidence in favor of deficit and adaptation-based perspectives. Both are established frameworks generating predictions that extend to other cognitive abilities beyond WM. Therefore, the current study could neither confirm nor disconfirm the frameworks in general.

However, our findings could be (partially) inconsistent with predictions derived from both frameworks. Deviating findings for RQ1 or RQ 2 would require revising theoretical predictions about the specific WM abilities that are adapted to/impaired by adversity. |
| 2. what is the association between adversity and WM updating after accounting for WM capacity? | Within adaptation-based frameworks, theories make two predictions.

First, if adaptive processes enhance WM updating and there are no impairment processes operating, we | | | | | |

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Research question	Hypotheses	Sampling plan	Analysis plan	Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
	can expect a positive association between adversity and WM updating. Second, if, adaptive processes operate in concert with general impairment processes, we can expect intact WM updating in combination with lowered WM capacity. If neither impairment nor adaptative processes are operating, we can expect both WM updating and capacity to be intact.	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'	through regression analyses. Each association will be controlled for: (1) age in years; (2) the quadratic effect of age; (2) environmental noise; (3) two items measuring interruptions. We will estimate the model in two. First, we will construct the measurement model of WM, without including the adversity measures. Once we obtain at least acceptable model fit, we will access and add the adversity measures to the model. We will control for multiple testing using the false discovery rate 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		adversity. Contrary to predictions of adaptation-based perspectives, we might find a practically equivalent association with adversity for both WM capacity and updating. This would suggest that WM is unaffected by adversity. If we find both a non-significant association and practical non-equivalence, we will conclude that our data neither support nor refute either framework.	In both cases, it would suggest that both frameworks need to be explicit in how they distinguish between different WM components.
3. Are the directions and strengths of these associations similar or different for neighborhood threat, material deprivation, and unpredictability?	We have two expectations based on prior studies. First, we expect the association between material deprivation and WM capacity to be more negative than the associations with unpredictability and neighborhood threat. Second, we expect WM				We might find that the association between threat or unpredictability with WM capacity is more strongly or equally strongly negative than with material deprivation. This would suggest that threat or unpredictability are more strongly	The hypotheses specified for RQ3 do not directly offer (non-) support for either framework. However, finding different patterns than hypothesized here would be inconsistent with findings of prior studies.

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Research question	Hypotheses	Sampling plan	Analysis plan	Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
	updating to be associated with unpredictability and neighborhood threat, but not with material deprivation.		equivalent, which we will interpret as evidence for intact performance.		associated with WM capacity than material deprivation. We might also find that material deprivation, but not unpredictability or neighborhood threat, is positively associated with WM updating. This would suggest that an enhanced updating ability has an adaptive benefit for individuals experiencing material deprivation.	