Daily Fluctuations in Children's Working Memory Accuracy and Precision: Variability at Multiple Time scales and Links to Daily Sleep Behavior and Fluid Intelligence

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Abstract

Children often experience better and worse days when performing cognitive tasks. Whether such fluctuations are systematic and how they are linked to fluctuations at faster time scales within days is less clear. To fill these gaps, we probed N=108 fifth graders on WM tasks twice daily in morning and afternoon sessions, and also assessed nightly sleep behavior, over a period of four weeks using ambulatory assessment. Children systematically fluctuated in their recall of visuospatial and numerical information in WM across multiple time scales. These fluctuations showed consistencies but also discrepancies among each other. Especially, fast variability of memory precision across moments was related to load and fluid intelligence. Daily WM accuracy was positively coupled to sleep quality, but only in a subset of children with larger daily WM fluctuations. We propose that short-term WM fluctuations and their couplings to other time-varying constructs could help to explain long-term cognitive development.

Keywords. Working memory, children, intraindividual variability, multiple time scales, sleep behavior, ambulatory assessment

1. Introduction

Working memory (WM), or the limited amount of information that is currently highly accessible and available for cognitive processing, is fundamental for human cognitive development (Baddeley & Hitch, 1974; Cowan et al., 2005). There is ample evidence that WM is central for learning, reasoning, problem solving, and academic achievement (Bull & Scerif, 2001; Engle et al., 1999; Swanson & Alloway, 2012), but our theoretical and mechanistical understanding of WM development over childhood is still incomplete (Cowan, 2016; Perone et al., 2021). Although most related research investigated WM from a person-level (trait) perspective under controlled laboratory settings (Alloway & Alloway, 2010; Swanson, 2011), we do not always show stable cognitive performance in our everyday lives. Rather, we tend to fluctuate in cognitive functions by performing well on one day and worse on another day (Li et al., 2001; Schmiedek et al., 2013; Sliwinski et al., 2006). These fluctuating states may not only occur across days, but also across faster time scales, that is, from session to session within a day, and even from moment to moment within sessions (Li et al., 2004; MacDonald et al., 2006; Schmiedek et al., 2009). Investigating WM fluctuations in children may help to explain the well-established long-term trends of increasing WM capacity throughout childhood and adolescence (Cowan, 2016; Deboeck et al., 2009). However, how fluctuations in WM at multiple time scales manifest in children, and whether such fluctuations are systematic – that is, whether they are related to mnemonic load, contextual factors, and/or other behavioral functions – is less clear. In the present work, we addressed these gaps in the following ways: i) We examined WM in secondary school-children (i.e., fifth graders) by considering fluctuations in WM within and across days, rather than defining WM as a stable person-level variable. ii) Most studies measured WM under decontextualized controlled laboratory settings, leading to conclusions of likely comparatively low ecological validity. Here, we used ambulatory assessment over a period of four weeks with several occasions per day, which allowed us to investigate WM fluctuations in children’s real-world contexts (i.e., during and after school). iii) Moment-to-moment variability in WM performance shows a considerable decline throughout childhood

(Mella et al., 2015), but the underlying mechanisms of these changes are less clear. Reduced neural noise in more matured brain systems could play a role (MacDonald et al., 2006). Here, we examined representational noise in terms of behavioral recall *precision* with which item features are remembered in WM (Ma et al., 2014). This allowed us to shed further light on the role for precision and within-person variability of precision in children's daily life. iv) Numerous studies identified sleep behavior as one of the major drivers for successful learning and mental health in children (e.g., El-Sheikh et al., 2019; Kopasz et al., 2010), but only little is known about whether fluctuations in sleep behavior affect fluctuations in WM within children (Könen et al., 2015). Within-person couplings may indicate that two variables fluctuate across time in a systematic way rather than by chance. We therefore tested if daily WM fluctuations in fifth graders were related to night-to-night fluctuations in sleep quality and sleep duration.

1.1. Development of fluctuations in cognitive functioning

WM performance revealed to be a strong predictor of between-person differences in learning and school-related outcomes (Alloway & Alloway, 2010; Bull & Scerif, 2001; Gathercole et al., 2004). However, systematic cognitive within-person fluctuations in WM are evident across different time scales ranging from spontaneous or transient changes in the ongoing flow of awareness or attention over milliseconds to seconds (e.g., trial-by-trial variability on reaction-time (RT) tasks) (Hultsch et al., 2002; Li et al., 2001; Schmiedek et al., 2009; Williams et al., 2005) to more enduring state shifts in the form of cognitive performance fluctuations across "good" and "bad" days (Li et al., 2004; Riediger et al., 2011; Schmiedek et al., 2013). Specifically, moment-to-moment fluctuations in cognitive RT measures were heightened in younger children (6 to 8 years) and older adults (60 to 81 years), and lowered in younger adults (18 to 29 years) (Williams et al., 2005). Increased moment-to-moment fluctuations were also observed in a wide spectrum of clinical populations such as children with attention deficit hyperactivity disorder (ADHD) or autism (Bellgrove et al., 2005; Dinstein et al., 2015), and in patients with focal frontal lesions (Stuss et al., 2003). Together, these results implicate that increased transient cognitive fluctuations are associated with impairments in broader cognitive abilities (Hultsch et al., 2002). It is less clear as to whether and how rapid moment-to-moment fluctuations in cognitive performance affect cognitive fluctuations across slower time scales (Schmiedek et al., 2013). Thus, an important goal of developmental and cognitive science is to understand how and why individuals fluctuate in cognition across different time scales.

Developmental studies on fluctuating working memory in children are scarce (Fagot et al., 2018; Gasimova et al., 2014; Judd et al., 2021; Mella et al., 2015). Some of these studies showed that WM becomes more stable with increasing age throughout childhood, particularly, in terms of reduced trial-to-trial variability in behavioral measures of RT and accuracy (Fagot et al., 2018; Mella et al., 2015). Studies on more enduring fluctuations in WM require intensive data collection, that is, many daily observations of each participant over several weeks (Sliwinski et al., 2018). Recently, ambulatory assessment has proven to be a fruitful approach to measure such day-to-day fluctuations in WM, and their relations to other variables, also in children (Dirk & Schmiedek, 2017; Könen et al., 2015; Kramer et al., 2021; Neubauer et al., 2019). These studies found that WM performance was enhanced on days when children reported higher sleep quality (Könen et al., 2015), lower perceived disturbance (Dirk & Schmiedek, 2017), or lower negative affect (Neubauer et al., 2019). Thus, examining within-person associations between WM and other time-varying processes may help to identify short-term regulatory effects on daily WM functioning. How and why children may fluctuate in their WM performance at multiple time scales, ranging from fast item-to-item variability to slower day-to-day fluctuations, has to date only revived little empirical attention (Dirk & Schmiedek, 2016a; Galeano Weber et al., 2018). A better understanding of these short-term processes in WM would however bring major progress in the analysis of how daily life experiences contribute to the well-documented long-term trends in WM observed with traditional developmental methods (Deboeck et al., 2009).

1.2. Measures of WM performance

WM performance has often been measured in terms of memory *span* (the length of lists that can be repeated without an error) (Dempster, 1981) and the *number* of information elements or chunks that can be held in WM (Cowan, 2000; Halford et al., 1998; Luck & Vogel, 1997) . These traditional measures of WM rely on the assumption of so called 'fixed capacity' or 'slot' models in which WM representations are thought to be 'all or none', that is, information is either stored in WM with perfect precision or is completely forgotten/not stored at all (Cowan 2000; Luck & Vogel, 1997). Cognitive modeling research on WM in adults has cast serious doubts on these assumptions because the *slot-based model* does not account for internal noise in memory, which is assumed to increase with increasing load (Bays & Husain, 2008; Oberauer & Kliegl, 2001). *Resource models* propose that the more of a mental resource is allocated to an item feature (e.g., location, color), the less noise is present in its representation, and the more precise is the recall of that feature (Bays & Husain, 2008). Further, the precision of memory representations is suggested to systematically vary across items and trials, whereby *variable precision models* provided better match to the data than slot-based models or models with fixed precision across moments (Fougnie et al., 2012; van den Berg et al., 2012, 2014). Based on studies in decontextualized laboratory settings, behavioral research showed that the precision with which item features are remembered indeed declines with increasing memory load (= the number of to-be-remembered items) (Bays & Husain, 2008; Zhang & Luck, 2008), and also increases throughout childhood and adolescence (Burnett Heyes et al., 2012, 2016; Sarigiannidis et al., 2016). However, the role of WM precision under natural environments is less well understood, as it is precision variability across different time scales (Galeano Weber et al., 2018). In the present work, we aimed to further examine precision variability for different item features in secondary school children. Specifically, we measured precision of the items' location and also of its numerical content obtained with a spatial and a numerical WM updating task, respectively. This allowed us to test if previous findings of systematic patterns in precision variability can be generalized across distinct item features and to older children.

1.3. Sources of fluctuating WM in children

While moment-to-moment fluctuations in WM have been identified as an important aspect in describing age-related improvements in WM (Fagot et al., 2018; Galeano Weber et al., 2018; Judd et al., 2021; Mella et al., 2015), past studies did not specify the origin of fluctuating WM or their coupling to potential antecedents. Fluctuations in attentional control may reflect a likely predictor of transient WM fluctuations (Bays & Husain, 2008; Ma et al., 2014; van den Berg et al., 2012). Thus, the observed age-related decline of rapid moment-to-moment variability in WM could be explained by developmental increases in children's ability to selectively focus on task-relevant information, to actively maintain the encoded items, and/or to maintain and sustain attention on task to reduce trial-to-trial fluctuations (Unsworth & Robison, 2015, 2016). Another potential source of lowered WM variability may be reduced neural noise based on synaptic pruning processes throughout childhood and adulthood, which has been linked to reductions in gray matter density, particularly in the frontal lobe (MacDonald et al., 2006). In view of the important role sleep plays in human cognitive development (de Bruin et al., 2017; Durmer & Dinges, 2005; El-Sheikh et al., 2019; Kopasz et al., 2010; Lowe et al., 2017; Tarokh et al., 2016; Wee et al., 2013; Zinke et al., 2018), internal process-related variability based on circadian functions, such as night-to-night fluctuations in sleep duration and sleep quality, could reflect another important contributor to WM fluctuations. Fluctuating sleep in terms of having "good" or "poor" nights may imply that on some days children have trouble falling or staying asleep and often wake up at night, whereas on other days they do not suffer from these difficulties in sleep behavior. Nightly fluctuations in sleep could be coupled to daily fluctuations in cognition. Most previous studies focused on between-person associations and found small positive correlations between cognitive functions and sleep duration (Astill et al., 2012; Short et al., 2018). However, there have been very few empirical studies on within-person associations between sleep and cognitive fluctuations in younger individuals in their everyday lives (Hennig et al., 2017; Könen et al., 2015, 2016). These studies yielded mixed results as to whether nightly sleep duration and/or sleep quality affects daily cognitive performance. Different dependent measures (WM vs. inattention; subjective ratings vs. objective measures) and/or ages of participants (elementary school children vs. adolescents) could potentially explain these inconsistencies.

1.4. The present work

In the present study, we aimed to examine fluctuations in children's daily WM using smartphone-based ambulatory assessment over a period of four weeks. Building on evidence that items can be represented with varying degrees of fidelity (e.g., Burnett-Heyes et al., 2012, 2016; Galeano Weber et al., 2018), we obtained continuous measures of WM precision. Specifically, we probed all items in each trial with two different WM updating tasks, that is, a spatial and a numerical task adapted for mobile devices (Dirk & Schmiedek, 2016; Galeano Weber et al., 2018; Lewandowsky et al., 2010), yielding precision data for the whole set of items within each task. Children performed these tasks twice daily in a morning and in an afternoon occasion during and out of school, respectively, over a period of four weeks. In contrast to the majority of related studies, this design allowed us to examine within-person fluctuations in WM at multiple time scales including variability in WM from day to day and across faster time scales within days, occasions, trials, and items. Further, we tested whether such fluctuations systematically differ between children. This novel approach of investigating variability of precision in several WM tasks with different item features (i.e., visuospatial location vs. numerical content) embedded within an ambulatory assessment design allowed us to measure to what degree performance fluctuations are not only task-specific but generalize to a broader representation of WM. Finally, analyses of within-person couplings between daily WM and other time-varying constructs may reveal further indications as to whether fluctuations are systematic rather than noise. We therefore tested the role of subjectively reported sleep behavior (i.e., sleep quality and sleep duration) for daily WM fluctuations, aiming to replicate the previously observed within-person coupling in elementary school children (Könen et al., 2015) in a new sample of older children. Based on assumptions of cognitive resource models of WM capacity (Bays & Husain, 2008; van den Berg et al., 2012), and recent experimental and ambulatory assessment studies on WM in children (Burnett-Heyes et al., 2012, 2016; Dirk & Schmiedek, 2016; Sarigiannidis et al.

2016; Galeano Weber et al., 2018), we expected that a) mean WM performance (accuracy and precision) declines as memory load in the WM updating tasks increases, and b) Mean WM performance (accuracy and precision) is higher in the morning than the afternoon session within days (cf. Dirk & Schmiedek, 2016; Galeano Weber et al., 2018); c) Spatial and numerical WM precision vary within children from day to day and within days (i.e., occasions, trials, and items), and the amount of within-person fluctuations differs between children; d) It has been proposed that specifically a load-related increase in transient variability of representational precision across items plays a role for limited WM capacity (Fougnie et al., 2012; van den Berg et al., 2012). We therefore assume that WM load particularly affects the fast item-to-item variability of precision measures whereby transient variability across items shows systematic increases with increasing memory load; e) Children with more precise and transiently stable representations of spatial locations from item to item score higher in a test of fluid intelligence (Galeano Weber et al., 2018). We therefore expected a negative correlation between these two variables, and a similar relation for the numerical item-to-item variance. By taking into account results on daily coupling of sleep behavior and WM updating in elementary school children (Könen et al., 2015), we further hypothesized f) that within-person variations in sleep quality and time in bed independently predict within-person variations in WM accuracy in the morning occasion, but not in the afternoon occasion; g) a negative quadratic effect for time in bed (Könen et al., 2015), corresponding to an inverted U-shaped within-person association of time in bed and WM accuracy with performance being best at the individual average sleep duration, and h) that there will be between-person differences in the within-person effect of sleep quality on WM accuracy in the morning occasion. Hypotheses f to h were pre-registered before data collection at https://osf.io/kmgtu.

2. Method

The present study is based on an intensive longitudinal study design with daily measurements of WM performance and sleep behavior over a period of four weeks (28 consecutive days including weekend days) using smartphone-based ambulatory assessment. These data were collected within the SASCHA project ('Social and Academic School transition CHAllenges') of the IDeA Research Center on Individual Development and Adaptive Education of Children at Risk in Frankfurt am Main, Germany. SASCHA consisted of two measurement bursts (Burst 1, Grade 4; Burst 2, Grade 5) and a follow-up measurement (Grade 6). Each measurement burst was embedded within pre- and posttests at which children were instructed on how to operate on the research smartphones, and provided background and trait data (for more detailed information, see study protocol: https://osf.io/yvfpj/). The present work is based on data from the second measurement burst.

2.1. Participants

One-hundred and eight children (60 girls) aged nine to eleven years (*M* = 10.11 years, *SD* = 0.44) participated in the second measurement burst. Children were fifth graders from six participating classes of one secondary school (Gymnasium, the academic tier of secondary education in Germany) in an urban neighborhood near Frankfurt am Main, Germany. Participation was voluntary and could be canceled anytime without giving reasons. The sample consisted of 64 out of 108 children (59 %) whose native language was German, 24% children with German and another language as their native languages, and 17 % children whose first language was different from German. The majority of parents were employed in full- or part-time work (97 % of children's fathers; 80 % of children's mothers). Children's fluid intelligence, which was measured in a pretest assessment (*N* = 106) using the CFT 20-R (Jacobs et al., 2017), was in an average to above-average range with *M* = 111.3 (*SD* = 14.2). Children received gift certificates of 25€ as remuneration for participation and could earn bonus gift certificates of 5€/10€ if they completed at least 60%/85% of all assessments, respectively. Informed consent was obtained in accordance with a protocol approved by the ethics committee of the German Psychological Society.

2.2. Procedure

Sleep quality, sleep duration (time in bed), and current tiredness were assessed in the early morning (6:00 - 7:50 am). WM performance was tested in the late morning (9:50 am) and in the afternoon (3:00-5:15 pm or 4:00-5:45 pm on longer school days). Each day, there was an additional occasion (6:30-8:30 pm) at which several self-report data were collected that were not relevant for the present research. Compliance rates were satisfactory with 74% in the early morning occasion (2228 out of 3024 days), 80% in the late morning occasion (2412 out of 3024 days), and 68% in the afternoon occasion (2060 out of 3024 days) completed. Within each occasion (late morning and afternoon), the spatial updating task followed the numerical updating task (see next sections for a detailed description of task designs and measures). Each task comprised eight trials per occasion whereby each occasion started with four trials of low load conditions (i.e., two items in the spatial task and three items in the numerical task), followed by four trials of high load conditions (i.e., three items in the spatial task and four items in the numerical task). We measured responses for each item. Thus, in one occasion, children were instructed to give 20 responses for the spatial WM task and 28 responses for the numerical WM task.

2.3. Working Memory Updating Tasks

Spatial WM. Children had to memorize and update locations of differentially colored and shaped cartoon creatures (= items) presented in a 4 x 4 grid. During the encoding phase, two or three items were presented simultaneously at different locations in the grid for 3000 ms. After an inter-stimulus-interval (ISI) of 250 ms, three or four updating cues were presented for Load 2 and Load 3 conditions, respectively. Updating cues were shown in the center of the grid and were presented sequentially. Each cue was shown for 1500 ms with an ISI of 250 ms. Each item of the sample display was assigned to one respective cue. Cues were cartoon arrows that matched the item's color and had the respective item placed at the center. The direction of the arrow prompted children to mentally shift the spatial position of the respective item to the adjacent location in the grid (= updating operation). Directions of arrows were horizontal (left, right), vertical (up, down), or diagonal. No item's position could be updated twice in a row. Intermediate and end positions were never doubly assigned (i.e., items could not concurrently be at the same position). After updating, children had to retrieve updated positions for each item within a trial. They responded by consecutively touching the remembered item location within a maximum of 20000 ms. Target locations were indicated by the corresponding item and a question mark sign shown left to the grid. After the final response was given, a feedback followed, showing color-coded crosses at correct locations (Figure 1) (cf. Dirk & Schmiedek, 2016; Galeano Weber et al., 2018).

Numerical WM. Children had to memorize and update three or four one-digit numbers (= items). At encoding, three or four digit numbers (i.e., 0 - 9) were presented simultaneously for 3000 ms, each located at one of three or four horizontally placed cells. After an ISI of 250 ms, a sequence of four or five updating operations was presented for Load 3 and Load 4 conditions, respectively. The updating operations were additions and subtractions in the range from +2 to -2 and had to be applied to the memorized digits. The total was never negative or above nine and no cell was updated twice in a row. The presentation time for updating operations was 1500 ms, the ISI was 250 ms. At the end of each trial, children were prompted to enter the three or four end results (within a maximum of 20000 ms). After they confirmed their responses, a feedback followed by showing color-coded correct and incorrect answers. After the updating operations, children were prompted to consecutively respond to each item by entering the updated digit. Responses were followed by a color-coded feedback showing the correct and incorrect results (cf. Dirk & Schmiedek, 2016).

2.4. Measurements

2.4.1. Scoring WM Performance

Response Accuracy. A given response was assigned a value of one for correct responses (i.e., when the correct location/digit of the target item was chosen) and a value of zero for erroneous responses (i.e., when any other location/digit except the correct location/digit was chosen). For analysis at the occasion level, the *mean accuracy* of all responses of the four trials per occasion (morning, afternoon), load condition (low, high), and task (spatial, numerical) was obtained. For data analysis across trials, accuracy scores were obtained by averaging across responses for each item within trials (Dirk & Schmiedek, 2016; Galeano Weber et al., 2018).

Spatial and Numerical Precision. In the spatial WM updating task, mnemonic precision was formulized as the Euclidean Distance between response location and correct location for each item (cf. Noack et al., 2013). The Euclidean Distance is defined as the distance between two points in space that corresponds to the length of a straight line drawn between them, where the distance from x to y or y to x is given by the following Pythagorean formula:

$$\delta(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2}$$

Here, we assume that a higher δ may reflect more dissimilar representations between presented and reported item location, which may result from less spatially precise memory representations due to increased memory noise (e.g., Bays & Husain, 2008). The Euclidean metric works well for two-dimensional spaces and reflects a more sensitive measure of spatial recall precision than the number of cells as a distance measure. For example, placing an item in a cell that touches the correct cell diagonally (δ = 1.41) is considered a somewhat larger error than placing it in a cell that touches the correct cell horizontally or vertically (δ = 1). The metric space was a 4 x 4 cell grid where one cell reflects one of 16 different item locations. Specifically, we computed the square root of the sum of the squares of the difference between all corresponding values within a 4 x 4 matrix (e.g., x(1,2) and y(2,3)) by using the dist function in R. This resulted in ten possible distinct δ values ranging from δ = 0 to a maximum of δ = 4.24 and 120 (= 16*15/2) possible pairs of presented and reported location (Galeano Weber et al., 2018). In the numerical WM updating task, mnemonic precision was formulized as the absolute difference between response and correct digit for each item.

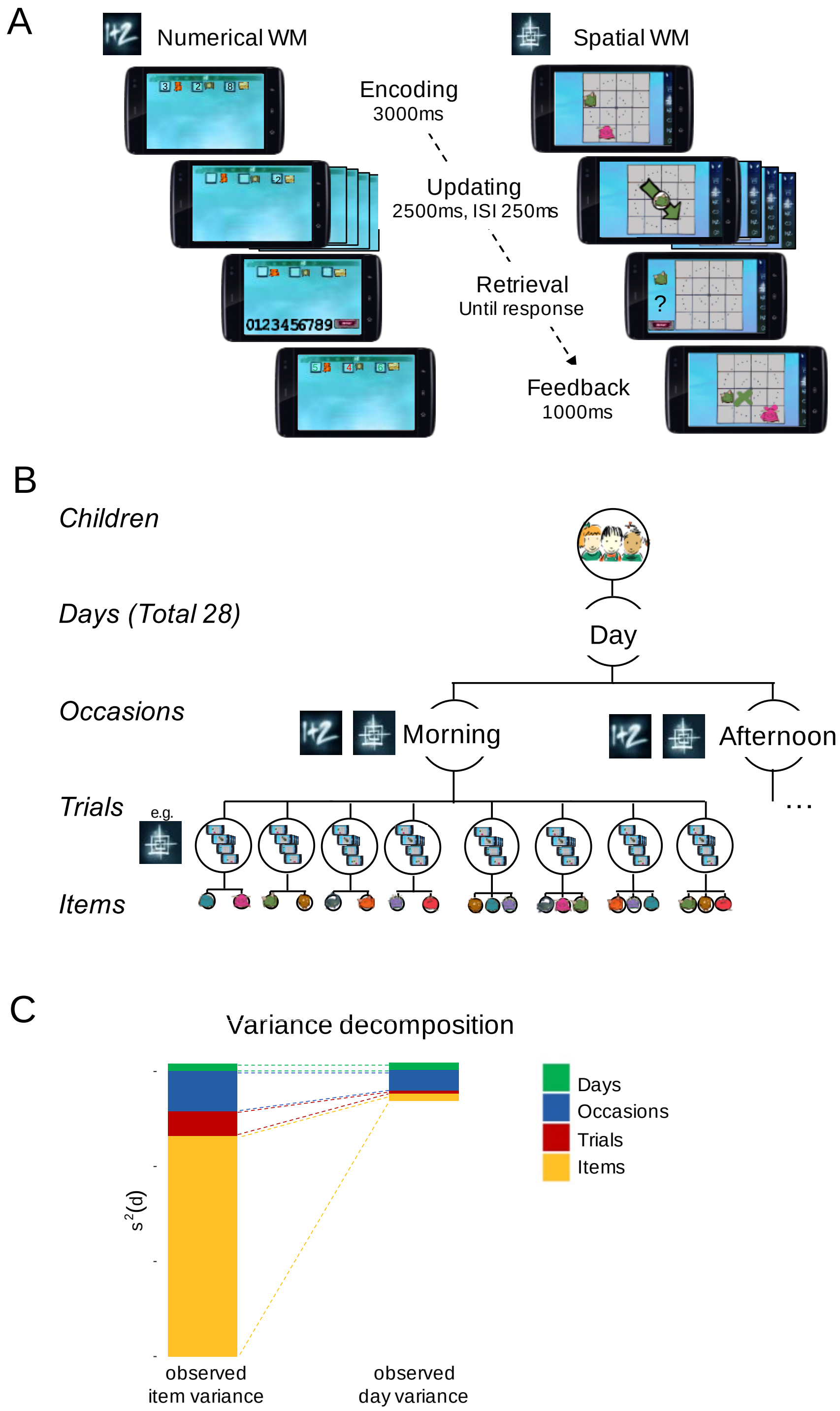

Figure 1. *Experimental task and design to model working memory fluctuations. A. WM updating tasks. Children had to encode, hold, and update digits or locations of several items in WM in a numerical and spatial WM updating task, respectively. After the updating operations, that were additions and subtractions to the encoded digits or sequential mental shifts within a 4 x 4 spatial grid, children were prompted to retrieve each item within a trial,*

followed by feedback to each response. B. For each individual child, the hierarchical data structure of the microlongitudinal design allowed to model WM fluctuations across transient to more enduring time scales that were nested within each other (items < trials < occasions < days). C. WM fluctuations were modeled by decomposing the observed day-to-day variability of WM precision (i.e., the variance of average recall precision across days) into four variance components (VC) for each individual. The stacked bar on the left shows the raw, non-aggregated VCs whereby the total size of this bar corresponds to the observed variance of item-to-item variability. These VCs were further aggregated (see stacked bar on the right) to identify the contribution of i) systematic or true day-to-day fluctuations (green) (= the proportion of daily mean variance that does not depend on variability of the faster time scales), ii) occasion-to-occasion variability (blue), iii) trial-to-trial variability (red), and iv) item-to-item variability (yellow) to observed day-to-day variability. The total size of the bar on the right corresponds to the variance of observed day-to-day variability.

2.4.2. Self-reports

Sleep Quality. Sleep quality was assessed in the early morning occasion using three items: (1) “How well did you sleep last night?”; (2) “How restlessly did you sleep last night?”; (3) “How easily did you fall asleep yesterday evening?” based on the sleep quality index by Åkerstedt et al. (2012) (cf. Könen et al., 2015, 2016). All items were answered on a five-point Likert scale. The three items were averaged into one measure of sleep quality per person and night (after Item 2 had been inverted).

Time in Bed. Time in bed reflects a proxy of sleep duration. Every morning, children were asked to indicate when they went to bed last night and when they woke up today using two items: (1) “When did you go to bed yesterday?” and (2) “When did you wake up today”. They responded by choosing the hour and the minutes (in ten-minute intervals) for both time points. Time in bed was computed as the difference between wake up time and bed time by checking for nonsensical responses as stated in our pre-registration (https://osf.io/kmgtu).

Current Tiredness. Tiredness was assessed using one item, that is, "How tired are you right now?", and was answered on a five-point Likert scale ranging from 1 ("not at all") to 5 ("very").

Children reported their current tiredness in the early morning occasion of each day.

2.5. Data analysis

Data were analyzed using the nlme package (Pinheiro et al., 2015) as well as core packages of the statistical software R (https://www.r-project.org, R Core Team, 2016).

2.5.1. WM updating

Effects of Task, Load, and Occasion. We tested whether daily WM performance depended on the type of task (i.e., spatial vs. numerical), memory load (i.e., Load 2 vs. Load 3 for spatial WM and Load 3 vs. Load 4 for numerical WM), and occasion (i.e., morning vs. afternoon) using a three-level model with two occasions per day (Level 1) nested within days (Level 2) nested within children (Level 3). Specifically, Child *j*'s WM performance, that is, the proportion of correct responses (mean accuracy) or the precision score at a given occasion (mean delta / δ) on day *d* and occasion *o* was entered as dependent variable (WMP_{doj}). As predictors, we included *study day* to account for retest effects (day_{dj}; the first day was centered at 0), *task* to test whether performance varies between the spatial and numerical WM task ($task_{doj}$; coded as factor; numerical task as 0, spatial task as 1), *load condition* ($load_{doj}$; coded as factor; high load as 0, low load as 1) and *occasion* to test whether performance varies between occasions ($occasion_{doj}$; morning occasions were coded as 0, afternoon occasions as 1). Further, we included *gender* as covariate ($gender_j$; boys were coded as 0, girls were coded as 1). We firstly tested for main effects of task, load, occasion, and gender (Model 1a), and then, in a second model, we tested for interactions among these four predictor variables (Model 1b). In both models, random effects on Level 3 were estimated for the effects of study day, load, and occasion, and covariances among random effects were freely estimated. In a follow-up, we ran the same models, but separately for each task, in order to differentiate effects of load, occasion, and gender on numerical and spatial WM. We also ran separate models for each task when the precision score was entered as dependent variable, since spatial and numerical precision varied on different scales. Significance of fixed effects was evaluated using the package's default estimation of degrees of freedom. Significance of the random effects was estimated via likelihood ratio tests, comparing the fit of the model with vs. without the random variance. A conventional alpha level of .05 was applied to all tests. Random effects were allowed to co-vary freely (i.e., unstructured G-matrix).

Variance Decomposition. WM data were hierarchically structured by repeated measures across items that were nested within trials, observations across trials were nested within occasions, assessment at occasions was nested within days, and assessment at days was nested within children. This nested data structure allowed us to decompose WM performance into several variance components across different time scales ranging from slow day-to-day fluctuations to rapid item-to-item variability for each individual child. Specifically, separately for each child, WM task and load condition, a multilevel model was set up using the lme function of the nlme package in R. The model's dependent variable was either spatial precision at the item level (i.e., the Euclidean distance between presented and reported location for each item), or numerical precision at the item level (i.e., the difference between presented and reported number). The model's intercept parameter was composed of a fixed and several random effects. In particular, the model allowed for random intercepts of each time scale level, which were nested within each other. Running trial number was included as a continuous predictor and modeled as fixed effect to take into account individual longer-term trends. This general model resulted in four different components of mnemonic precision: A variance component (VC) of day-to-day variability across the n daily occasions (σ^2_{Days}), a component of occasion-to-occasion variability across the m trials within occasions divided by the number of occasions (= 2) within days ($\sigma^2_{Occasion}$), trial-to-trial variance across the k item-responses within trials divided by the number of trials (= 8) within days (σ^2_{Trial}), and the VC of item-to-item variability, which included also error variance, divided by the number of responses (= 16 under Load 2 and 24 under Load 3 for the spatial task; = 24 under Load 3 and 32 under Load 4 for the numerical task) within days (σ^2_{Item}).

Each VC was divided by their respective total number of observations as we aimed to assess the contribution of each individual variance component to total daily variance (observed day-to-day variability/ the variance of average performance across days). To test whether variability of mnemonic precision across different time scales changed as a function of WM load, we conducted Wilcoxon signed rank test separately for each VC. Results were considered to be significant when $p < 0.05$, applying a Bonferroni correction to take into account multiple comparisons (4 VCs = 4 tests per memory task). Further, we assessed between-person differences in children's estimated VCs at different time scales. Finally, we assessed the relation between variance components and measures of fluid intelligence (i.e., CFT 20-R raw scores) using Spearman correlation analyses. Results were considered to be significant when $p < 0.05$, applying a Bonferroni correction (4 VCs * 2 loads = 8 tests per task).

2.5.2. Sleep and WM

Pre-registered Analyses. We aimed to conceptually replicate main findings reported in previous work on WM and sleep (Könen et al., 2015) in a sample of slightly older children (Grade 5 vs. Grades 3 and 4 in the previous studies) (see pre-registered project on osf: https://osf.io/kmgtu). Child *j*'s WMP (i.e., the proportion of correct responses at this measurement occasion) on day *d* was entered as dependent variable (WMP_{dj}). It was predicted by sleep quality and time in bed in the morning assessment of the same day. We ran separate models for WMP assessed at the morning occasion (Model 2a) and afternoon occasion (Model 2b). In all models, the following predictors were included: *study day* to account for retest effects (day_{dj}; the first day was coded as 0); *school day* ($school_{dj}$; school days were coded as 1, weekend days as 0); *tiredness* as a potential covariate ($tired_{dj}$; current tiredness report by a child); sleep quality (sq_{dj}); time in bed (tib_{dj}); and quadratic time in bed ($tib.squared_{dj}$). Sleep quality, time in bed, and tiredness were centered on their respective person means; the person means of sleep quality, time in bed, and tiredness were centered on their grand means. Hence, the respective effects are pure estimates of within-person effects and between-person effects, respectively (Wang & Maxwell, 2015).

Random effects were estimated for the effects of study day and sleep quality, and covariances among random effects were freely estimated. The formal description of the Model 2 is:

Level 1 (within children): $WMP_{dj} = \beta_{0j} + \beta_{1j}*day_{dj} + \beta_2*school_{dj} + \beta_3*tired_{dj} + \beta_{4i}*sq_{dj} + \beta_5*tib_{dj} + \beta_6*tib.squared_{dj} + \varepsilon_{dj}$

Level 2 (across children): $\beta_{0j} = \gamma_{00} + \gamma_{01}*sq.pmean_j + \gamma_{02}*tib.pmean_j + \gamma_{03}*tired.pmean_j + \upsilon_{0j}$

$\beta_{1j} = \gamma_{10} + \upsilon_{1j}$

$\beta_{4j} = \gamma_{40} + \upsilon_{4j}$

(*d* = day indicator; j = person indicator)

3. Results

3.1. Daily Fluctuations in WM Updating

We examined the systematicity of daily fluctuations in WM accuracy at the latent construct level by testing a two-level confirmatory factor model for the four WM task conditions (cf. Dirk & Schmiedek, 2016). We controlled for the specificity of the spatial WM task by adding the residual correlation (between the low and high spatial load indicators) on both levels (i.e., the between- and within-person level). We found statistically significant factor loadings on both levels, indicating systematic common variance at both levels (Figure 2A). At the within-person level, this implies that on occasions when children showed higher performance in one task condition, they also tended to show higher performance in the other task condition. At the between-person level, children who showed generally higher performance in one task condition tended to also perform better in the other task conditions when averaging across study occasions. Thus, the tasks in the present study allow assessing both systematic within-person and between-person differences in children's WM performance.

3.1.1. Effects of Load and Occasion on Spatial and Numerical Mean Accuracy

Table 1 shows descriptive statistics for daily WM accuracy measures, separately for each task condition and occasion. The mean accuracies in the single WM tasks under the

Load 3 condition ranged from .58 to .61 for spatial WM and from .62 to .67 for numerical WM. Hence, WM performance under the Load 3 condition was clearly above chance level and showed no ceiling effects for both tasks. The mean accuracies in the spatial WM task under Load 2 were .80 in the morning and .85 in the afternoon. Thus, remembering and updating two items in spatial WM was highly feasible for most children. The Load 4 condition of the numerical WM task showed mean accuracies of .44 in the morning and .48 in the afternoon indicating that this condition was most challenging for most children. Figure 2B shows children's average performance in the task conditions separately for boys and girls. The intraclass correlation (ICC; the portion of between person variance to total variance) ranged from .31 to .37 for the numerical task conditions, and from .19 to .33 for the spatial task conditions. Thus, the proportion of the daily within-person part of overall variance was relatively large for most task conditions, but somewhat smaller for the numerical than for the spatial WM task. Further, we observed substantial average within-person standard deviations across all task conditions ranging from 0.20 to 0.26 (Table 1). Figure 2C shows within-person spatial and numerical WM performance in the morning from day to day for each of three exemplary participants.

Table 1. Descriptive statistics of daily WM accuracy measures in a numerical and spatial WM updating task (N = 108)

	Load	Occasion	*mean*	*sd*	*mn ISD*	*sd ISD*	*ICC*
Numerical WM	3/low	Morning	0.67	0.20	0.24	0.09	0.35
		Afternoon	0.62	0.21	0.26	0.09	0.36
	4/high	Morning	0.48	0.19	0.25	0.07	0.31
		Afternoon	0.44	0.21	0.24	0.08	0.37
Spatial WM	2/low	Morning	0.85	0.11	0.20	0.09	0.19
		Afternoon	0.80	0.15	0.23	0.11	0.24
	3/high	Morning	0.61	0.17	0.24	0.06	0.31
		Afternoon	0.58	0.20	0.25	0.07	0.33

ICC = intraclass correlation (the portion of between person variance on total variance). ISD = intraindividual standard deviation.

We tested whether daily mean accuracy varied as a function of memory load, task, occasion, and gender with a three-level model with eight assessments per day (Level 1) nested within days (Level 2) nested within children (Level 3).

We found main effects of occasion, memory load, and type of task showing that mean accuracy was lower in the afternoon than in the morning occasion (b = -0.047, p < .0001), higher under low than high load conditions (b = 0.202, p < .0001), and higher in the spatial than the numerical task (b = 0.157, p < .0001). We observed no statistically meaningful main effect of gender (b = 0.043, p = .084). By adding the interactions, we found that memory load significantly interacted with type of task whereby the load effect was smaller in the numerical than the spatial task (load x task: b = 0.045, p = .0012). Load also interacted with gender such that girls showed smaller load effects than boys (load x gender: b = -0.047, p = .0053). Further, we observed a significant three-way interaction between occasion, memory load, and gender (b = 0.038, p = .047): Results from separate models for boys and girls revealed that boys showed a slightly smaller load effect in the morning than in the afternoon occasion (b = -0.028, p = .021), while girls showed no significant interaction between load and occasion (b = -0.006, p = .572).

3.1.2. Effects of Load and Occasion on Spatial and Numerical Mean Precision

Mean accuracy corresponds to the probability of remembering the correct target (i.e., location or digit), while mean delta (δ) is an absolute difference score between correct and reported target. A δ of 0 reflects memory representations with perfect precision, while a δ > 0 reflects less precise representations in WM. Figure S1 shows the relation between mean accuracy and mean δ at the trial-level for each child and indicates that mean δ varied widely when accuracy was not perfect within the numerical (Fig. S1A) and spatial (Fig. S1B) task. Table 2 shows descriptive results of mean δ at the occasion level, separately for spatial (a) and numerical (b) WM updating. Within both tasks, children showed higher WM updating precision (lower mean δ) under low versus high load conditions. Further, children responded more precisely in morning than afternoon occasions in each task. The ICC ranged from .10 to .14 for the numerical task conditions and from .08 to .14 for the spatial task conditions. Thus, the contribution of within-person variability to overall (within-person plus between-person) variance was relatively similar for numerical and spatial mean δ. Further, we observed substantial average within-person standard deviations across all task conditions (Table 2).

Table 2. Descriptive statistics of spatial (a) and numerical (b) WM updating precision for each load condition and occasion

(a) Spatial delta δ

Load	occasion	*mean*	*sd*	*min*	*max*	*m ISD*	*sd ISD*	*ICC*
2/low	Morning	0.280	0.211	0.034	1.301	0.644	0.209	0.084
	Afternoon	0.361	0.294	0.000	1.315	0.684	0.260	0.131
3/high	Morning	0.713	0.331	0.116	1.504	0.938	0.137	0.106
	Afternoon	0.758	0.392	0.000	1.900	0.925	0.164	0.140

(b) Numerical delta δ

Load	occasion	*mean*	*sd*	*min*	*max*	*m ISD*	*sd ISD*	*ICC*
3/low	Morning	0.883	0.599	0.064	2.612	1.3815	0.490	0.142
	Afternoon	1.053	0.662	0.033	2.604	1.4843	0.490	0.150
4/high	Morning	1.445	0.607	0.181	2.968	1.7410	0.309	0.104
	Afternoon	1.610	0.698	0.224	3.003	1.7713	0.332	0.128

We tested whether daily mean delta δ varied as a function of memory load, occasion, and gender with a three-level model with eight assessments per day (Level 1) nested within days (Level 2) nested within children (Level 3). We performed these analyses based on all observations, that is, correct responses (i.e., mean δ = 0; mean accuracy = 1) and erroneous responses (i.e., mean δ > 0; mean accuracy = 0). Because precision and accuracy are correlated in these data, we ran the same models, but only for the erroneous responses, to identify the unique contributions of precision for the effects (see results in squared brackets).

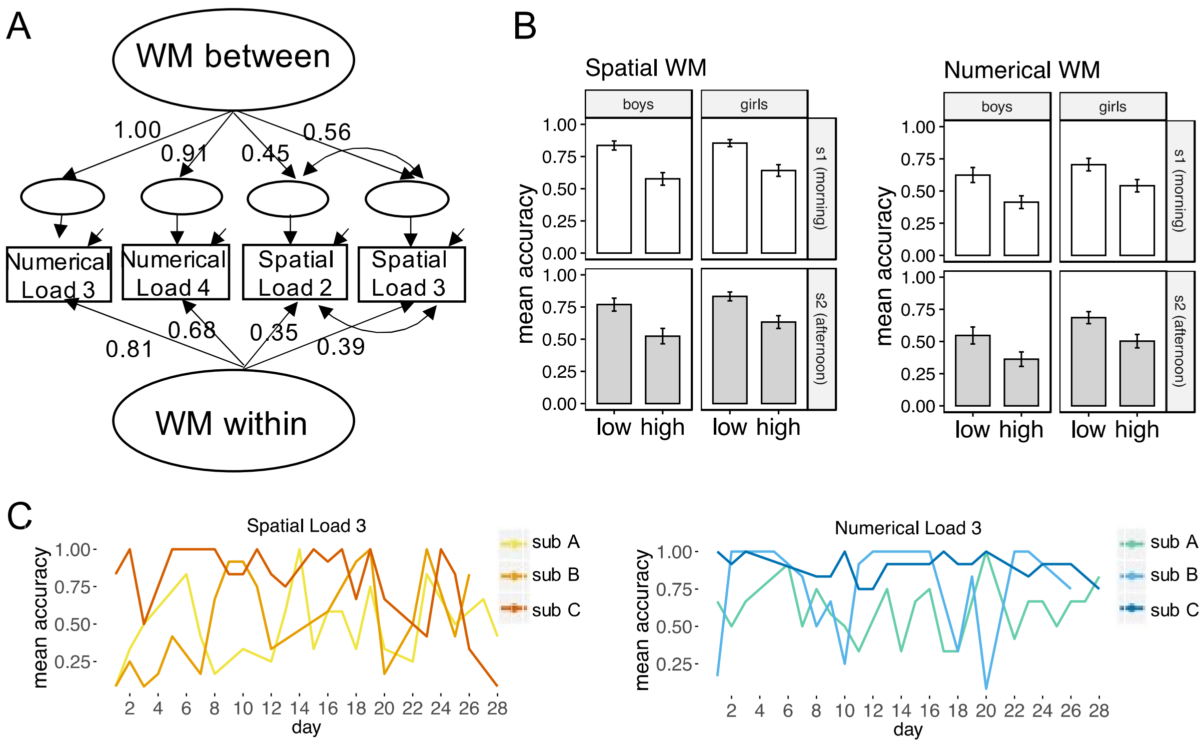

Figure 2. *Daily working memory (WM) accuracy of a numerical and spatial WM updating task in N = 108 children.* ***A.*** *Within- and between-person factor of WM performance: The model fit was good: χ^2= 27.87, df = 2, p = .00; comparative fit index (CFI) = .987; root mean square error of approximation (RMSEA) = .057; standardized root mean square residual (SRMR) within = .012; SRMR between = .020. Figure depicts standardized coefficients.* ***B.*** *Children's average performance in the morning (white bars) and afternoon (grey bars) occasion for each task and load condition, and gender. Spatial WM: low = Load 2, high = Load 3; Numerical WM: low = Load 3, high = Load 4; error bars correspond to the 95% confidence intervals.* ***C.*** *Individual time courses of spatial and numerical WM performance under Load 3 assessed in the morning over 28 days for three exemplary participants.*

For both spatial and numerical mean δ, we found main effects of occasion and memory load showing that mean δ was higher (i.e., corresponding to lower precision) in the afternoon than in the morning occasion (Spatial: *b* = 0.083, *p* < .0001, [*b* = 0.079, *p* < .0001]; Numerical: 0.22, *p* < .0001, [*b* = 0.184, *p* < .0001]) and lower (i.e., higher precision) under low than high load conditions (Spatial: *b* = -0.408, *p* < .0001, [*b* = -0.209, *p* < .0001]; Numerical: *b* = -0.545, *p* < .0001, [*b* = -0.491, *p* < .0001). A main effect of gender was only evident for numerical δ such that girls showed lower mean δ (i.e., higher precision) than boys (b = -0.338, p = .003, [b = -0.298, p = .005]), while there was no such effect for spatial δ (b = 0.012, p = .77, [b = -0.048, p = .25]). By adding the interactions to each model, we found that memory load significantly interacted with occasion showing a higher load effect in the morning than in the afternoon occasion for both spatial (b = 0.061, p = .022, [b = 0.079, p = .027]) and numerical δ (b = 0.101, p = .027, [b = 0.100, p = .044]). For the analyses with all responses (erroneous and correct), load also interacted with gender whereby boys showed a higher load effect than girls (Spatial: b = 0.107, p = .006, [b = 0.084, p = .056]; Numerical: b = 0.136, p = .017, [b = 0.079, p = .199]). We found no statistically meaningful three-way interaction between occasion, load, and gender for both spatial (b = -0.018, p = .603, [b = -0.057, p = .244]) and numerical δ (b = -0.115, p = .06, [b = -0.050, p = .465]).

3.1.3. Daily Fluctuations in Children's Sleep Behavior and WM

We found systematic day-to-day fluctuations of mean accuracy scores within spatial and numerical WM updating tasks (cf. 3.1). The reasons of why children fluctuate in their performance across days are less clear. Therefore, we aimed to test as to whether facets of sleep behavior such as sleep quality, time in bed, and morning tiredness predict WM performance fluctuations in children's school and daily life. Table 3 shows the descriptive statistics for the daily sleep measures. The ICC ranged from .26 to .40 for the sleep measures, indicating that the overall variance was dominated by within-person fluctuations (see Table 3). We found no significant differences between boys and girls in their sleep variables (p > .63).

Pre-registered analysis. We found no statistically significant within-person effect of sleep quality (b = 0.005, p = .390) on WM accuracy assessed in the late morning occasion (see Model 2a). By contrast, WM assessed during afternoon showed a positive association with sleep quality (Model 2b, b = 0.017, p = .015). We next tested if children showed meaningful between-person differences in their within-person effect of sleep quality on WM accuracy (cf. Hypothesis h). Model comparisons showed that a model with a random effect for sleep quality did not significantly differ from a model without a random effect for WM assessed in the late morning ($\chi^2(3)= 0.00026$, *p* > .999) and afternoon ($\chi^2(3)= 0.00482$, *p* = .99). Time in bed did not significantly predict WM accuracy in the morning (Model 2a, linear effect: *b* = -0.001, *p* = .759; quadratic effect: *b* = -0.000, *p* = .559), nor the afternoon occasion (Model 2b, linear effect: *b* = 0.006, *p* = .206; quadratic effect: *b* = -0.000, *p* = .698).

In sum, our pre-registered hypotheses were not confirmed: sleep quality was not statistically meaningfully related to WM accuracy in the morning occasion, but it was associated with higher WM accuracy in the afternoon occasion (Hypothesis f). Time in bed was not meaningfully related to WM accuracy at either occasion (Hypothesis g). There were no statistically meaningful between-person differences in the effect of sleep quality on WM accuracy (Hypothesis h). Hence, we could not replicate the finding of a negative quadratic effect of time in bed on WM accuracy within the new sample of older children. Although results suggested that higher than usual sleep quality was linked to higher WM accuracy this effect was, contrary to our expectations, evident for WM assessed in the afternoon but not in the morning.

Table 3. Descriptive statistics of daily sleep measures.

Variable	Scale	*M*	*SD*	*M ISD*	*SD ISD*	*ICC*
Sleep quality						
How well did you sleep last night?	0-1 (5-point)	0.68	0.20	0.25	0.10	0.28
How restlessly did you sleep last night?	0-1 (5-point)	0.76	0.17	0.23	0.11	0.34
How easily did you fall asleep yesterday evening?	0-1 (5-point)	0.64	0.20	0.25	0.09	0.32
Mean sleep quality	0-1 (5-point)	0.69	0.17	0.18	0.07	0.40
Time in bed						
	Time (H. M)	9.16	0.74	0.96	0.74	0.26
Morning tiredness						
How tired do you feel right now?	0-1 (5-point)	0.46	0.23	0.28	0.09	0.36

Exploratory analyses. We aimed to identify factors that might explain inconsistencies between the present findings and our previous results reported in Könen et al. (2015). Therefore, we performed a set of exploratory analyses to test (i) whether differences in the level of task performance might have influenced effects of sleep measures on WM accuracy; (ii) how mnemonic accuracy of each of the four WM task conditions (i.e., Spatial Load 2, Spatial Load 3, Numerical Load 3, Numerical Load 4) was related to the sleep measures; iii) whether between-person differences in gender might have influenced the association between sleep and WM, and iv) the role of systematic day-to-day variability in WM performance for the WM-sleep coupling.

i. We ran the same models as in our pre-registered analyses (i.e., Model 2a and b corresponding to one model for WM assessed in the morning and another model for WM in the afternoon) but this time using data of a subsample. The subsample consisted of N = 103 children who showed mean accuracies for the single WM task conditions ranging from .47 to .77, as in Könen et al. (2015, see p. 175). Results were similar to the findings of our pre-registered analyses, that is, we found a positive within-person association between sleep quality and WM accuracy in the afternoon (b = 0.018, p = .015). Sleep quality was not significantly linked to WM assessed in the morning; time in bed was not significantly associated with WM in the morning nor afternoon occasion.

ii. In our pre-registered analyses, we focused on the mean of all WM task and load conditions as dependent variable. Averaging across all conditions might have obscured potential associations between sleep and WM performance in a single task condition. In addressing this subject, we ran the same model as in our pre-registered analyses (i.e., Model 2a and b), but separately for each task condition, leading to four models (2 loads x 2 occasions) of each task. For spatial WM, we found a negative quadratic effect of time in bed on accuracy under Load 2 assessed in the morning (b = -0.003, p = .015), corresponding to the anticipated inverted u-shaped within-person association reported by Könen et al. (2015). In addition, we observed a positive linear within-person association between time in bed and spatial accuracy under Load 3 assessed in the afternoon, such that more than usual reported hours of sleep were linked to higher accuracies (*b* = 0.019, *p* = .004). For numerical WM, we found a positive within-person association of sleep quality and WM accuracy under Load 3 (*b* = 0.020, *p* = .039) and Load 4 (*b* = 0.023, *p* = .022) assessed in the afternoon. No other significant effects of the sleep variables were found and no such association was found for any of the other WM task conditions.

iii. The sample of the present study consisted of fifth graders aged nine to eleven years (*M* = 10.11, *SD* = 0.44); the proportion of girls was 56%. The sample of the study by Könen et al. (2015) included slightly younger children, that is, third- and fourth-graders aged eight to eleven years (*M* = 9.88, *SD* = 0.61), and a slightly smaller proportion of girls (42%). We tested for gender differences by running the same models as in the previous exploratory analyses, which showed significant associations between sleep and WM performance, separately for boys and girls. We found a negative quadratic effect of time in bed on spatial WM accuracy assessed in the morning under the Load 2 condition for boys but not girls (boys: *b* = -0.003, *p* = .024; girls: *b* = -0.002, *p* = .353). Further, boys showed a positive linear within-person association between time in bed and spatial WM accuracy assessed in the afternoon under the Load 3 condition (linear effect: *b* = 0.026, *p* = .006), while we observed no such effect for girls (linear effect: *b* = 0.012, *p* = .196). In addition, we observed a positive within-person association between sleep quality and spatial WM accuracy assessed in the afternoon under the Load 3 condition in girls (*b* = 0.028, *p* = .036), but not in boys (*b* = 0.001, *p* = .944). Sleep quality was positively associated with numerical WM accuracy assessed in the afternoon under the Load 4 condition in girls (*b* = 0.03, *p* = .014) but not in boys (*b* = 0.006, *p* = .68). Further, also in the afternoon and for Load 4, girls showed a positive linear effect of time in bed on numerical accuracy (girls: *b* = 0.023, *p* = .025; boys: *b* = -0.011, *p* = .19).

iv. A sizeable proportion of children showed relatively small true day-to-day fluctuations in WM performance and some of these children showed no true daily variation at all, especially in the spatial task (cf. Figure 3B; results reported in the next section 3.2).

Thus, the findings of the pre-registered analyses are based on data in which only a fraction of children had true daily WM variability to be predicted by daily fluctuations in the sleep variables. To test whether this could explain inconsistencies between studies, we ran the same models as in our pre-registered analyses (i.e., Model 2a and b) based on data from children who showed systematic WM fluctuations across days. We identified those children by comparing two multi-level models estimated separately for each child and load condition with the dependent variable being mean accuracy in the spatial WM task. Model 1 was a three-level model allowing for random intercepts of days, occasions, and trials (i.e., the same model as we used for the variance component analysis), and Model 2 was a two-level model, which was nested in Model 1, and allowed for random intercepts of occasions and trials only. Children who showed lower AICs in Model 1 than Model 2 and a significant likelihood ratio test either under Load 2 or Load 3 were included in the following analysis. With this approach, we could identify N = 50 children with substantial day-to-day WM fluctuations. Results of the WM-sleep analysis showed that for these children higher sleep quality was significantly related to higher WM accuracy in the morning occasion (b = 0.021, p = .028), but showed no statistically meaningful association in the afternoon occasion (b = 0.023, p = .07), in line with our Hypothesis f. We found no evidence in favor of Hypotheses g and h as time in bed was not meaningfully related to WM accuracy at either occasion (morning: linear effect: b = -0.006, p = .29; quadratic effect: b = 0.000, p = .96; afternoon: linear effect: b = 0.005, p = .38; quadratic effect: b = -0.001, p = .46) and there were no statistically meaningful between-person differences in the effect of sleep quality on WM accuracy (p = .86) (Hypothesis h).

3.2. Fluctuations in WM Updating Precision at Different Time Scales

We aimed to examine fluctuations in WM across fast and more enduring time scales. Therefore, we decomposed children's performance fluctuations across days, occasions within days, trials or moments within occasions, and items/responses within trials. Measures of mnemonic precision allowed us to analyze within-person variability across the full hierarchical data structure including the aforementioned four time scales. Variance components at the different time scales were estimated separately for each child and task condition (i.e., Spatial Load 2, Spatial Load 3, Numerical Load 3, and Numerical Load 4). Results are based on subsets of children (N = 85, spatial WM task and N = 87, numerical WM task) for whom sufficient data was available to estimate the variance components at the different time scales. For the sake of completeness, we also analyzed fluctuations of memory accuracy by using mean accuracy at the trial level (i.e., the average proportion across responses for each trial) as dependent variable for variance decomposition. This results in three variance components (days, occasions, trials), thereby missing information at the item level. Results of these analyses can be found in the Supplemental S2.

3.2.1. Load Effects on Variance Components of Spatial and Numerical Precision

Descriptive statistics for each VC can be found in Table 4. Figure 3 summarizes the findings whereby the total size of bars reflects the average amount of observed day-to-day variability (i.e., the variance of average performance across days). This variance is decomposed into a VC of systematic or true day-to-day fluctuations (green), and the contribution of occasion-to-occasion (blue), trial-to-trial (red), and item-to-item variability (yellow) to observed day-to-day variability (= variance of average recall precision performance across days). On average across children, each VC contributed to the variance of average performance across days. Next, we tested whether the amount of each VC systematically varied as a function of memory load, separately for spatial and numerical delta. Results of Wilcoxon signed rank tests showed significantly higher item-to-item variability under low than high memory load conditions for both spatial and numerical deltas (Spatial δ : $V = 0$, $p < .0001$; Numerical δ : $V = 522$, $p < .0001$). A similar effect was observed for spatial trial-to-trial VC ($V = 1098$, $p = .001$), while numerical trial-to-trial VC showed no significant differences between load conditions ($V = 2245$, $p = .16$). We observed no statistically meaningful differences among loads for occasion-to-occasion (Spatial: V =

1325, p = .03; Numerical: V = 1463, p = .06) nor true day-to-day variability (Spatial: V = 1347, p = .04; Numerical: V = 1623, p = .22).

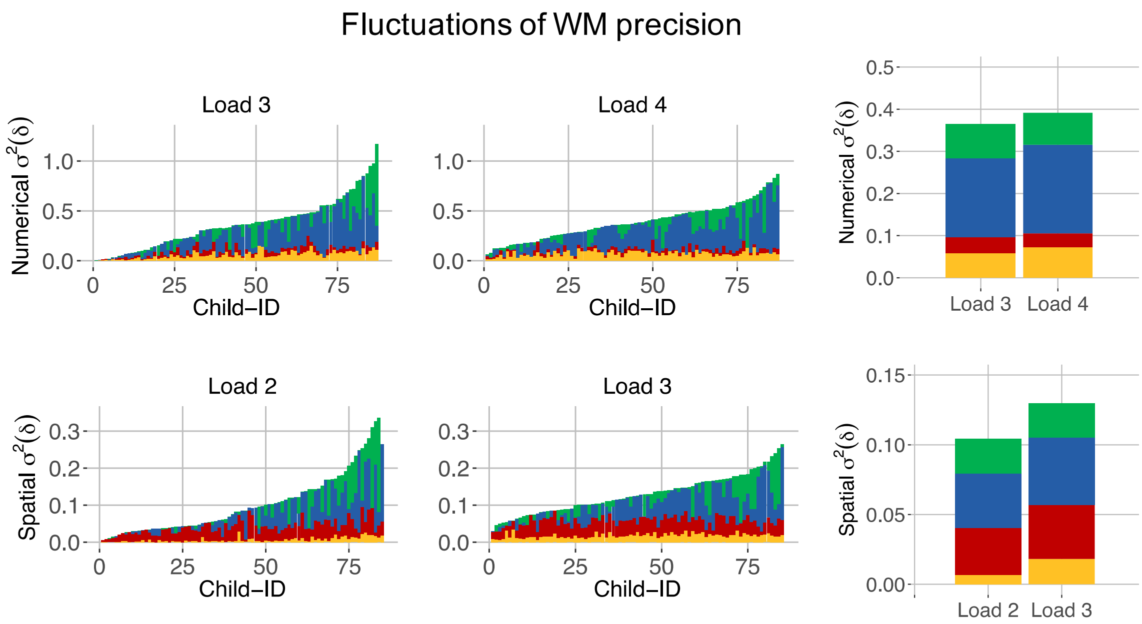

Figure 3. *Children's estimated variance components (VCs) of precision measures of numerical and spatial WM. Each child's observed day-to-day variability (i.e., the variance of average performance across days) was decomposed into a VC of true day-to-day fluctuations (green), of occasion-to-occasion variability (blue), of trial-to-trial variability (red), and of item-to-item variability (yellow). The total size of the stacked bar plots correspond to the variance of observed day-to-day variability of each individual child and of averaged VCs across children (i.e., the two plots on the right side) for each load condition (Spatial: N = 85; Numerical: N = 87). The total size of the bars corresponds to the variance of observed day-to-day variability.*

3.2.2. Between-Person Variance in WM Fluctuations across different Time Scales, and Their Relation to Fluid Intelligence

We found large individual differences in the amount of children's WM fluctuations of precision at the different time scales. Across task conditions, some children showed variance of average performance across days being dominated by performance fluctuations across trials and occasions without any contribution of true day-to-day variability. By contrast, other children showed high true day-to-day variability but low within-day variability or had similarly high variance components (Figure 3, left side). We assessed whether individual differences in the amount of VCs are consistent across time scales by computing Spearman correlation coefficients between the observed day-to-day, occasion-to-occasion, trial-to-trial, and item-to-item VC of spatial and numerical delta, and how VCs are linked to fluid intelligence.

For spatial δ, we observed moderate to large positive correlations for the observed day-to-day VC (= 'VC total'; variance of average performance across days) with all other VCs ranging from *rho* = .42 to *rho* = .75, except the trial-to-trial VC under Load 3 showing a very weak correlation (*rho* = .11). Occasion-to-occasion variability showed a high positive correlation with item-to-item variability under Load 2 (*rho* = .61), a weak positive correlation under Load 3 (*rho* = .25), and was very weakly linked to the trial-to-trial VC (Load 2: *rho* = .10; Load 3: *rho* = -.07). Trial-to-trial variability was weakly positively related to item-to-item variability under both loads (Load 2: *rho* = .31; Load 3: *rho* = .27) (Table 5a).

For numerical δ, we found moderate to large positive correlations between observed day-to-day variability (= 'VC total') and true day-to-day VC and occasion-to-occasion VC across memory load conditions ranging from *rho* = .44 to *rho* = .83. Observed day-to-day VC was also highly positively linked to item-to-item variability under Load 3 (*rho* = .77) but only weakly positively linked to item-to-item VC under Load 4 and to trial-to-trial variability ranging from *rho* = .20 to *rho* = .31. Numerical occasion-to-occasion VC showed a moderate positive correlation with item-to-item variability under Load 3 (*rho* = .61), and very weak positive correlations with item-to-item VC under Load 4 (*rho* = .04) and with trial-to-trial VC (Load 3: *rho* = .07; Load 4: *rho* = -.04). Numerical trial-to-trial variability was weakly positively related to item-to-item VC under Load 3 (*rho* = .35) but to a smaller degree under Load 4 (*rho* = .06) (Table 5b).

Together, these results indicate that children who show larger fluctuations in their average recall precision across days (= observed day-to-day variability in precision) tend to be children who also have higher true day-to-day fluctuations in precision and higher fluctuations across occasions within days. By contrast, the relations between observed day-to-day variability in precision and variability across the faster time scales show higher variation across load and task conditions ranging from a very weak link to trial-to-trial variance (spatial load 3) to a very high association to item-to-item variability (spatial load 2). The results also suggest that children whose recall precision deviates more strongly across trials within an occasion do not always tend to be children who differ in their performance across items within a trial, implicating that a distinction between these two fast time scales may be important.

Table 4. Descriptive statistics of variance components (VC) for spatial (a) and numerical (b) WM updating delta under each load condition

(b) Spatial VC delta

Time scale	Load	n	*mn*	*sd*	*median*	*min*	*max*
day	2	85	0.0247	0.0480	0.0011	0.0000	0.2537
occasion			0.0392	0.0492	0.0185	0.0000	0.2204
trial			0.0336	0.0166	0.0317	0.0042	0.0763
item			0.0066	0.0065	0.0039	0.0002	0.0294
day	3		0.0243	0.0348	0.0092	0.0001	0.1518
occasion			0.0485	0.0421	0.0443	0.0001	0.1965
trial			0.0387	0.0116	0.0388	0.0101	0.0610
item			0.0182	0.0063	0.0172	0.0064	0.0343

(b) Numerical VC delta

Time scale	Load	n	*mn*	*sd*	*median*	*min*	*max*
day	3	87	0.0807	0.1368	0.0148	0.0000	0.8215
occasion			0.1881	0.1566	0.1740	0.0000	0.6495
trial			0.0370	0.0298	0.0302	0.0000	0.1458
item			0.0590	0.0369	0.0551	0.0019	0.1502
day	4		0.0757	0.1015	0.0331	0.0002	0.4855

occasion	0.2103	0.1545	0.1860	0.0000	0.7080
trial	0.0329	0.0255	0.0299	0.0000	0.1276
item	0.0725	0.0278	0.0759	0.0170	0.1391

Results of Spearman correlation analyses demonstrated significant negative correlations between scores in a test of fluid intelligence and item-to-item variability of spatial (Load 3) and numerical δ (Spatial Load 3: *rho* = -.47, *p* < .0001; Spatial Load 2: *rho* = -.30, *p* = .006 > bonf. corrected *p* = .003, n.s.; Numerical Load 3: *rho* = -.34, *p* = .0017; Numerical Load 4: *rho* = -.32, *p* = .0030). We found no statistically significant correlations between fluid intelligence and any of the other VCs (all *p* > .045).

Table 5. Spearman correlation coefficients of variance components for spatial (a) and numerical (b) WM updating delta

(a) Spatial WM updating delta (N = 83)

Load		fluid IQ	VC day	VC occ	VC trial	VC item	VC total
2	fluid IQ	1					
	VC day	-.08	1				
	VC occ	-.22	.34	1			
	VC trial	-.15	.22	.10	1		
	VC item	-.30	.48	.61	.31	1	
	VC total	-.23	.69	.75	.48	.75	1
		fluid IQ	VC day	VC occ	VC trial	VC item	VC total
3	fluid IQ	1					
	VC day	-.08	1				
	VC occ	-.14	-.15	1			
	VC trial	-.09	-.03	-.07	1		
	VC item	-.47	.10	.25	.27	1	
	VC total	-.20	.42	.70	.12	.48	1

(b) Numerical WM updating delta (N = 85)

Load		fluid IQ	VC day	VC occ	VC trial	VC item	VC total
3	fluid IQ	1					
	VC day	-.23	1				
	VC occ	-.12	.18	1			
	VC trial	-.08	.19	.07	1		
	VC item	-.34	.32	.61	.35	1	
	VC total	-.19	.55	.83	.31	.77	1
		fluid IQ	VC day	VC occ	VC trial	VC item	VC total
4	fluid IQ	1					
	VC day	-.18	1				
	VC occ	-.08	-.12	1			
	VC trial	-.14	.25	.04	1		
	VC item	-.32	-.05	.04	.06	1	
	VC total	-.26	.44	.74	.29	.20	1

4. Discussion

We examined fluctuations in children's WM by modeling within-person variability at multiple time scales based on an working memory tasks embedded within an intensive longitudinal measurement design. We obtained categorical (accuracy) and continuous measures (precision) of WM performance on a numerical and a spatial WM updating task under low and high loads. By adopting these tasks for mobile devices, we assessed fifth graders in their natural environments twice daily in a morning and an afternoon session over a period of four weeks. We found systematic common variance in WM across our experimental task conditions at both the within- and between-person level. On this basis, we took a closer look at both levels by estimating within-person fluctuations in recall performance across days and within days. We examined between-person differences in these within-person fluctuations, and daily couplings of WM with facets of sleep behavior.

Our main results suggest that children show systematic within-person variability in WM performance from day to day, but also within days, that is, from morning to afternoon sessions, across trials within a session, and also at the level of single items within trials. These fluctuations in mnemonic performance substantially varied in their amounts across time scales and children, showed consistencies but also discrepancies among each other, were differentially affected by memory demands, and were differentially associated with measures of fluid intelligence. All findings and their implications are discussed in more detail below.

A growing body of empirical evidence suggests that within-person fluctuations in cognitive performance constitute a meaningful indicator of human cognitive functioning (Dirk & Schmiedek, 2016; Galeano Weber et al., 2018; Li et al., 2004; MacDonald, 2006; Mella et al., 2015; Nesselroade & Salthouse, 2004; Riediger et al., 2011; Schmiedek et al., 2013; Sliwinski et al., 2006). The present results support this assumption and add significantly to better understanding within-person fluctuations in working memory – a fundamental cognitive process which enables the use of psychological processes to engage, direct, or coordinate other processes in the service of goals (Baddeley & Hitch, 1974; Cowan, 2000; Miyake & Shah, 1999). The present data tell relatively consistently that children show substantial average within-person variation across WM task and load conditions, and the proportion of the daily within-person variability of overall variance was relatively large for most load conditions. Thus, children's WM resource may be better characterized in terms of a potential range of WM scores across many occasions over an extended period of time (i.e., several weeks) rather than defining WM ability only by a single occasion of measurement (cf. Nesselroade & Salthouse, 2004). This within-person perspective on WM may be particularly important to better understand how and why WM performance improves with development (Cowan, 2016) and how this affects successful learning.

In contrast to many previous studies on WM in children, we considered that representations in WM may vary in precision (cf. Bays & Husain, 2008; van den Berg et al., 2012) rather than defining WM to be 'all or none', that is, children remember items with perfect precision or not at all (Cowan 2000; Luck & Vogel, 1997). Here, we obtained measures of both, recall precision (continuous difference between presented and reported location/number) and accuracy (categorical ‘correct/incorrect’ location/number) at the level of single items. In line with our hypothesis, we found effects of occasion and load on both accuracy and precision, whereby mean performances were lower in the afternoon than in the morning session and decreased with increased loads within both the numerical and spatial WM tasks. Reduced precision with increasing load is in line with theoretical assumptions of cognitive resource models of WM capacity (Bays & Husain, 2008; van den Berg et al., 2012) and with recent empirical findings on WM precision in children (Burnett-Heyes et al., 2012, 2016; Sarigiannidis et al. 2016; Galeano Weber et al., 2018). In addition, our results show that children’s recall precision depends on contextual factors, that is, the time of day whereby children remembered items more precisely earlier in the day than during afternoons.

The sampling rate and time over which measurements are collected has often been neglected in previous studies on WM fluctuations because these fluctuations were only defined in terms of the within-person or intraindividual SD and/or variance (e.g., Fagot et al., 2018; Mella et al., 2015). This can result in different conclusions among studies because some constructs may differentially affect other constructs depending on the time over which a time series is collected (Deboeck et al., 2009). Going beyond measures of dispersion, we assessed performance fluctuations in a different way by decomposing variance across multiple time scales. This allowed us to identify and partial out variability in WM precision across fast and more enduring time scales. More specifically, we assessed the contribution of four different variance components to total daily variance. These were i) true day-to-day variance (= the proportion of daily mean variance which does not depend on variability of the faster time scales), ii) occasion-to-occasion variance, iii) trial-to-trial variance, and iv) item-to-item variance. Results suggest that each variance component contributes to the observed total amount day-to-day variability.

Further, children differed in their amount of fluctuations across time scales, for example, some children showed high fluctuations in WM precision from day to day, but low precision variability across the faster time scales within days, while others were more stable in their performance across and within days. These results emphasize the importance of considering different short-term WM processes (here: fluctuations across moments, sessions, or days) underlying WM development (cf. Nesselroade, 1999, Deboeck et al., 2009). They further indicate that WM fluctuations at slower and faster time scales progress in a highly individual manner rather than following a general pattern across children. Another important finding is that the transient moment-to-moment variability across the faster time scales was positively related to load and negatively linked to scores in fluid intelligence. By contrast, no such associations were observed for the slower more enduring day-to-day and occasion-to-occasion WM fluctuations. These results replicate previous findings on spatial WM fluctuations (Galeano Weber et al., 2018) and extend these effects to numerical WM in a new sample of slightly older children. Thus, systematic fluctuations in WM precision do not seem to be task-specific but rather generalize across spatial and numeric WM domains.

Transient variability in WM, in comparison to the slower day-to-day fluctuations in WM, could be more tightly linked to cortical systems that are important for precise and stable information processing over short periods of time (ranging from ms to sec). Neural systems that underly children's ability to control their attention to task-relevant information may play an important role for the observed effects on transient WM precision fluctuations. More specifically, lower moment-to-moment variability or more stable WM representations could be based on reduced neural noise in frontoparietal brain activation patterns due to increased executive control and lower attentional fluctuations while performing the task (cf. Ma et al., 2014; MacDonald et al., 2006; Unsworth & Robison, 2016). Future studies could test this assumption by simultaneously measuring fluctuations in attention and WM precision and/or by obtaining neuroimaging data while performing these tasks.

Another compelling finding of systematic fluctuations in children's WM was that within-person variability in WM precision showed considerable consistencies but also discrepancies among multiple time scales (i.e., the amount of shared between-person variance across fast and slow WM variability). Children who showed high fluctuations in their mean recall precision across days tended to be children with higher true day-to-day fluctuations in precision and higher precision fluctuations across sessions within days. The pattern was less consistent for the relation between observed day-to-day variability and the moment-to-moment variance components (items, trials), and the relation of item-to-item and trial-to-trial fluctuations. Children who showed a high variance of average recall precision across days were not always children who differ in their performance across items or trials. Additionally, children whose performance deviated more strongly across trials within an occasion were not always children who differ in their performance across items within a trial. These findings highlight the importance of a nuanced distinction of WM fluctuations across different time scales. More generally, analyzing the covariation of fluctuations at different time scales may be important to better understand short-term regulatory dynamics in WM functioning that are suggested to affect long-term development in cognitive functions (cf. Deboeck et al., 2009). An interesting and open question is whether individual differences in momentary and/or daily fluctuations in WM predict differences in long-term cognitive development across years.

Further, we assessed daily couplings between fluctuations in WM and facets of sleep behavior by testing for systematic within-person associations between these constructs at a daily level (Könen et al., 2015). Contrary to our pre-registered hypotheses, higher than usual sleep quality predicted higher mean accuracy in the afternoon (but not in the morning session), and time in bed had no effect on WM. These findings stand in contrast to results from a previous ambulatory assessment study in elementary school children (Könen et al., 2015). Results of exploratory analyses helped us to identify factors that might explain these inconsistencies. When we assessed WM-sleep couplings separately for each task condition, results of Könen et al. (2015) were partly replicated in terms of a negative quadratic effect of time in bed on accuracy in the morning for spatial WM in the low load condition. By analyzing gender-related differences, we found the hypothesized negative quadratic effect of time in bed on spatial WM accuracy assessed in the morning (in the low load condition) for boys but not girls. The amount of true day-to-day fluctuations in WM may be another reason for inconsistent results which is why we analyzed data of a subsample of *N* = 50 children who showed substantial day-to-day WM fluctuations. Results of this subgroup analysis showed that on days when children report higher sleep quality they also showed higher WM accuracy in the morning session, but no meaningful association in the afternoon session, in line with our hypothesis. We found no evidence for the other two hypotheses in this analysis, possibly due to reduced power (*N* = 50 vs. *N* = 110 participants in Könen et al., 2015). In sum, the present findings suggest that within-person associations between WM and sleep behavior may be more complex than thought. More research in different populations with varying age and gender composition, and different measures of sleep behavior (e.g., actual sleep minutes and short-awakenings measured with actigraphy) are needed to establish within-person relations between WM and sleep under natural settings more robustly.

In conclusion, we found that secondary school children showed substantial WM fluctuations across and within days in their natural environments. These fluctuations across slower and faster time scales showed consistencies but also discrepancies among each other, which highlights the importance of a nuanced distinction of cognitive fluctuations at multiple time scales. Specifically, momentary variability in mnemonic precision, but none of the slower fluctuations, was systematically associated to WM load and reasoning. Within-person associations between children's previous night's sleep and daily WM performance were less consistent, suggesting that daily couplings between sleep and WM may be more complex than thought. Objective measures of sleep behavior and of contextual information throughout a day in addition to measures of person-level variables could help to better understand these more complex daily within-person dynamics. Together, our results suggest that the analysis of slower and faster fluctuations in children's WM is important to identify short-term regulatory dynamics in cognitive functioning. A better understanding of these dynamics may in turn help to explain the development of WM capacity in the long run.

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