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The near and far transfer effects of computerized working memory training in typically developing preschool children: Evidence from event-related potentials

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ABSTRACT

Working memory (WM) refers to the ability to actively maintain and process information needed to complete complex tasks such as comprehension, learning, and reasoning. Recent studies have examined the efficacy of computerized working memory training (WMT) in improving cognitive functions in general and WM in particular, with mixed results. Thus, to what extent can WMT produce near and far transfer effects to cognitive function is currently unclear. This study investigated the transfer effects of a computerized WMT for preschool children and also examined the possible neural correlates using the event-related potential (ERP) technique. A total of 50 Chinese preschoolers (64.44 ± 7.76 months old; 24 girls) received 4-week training during school hours. Compared with those in the active control group, children in the training group showed better gains in behavioral performance in the WM task and significantly more changes in ERP markers of the WM and inhibitory control tasks (near transfer effect). However, no evidence was found for transfer to fluid intelligence (far transfer effect). These findings suggest that WMT is capable of enhancing cognitive functioning in preschool children, and as such this work has

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important implications for educational practice and it may help to design and refine cognitive interventions for typically developing children and those with WM problems or other cognitive deficits (e.g., children with attention-deficit/hyperactivity disorder).

Introduction

Working memory (WM) refers to a limited capacity system allowing the temporary storage and manipulation of information necessary for complex tasks such as comprehension, learning, and reasoning (Baddeley, 1992, 2012). WM is considered to be at the core of human cognitive abilities and plays a crucial role in learning, reasoning, problem-solving, and intellectual activity (Baddeley, 1992). Working memory capacity (WMC) is a positive correlate with other cognitive abilities, especially inhibitory control (Redick et al., 2011), and it is closely related to nonverbal intelligence (also called fluid intelligence; Engel de Abreu et al., 2010) as well as verbal intelligence, such as mathematical, reading and writing skills (e.g., Sedek et al., 2016). In recent years, a growing number of studies have examined whether repeated training in WM paradigms is capable of improving WMC and, if it does, whether such a training effect can generalize or transfer to other untrained tasks, including tasks of inhibitory control, fluid intelligence, and academic achievement (e.g., Jaeggi et al., 2008; Swanson & Mcmurran, 2018; Wang et al., 2022; Zhang et al., 2018; Zhao et al., 2013). The transfer effects on tasks closely resembling those trained are termed *near transfer* effects, whereas those on other cognitive tasks quite different from those trained are called *far transfer* effects (Melby-Lervåg et al., 2016). Despite the increasing interest in working memory training (WMT), different studies have reported contradictory findings concerning the degree of improved WM performance, the magnitude of far and near transfer effects, and specific structural and functional neural changes.

Preschool is a significant developmental period for children's cognitive function, social communication, and emotional and brain maturity. WM begins to develop most rapidly in the preschool period (e.g., Cheng & Kibbe, 2022; Ross-Sheehy et al., 2021), and these changes occur in parallel with structural and functional changes in the nervous system involving the prefrontal cortex (Diamond, 2013). The development of WM in the preschool period is such an important event for children that their WMC often closely relates to their mathematic, reading, and writing achievements in the future (Sedek et al., 2016). For example, WMC in the preschool period is found to predict school-age mathematic and reading achievements (Shipstead et al., 2012), academic achievements (Snyder & Munakata, 2010), and fluid intelligence (Engel de Abreu et al., 2010). Given that the preschool period witnesses a high degree of brain plasticity and cognitive plasticity, cognitive training might have a better and stronger effect during this period than other periods of a person's life (Wass et al., 2012). Therefore, understanding the transfer effects of WMT from a developmental perspective may help to understand its efficacy in a stage-specific manner. Research on WMT in preschool children can also help to design better cognitive training and intervention programs to help the behavioral development of children, especially those with mild cognitive impairments (e.g., autism, attention-deficit/hyperactivity disorder [ADHD]), develop better cognitive abilities. In addition, WMT is shown to strongly influence other components of executive function, and higher executive functions have a long-term impact on children's lifelong achievement, health, wealth, and quality of life (Diamond, 2013); thus, WMT in the preschool period has clinical significance.

Despite its significance, research on computerized WMT for preschool children is rather limited, and evidence of far transfer is scarce. Thorell et al. (2009) adopted the Cogmed JM program to train WM of the visuospatial sketchpad in 4- and 5-year-old preschool children for 5 weeks. They found that this training brought significant improvements in untrained WM tasks but had no effect on inhibitory control, as assessed by the day–night Stroop and go/no-go tasks, or on fluid intelligence. Bergman Nutley et al. (2011) also chose the Cogmed JM program to train 4-year-old children but failed to observe any significant improvement in fluid intelligence scores in the WMT group. Zhang et al. (2019) conducted 20 sessions of WMT using the WM animal span task with preschool children. They also did not find any improvement in inhibitory control measures of the AX–CPT (the AX version of continuous performance task) and post-test fluid intelligence scores. Nevertheless, Peng et al. (2017) used the *n*-back task to train preschool children, and their results illustrated that the training group showed higher fluid intelligence scores in the post-test and in the 6- and 12-month follow-up tests.

Based on the above analysis, we thought that there may be two reasons for the discrepancy in the reported findings. First, the training programs target different components of WM across different studies. The Cogmed program (https://www.cogmed.com), designed and developed by Klingberg and colleagues (Klingberg et al., 2005), is one of the most widely used WMT programs. Cogmed JM is the version specifically tailored for 4- to 6-year-olds. The Cogmed JM program contains short-term memory and WM tasks; the WM tasks target both the storage and manipulation components of visuospatial WM (Yu et al., 2015). The WM animal span task also contains both storage and processing components that emphasize the maintenance function in the face of distraction (Oberauer et al., 2012). However, the *n*-back task emphasizes the updating components involving coding, monitoring, and maintenance (Jaeggi et al., 2010). A comparison of *n*-back training with WM complex span training showed that *n*-back training has a more extensive transfer effect in adults (Blacker et al., 2017). In addition, in an intervention study of children with ADHD, compared with the Cogmed program, the running memory task, with a focus on the central executive function component of WM, yielded better effects on WM and ADHD symptoms (Yu et al., 2015). Therefore, the specific training components of different training programs may be the key determining factor to the transfer of WMT to fluid intelligence. Second, previous studies used behavioral indicators to evaluate the transfer effect of WMT in children by comparing the differences between the pre- and post-tests. Nevertheless, behavioral indicators may be insensitive and unable to capture the specific cognitive process and identify the characteristics of information processing in different cognitive stages. Other indices of WMT such as those based on neural responses may be needed to detect the WMT transfer effects, especially when the effects are subtle.

The current study used the event-related potential (ERP) technique to further examine the far and near transfer effects of WMT in preschool children. Previous studies demonstrated that ERP is effective in capturing the temporal dynamics of brain activation patterns in a fine-grained manner, has greater sensitivity to detect differences in executive functioning tasks (Thomas et al., 2022), and is a promising approach to understanding children's WMC and inhibitory control (Buss et al., 2011; Lotfi et al., 2020). In addition, ERP provides biomarkers for the development of executive function (Downes et al., 2017), and ERP-derived indicators can predict the later development of executive function and academic performance (Harms et al., 2014).

In WMT studies, there are two main categories of ERP signals commonly used to assess the training and transfer effects: exogenously driven components reflecting early attention and perceptual processes, including P1, N1, and P2, and endogenously driven components representing higher-order cognitive processes, such as N2 and P3, which measure inhibitory control, WM, and so on (Wang & Covey, 2020). The P3 amplitude is the positive waveform that appears after 300 ms of the stimulus onset and is intimately related to information processing and context updating (Lenartowicz et al., 2010; Polich, 2007) and can be modified by WMT. An increase in the *n*-back related P3 amplitude after WMT in healthy adults has been reported (Zhao et al., 2013), and the same increase was observed in 7- to 12-year-old children with dyslexia (Lotfi et al., 2020) and in 10- to 13-year-old children with learning difficulties (Zhang et al., 2018). The P3 amplitude has also been observed in inhibitory control tasks, reflecting inhibitory processes and sustained attention (Grammer et al., 2014). For example, Wang et al., (2022) found that the go/no-go related P3 amplitude was enhanced in children aged 9 to 11 years after WMT.

The N2 component of ERP has also been used to study the transfer effects of WMT on inhibitory control. N2 is a negative electrical waveform following successful inhibition with a peak latency of approximately 200 to 400 ms after stimulus onset. It is generated in the frontal cortex, superior temporal cortex, and anterior cingulate cortex, reflecting conflict-monitoring processes, continuous novel anisotropy, and mismatch recognition (Lo, 2018). For example, recent studies found that after WMT, the N2 amplitude was increased in healthy adults in the *n*-back task (Covey et al., 2019) as well as in the combined go/no-go flanker task (Wang & Covey, 2020). The N2 effect is also found in inhibitory control tasks, with the high-conflict condition (e.g., incongruent trials in the flanker task, no-go trials in the go/no-go task) generating a greater N2 amplitude than the low-conflict condition (e.g., congruent trials in the flanker task, go trials in the go/no-go task). Although the N2 effect is typically absent in children before 6 years of age (Buss et al., 2011), it has been observed in preschool children after executive attention training (Rueda et al., 2005).

WMT also affects early components of ERP, mainly N1, P1, and P2. These components are exogenously driven and reflect the level of attentional resource investment, the degree of attentional focus on the target stimulus, and so on (Vogel & Luck, 2000). WMT is found to increase N1 amplitude in healthy adults (Wang & Covey, 2020; Zhao et al., 2013).

As mentioned above, because preschool children are in a rapid brain and behavioral developing phase, they are more cognitively and neurologically plastic. WMT in this population is likely to be more efficacious in inducing near and far transfer effects. The current study examined this issue and explored the potential neural mechanisms underlying the WMT effects. Specifically, we explored whether the running memory task, which places a greater emphasis on the component of updating (Pappa et al., 2020), is capable of achieving near and far transfer effects in preschool children. We also tested the idea of whether the updating component in WMT is key to the transfer effects. The running memory task was chosen because it is one of the most common tasks targeting the updating component of WM and is closely related to intelligence (Salthouse, 2014). Peng et al. (2017) demonstrated the transfer of *n*-back training to fluid intelligence mainly due to its ability to target the updating component. Unfortunately, they did not find the near transfer effect. Reporting only an increase in intelligence scores (far transfer) without identifying an increase in WMC (near transfer) is puzzling given that the effects of WMT on fluid intelligence or academic achievement are thought to be mediated by improvements in WMC (Melby-Lervåg et al., 2016). In the current study, we selected the *n*-back task and related ERP components as indicators for the near transfer effect, whereas fluid intelligence as assessed in Raven's Coloured Progressive Matrices was used as indicators for the far transfer effect. Meanwhile, we measured inhibitory control ability as the far transfer effect based on the observations that inhibitory control is closely related to WM and is often used as an important measure of the transfer effect in WMT studies (e.g., Thorell et al., 2009; Wang et al., 2022; Zhang et al., 2019). Thus, we used the go/no-go task and recorded the related ERP components (e.g., St. John et al., 2019). We hypothesized that the running memory training would transfer to preschool children's WM, inhibitory control, and fluid intelligence. Second, we hypothesized that both the exogenous components of ERP (N1, P1, and P2, reflecting early attention) and endogenous components (P3 and N2, representing WM and inhibitory control) would be enhanced in the post-training tests.

Method

Participants

A total of 50 typically developing children from a preschool in Huaian, Jiangsu province, China, participated in this study. They were randomly assigned to the experimental group or the active control group with a balanced grade and gender. There were 26 children in the training group (52–82 months of age, M = 65.65, SD = 8.12; 13 girls) and 24 in the control group (52–75 months of age, M = 63.12, SD = 7.29; 9 girls). None of the children had received a psychiatric diagnosis or participated in a similar study. All participants provided informed written consent by their caregivers. This study was approved by the Psychology Study Ethics Committee of Nanjing University (Approval number: NJUPSY201904005). Calculated by the G*Power software (Erdfelder et al., 1996), using a medium effect size (η_p^2 = .25), a desired efficacy value ($1 - \beta$ = .80), and a significance level of α = .05, the calculation required a sample size of 34 participants, so the experimental sample met the requirements.

Procedure

The experimental programs were compiled with E-Prime software and run on the Windows operating system. The experimental computer had a 14-inch display with a resolution of 1366 × 768 pixels and a refresh rate of 60.059 Hz.

All participants completed three pre-test tasks. Behavioral and electroencephalographic (EEG) data were recorded simultaneously throughout the 1-back and go/no-go tasks, and scores on the Raven's Coloured Progressive Matrices were also recorded. Participants in the training and control group were trained on school days for 4 consecutive weeks, with a gap of a few days in between due to the New Year's Day holiday and other events, for a total of 18 to 20 training days across the 4-week period. At the end of the training phase, participants completed the post-test task, which was the same as the pre-test. Fig. 1 shows the flow chart of the experimental procedure.

Pre- and post-test measures

WM: The 1-back task. The *n*-back task is a classic and commonly used measure of WMC, and the 1-back condition (Fig. 2A) is a more targeted measure of the updating process while excluding complex management of the information involved in 2- and 3-back conditions (Harvey et al., 2004).

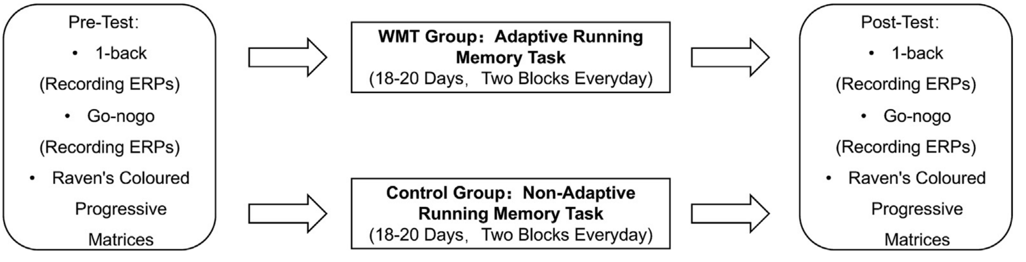

Fig. 1. Flowchart of the current study. ERPs, event-related potentials; WMT, working memory training.

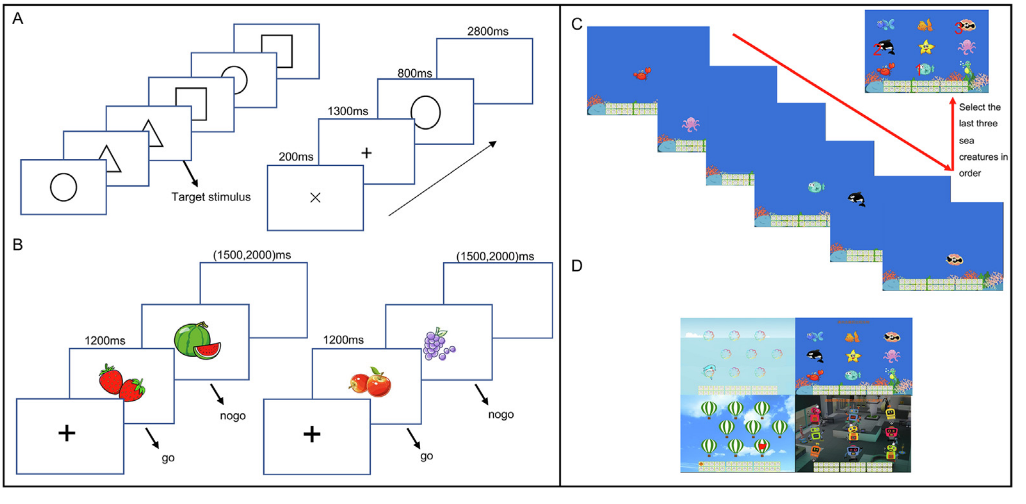

Fig. 2. Schematic representation of the tasks of pre- and post-test measures and the training task. (A,B) The tasks of pre- and post-test measures that measure working memory (WM) and inhibitory control. WM was measured by the 1-back task (A). Children were asked to judge whether the current graphic was the same as the previous one. Inhibitory control was measured by the go/no-go task (B). Children were asked to press the space button if they saw strawberries and not to press any button when they saw watermelons in two blocks, and they were asked to press the space button if they saw apples and not to press any button when they saw grapes in the other two blocks. (C,D) The training task: The running memory task. In the sea creatures task (C), children were asked to choose the last three sea creatures in the presentation order after a random number of sea creatures had been presented, with the correct sea creatures and order recorded as correct. After each correct or incorrect response, the correct and incorrect feedback, including visual images and sound feedback, were given. The tasks were divided into two forms: choosing positions (D, upper left and lower left) and choosing images (D, upper right and lower right).

The procedure of the task was as follows. First, a fixation was presented in the center of the screen, and after the fixation a graphic appeared and children were instructed to judge whether the current graphic was the same as the previous one by pressing the "Z" button on the keyboard if it was the same or pressing the "M" button if it was not. The first trial of each block did not require a response, and children were required to complete a total of 103 trials, with half of the stimuli in the matching condition and the other half in the nonmatching condition. Accuracy, reaction time, and ERP data were recorded.

Inhibitory control: The go/no-go task. Children were told to play a game of picking fruits in an orchard on the computer screen (Fig. 2B). They were told that some fruit items needed to be picked, whereas others did not need to be picked. Specifically, when they saw strawberry in two blocks and apple in the other two blocks, they were told to pick them by pressing the space button as quickly as they could (go trial). However, when they saw watermelon in two blocks and grape in the other two blocks, they were told to withhold any response and not press any button (no-go trial). The fruit stimuli were presented for 1200 ms, followed by a blank screen after a random interval between 1500 and 2000 ms. Children could respond during the presentation of the stimulus. There were a total of 208 trials, of which 75% were go trials and 25% were no-go trials. Thus, participants needed to inhibit their dominant responses on no-go trials. The trials were broken up into four blocks. Accuracy, reaction time, and ERP data were recorded. To increase the fun of the game and reduce the effect of children's personal fruit preferences, two combinations of strawberry–watermelon and apple–grape were adopted.

Fluid intelligence: Raven's coloured progressive matrices. The Raven's Colored Matrices Intelligence Test (Raven, 1998) is a nonverbal intelligence test developed by the British psychologist John C. Raven to measure the fluid intelligence of young children and people with below-average intelligence. Raven's Coloured Progressive Matrices included three sets (A, B, and AB), and each set comprised 12 items with increasing difficulty. Referring to the split-half treatment of previous studies (Jaeggi et al., 2008; Wang et al., 2022; Zhang et al., 2018), 36 items were split into two equal portions based on their serial numbers. Half of the children from each group were requested to answer the odd-numbered items in the pre-test and the even-numbered items in the post-test and vice versa for the other half. The order of presentation showed no significant difference between the two groups, $\chi^2(1) = 0.074$, $p = .786$. All participants were instructed to complete the task within 20 min.

Training task

The training task for the training group was an adaptive running memory task (Wang et al., 2022; Zhang et al., 2018; Zhao et al., 2013) focusing specifically on visuospatial WM, including types of stimuli for location and cartoon images of various forms (Fig. 2C and 2D).

The training was divided into three phases. The first phase (4 days of training) was to memorize the last stimulus of each trial, the second phase (8 days of training) was to memorize the last two stimuli of each trial, and the third phase (8 days of training) was to memorize the last three stimuli of each trial. The stimulus display time was constantly changing according to participants' performance, starting with an initial presentation time of 1750 ms. Each block contained 5 trials. If 3 or more trials were completed correctly, the stimulus intervals were shortened by 100 ms in the subsequent block. By contrast, if 3 or more trials were completed incorrectly, the stimulus intervals were lengthened by 100 ms in the subsequent block.

The training group completed two tasks per day, six blocks in one task, with each block containing 5 trials for a total of 60 trials. The final accuracy for each task was recorded. We found that children with high accuracy in the early days of training would have lower accuracy due to faster stimulus presentation in the middle and late stages, whereas children with moderate or low accuracy in the early days of training would have higher or relatively stable accuracy due to the same or lower speed of stimulus presentation. Therefore, accuracy did not reflect performance, so the accuracy curves for each training session were not analyzed.

Children in the control group completed the non-adaptive version of the tasks, during which they were asked to always choose only the last stimulus and the stimulus presentation time was fixed at 1750 ms.

EEG data acquisition and data analysis methods

EEG data acquisition

EEG data were collected using 32 sponge electrodes combined with saline placed according to the International 10–20 system with the st-EEG wireless transmission amplifier. Data were sampled at 500 Hz. Prior to recording, impedances were below 50 kΩ whenever possible. During recording, the ground lead was located at the midpoint of FP1 and FP2 on the forehead, and bilateral mastoids were set as the reference. The acquisition environment could not be electromagnetically shielded, and low-pass filtering was selected at 30 Hz, shielded from 50 Hz utility interference.

Data analysis

Data analysis was conducted using EEGLAB, SPSS 25, and Excel 2019. The presence of differences in the baseline of some indicators affected the results of the repeated-measures analysis of variance (ANOVA). Therefore, referring to Dimitrov and Rumrill (2003) and to examine the specificity of training effects between the pre- and post-test sessions for all of the tasks, we employed analyses of covariance (ANCOVA) with the group (WMT or control) as the between-participants factor, pre-test scores as the covariate, and difference scores (post-test minus pre-test) as the dependent variable. Effect sizes are reported as partial eta squared (η^2_p).

Behavioral data analysis. The *n*-back task was analyzed for accuracy, and the go/no-go task was analyzed for accuracy and reaction time. Because the *n*-back task is relatively difficult for preschool children, the instruction was written to ensure that children could understand and perform the task correctly. There was no requirement for a speedy reaction; thus, the reaction time on the *n*-back task was not analyzed. Reaction time was calculated as the mean reaction time on the correct go trials only. Trials with reaction times < 150 ms were excluded before computing the mean reaction time (St. John et al., 2019). Statistical analyses were conducted without outliers (>3 standard deviations from the reaction times based on the individual mean). By this standard, 1.28 ± 2.37 trials per child were excluded on average in the pre-test, and 1.60 ± 1.75 trials per child were excluded on average in the post-test.

EEG data analysis. EEG data were analyzed offline using EEGLAB (Delorme & Makeig, 2004; https://sccn.ucsd.edu/eeglab/index.php), an open-source toolbox running in the MATLAB environment. First, 30 Hz low-pass filtering and 0.1 Hz high-pass filtering were performed on the data. Second, the data were re-referenced to the average reference. Third, the EEG epochs were extracted using a window time from − 200 to 800 ms that was time-locked to the feedback onset and was baseline corrected using the prestimulus interval (−200 to 0 ms). Fourth, the data of bad electrode sites were replaced with the arithmetic mean of adjacent electrode sites using the linear interpolation method, epochs with large drift at any electrode were manually removed, and trials contaminated by eye blinks and motion artifacts were corrected using an independent component analysis algorithm. Finally, data from trials with amplitude values exceeding ± 120 μV at any electrode were removed. Each child needed to have at least 10 usable trials for each trial type to be included in the analyses (St. John et al., 2019). This resulted in an average of 73.32 (*SD* = 16.64) usable trials in the *n*-back task and in 103.67 (*SD* = 20.35) usable go trials and 32.20 (*SD* = 8.13) usable no-go trials in the go/no-go task.

Number of participants included in the analysis

The *n*-back task excluded the data of 1 child because the final number of usable trials in the pre-test of the EEG data of that child was less than 10, and a total of 49 children were included in the final analysis. There were 25 in the training group (53–82 months of age, *M* = 66.20, *SD* = 7.79; 12 girls) and 24 in the control group (52–75 months of age, *M* = 63.12, *SD* = 7.29; 9 girls). There were no differences in child age between the two groups of children (t = 1.428, p = .161).

The go/no-go task excluded the data of 1 child because the final number of usable no-go trials in the pre-test of the EEG data for that child was less than 10, and a total of 49 children were finally included in the analysis. There were 25 in the training group (52–82 months of age, *M* = 65.44, *SD*

= 8.22; 13 girls) and 24 in the control group (52–75 months of age, M = 63.12, SD = 7.29; 9 girls). There were no differences in the children's average age between the two groups (t = 1.042, p = .303).

All children were included in the analysis for Raven's Coloured Progressive Matrices.

Electrodes and time window analyzed for EEG data

The n-back task. Based on visual inspection of ERP waveforms and topographical maps, N1 amplitude was quantified as the mean amplitude at the frontal region between 120 and 170 ms post-stimulus onset, P2 amplitude was quantified as the mean amplitude at the frontal region between 210 and 270 ms post-stimulus onset, P1 amplitude was quantified as the mean amplitude at Pz of the parietal region between 120 and 170 ms post-stimulus onset, and P3 amplitude was quantified as the mean amplitude at Pz of the parietal region between 350 and 500 ms post-stimulus onset. The following electrodes were averaged into one frontal region: FZ、FCZ、F3、F4、FC3、and FC4.

The go/no-go task. Based on visual inspection of ERP waveforms and topographical maps and methods used in previous studies (e.g., Wang et al., 2022), N1 amplitude was quantified as the mean amplitude at the frontal region between 120 and 170 ms post-stimulus onset, N2 amplitude was quantified as the mean amplitude at the frontal region between 310 and 410 ms post-stimulus onset, P1 amplitude was quantified as the mean amplitude at Oz of the occipital region between 120 and 170 ms post-stimulus onset, and P3 amplitude was quantified as the mean amplitude at Oz of the occipital region between 310 and 410 ms post-stimulus onset. The following electrodes were averaged into one frontal region: FZ、FCZ、F3、F4、FC3、and FC4.

The data and analytic code are available upon request from the corresponding author (rlzhou@nju.edu.cn).

Results

The n-back task: Significant effects in both behavioral and EEG results

Results of the descriptive statistics of the 1-back task are shown in Table 1. The ANCOVA on accuracy in the 1-back task revealed a main effect of the group after controlling for the pre-test scores, $F(1, 47)$ = 8.642, p = .005, η_p^2 = .158, reflecting the differential effect of treatments. The training group exhibited a larger increase in accuracy (M = .11, SD = .17) than the control group (M = .05, SD = .15).

The ERP waveforms and topographical maps are shown in Fig. 3. Descriptive statistics of the mean amplitude are presented in Table 1. The ANCOVA revealed a main effect of the group on the mean amplitude of N1, $F(1, 47)$ = 11.208, p = .002, η_p^2 = .196, and P2, $F(1, 47)$ = 4.834, p = .033, η_p^2 = .095, at the frontal region and also on the mean amplitude of P1, $F(1, 47)$ = 6.753, p = .013, η_p^2 = .128, and P3, $F(1, 47)$ = 4.668, p = .036, η_p^2 = .092, at Pz. The training group showed a larger difference (N1: M = – 2.76, SD = 2.93; P2: M = 2.24, SD = 2.99; P1: M = 6.47, SD = 8.49; P3: M = 4.06, SD = 7.05) than the control group (N1: M = – 1.06, SD = 2.41; P2: M = – 0.09, SD = 3.29; P1: M = 2.84, SD = 6.15; P3: M = 0.60, SD = 7.38) on these amplitudes.

Table 1
Descriptive behavioral and EEG statistics of the 1-back task (M ± SD).

	Training group (n = 25)		Control group (n = 24)	
	Pre-test	Post-test	Pre-test	Post-test
Behavioral data				
Accuracy	0.60 ± 0.14	0.71 ± 0.11	0.50 ± 0.17	0.54 ± 0.19
EEG data				
N1 amplitude	−2.87 ± 1.84	−5.63 ± 2.61	−1.72 ± 1.73	−2.78 ± 2.36
P2 amplitude	2.13 ± 2.66	4.37 ± 3.43	3.21 ± 3.15	3.16 ± 2.91
P1 amplitude	5.80 ± 6.94	12.27 ± 7.63	4.00 ± 3.86	6.85 ± 5.37
P3 amplitude	1.47 ± 4.45	5.53 ± 6.93	1.22 ± 6.08	1.82 ± 4.73

Note. EEG, electroencephalographic.

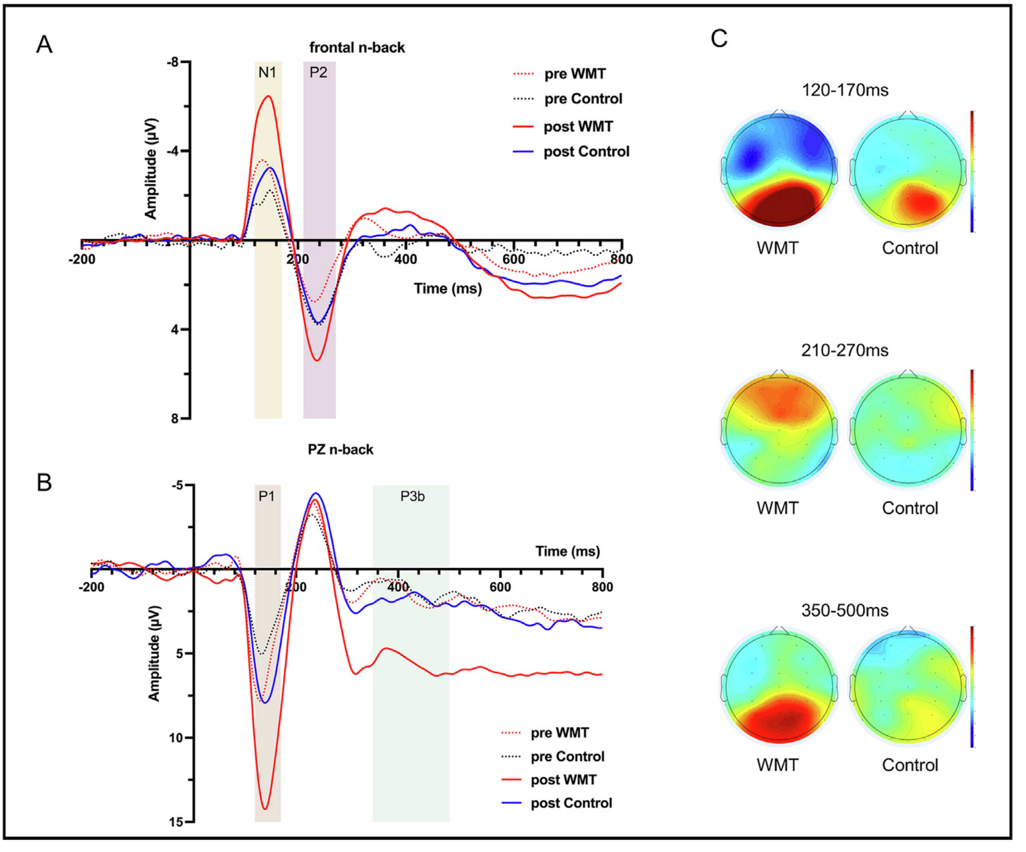

Fig. 3. Waveforms and topographical maps in the 1-back task. (A) Waveforms at the frontal region for the average of FZ, FCZ, F3, F4, FC3, and FC4. (B) Waveforms at Pz of the parietal region. (C) Topographical maps for the differences (post-test minus pre-test) in the two groups and among the three time windows. WMT, working memory training.

The go/no-go task: No significant effects in behavioral results but significant EEG results

Results of the descriptive statistics of the go/no-go task are shown in Table 2. The ANCOVA on the descriptive statistics in the go/no-go task revealed no significant effect of the group after controlling for the pre-test scores (all *F*s < 0.794, all *p*s > .378).

Fig. 4 shows the ERP waveforms and topographical maps. The same trend exists in both conditions; therefore, the combined data from both conditions are presented. Descriptive statistics of the mean amplitude are shown in Table 2. The ANCOVA revealed a main effect of the group on the mean amplitude of N1, $F(1, 47) = 6.564$, $p = .013$, $\eta_p^2 = .126$, and N2, $F(1, 47) = 10.743$, $p = .002$, $\eta_p^2 = .189$, at the frontal region and also on the mean amplitude of P1, $F(1, 47) = 4.932$, $p = .031$, $\eta_p^2 = .097$, and P3, $F(1, 47) = 9.198$, $p = .004$, $\eta_p^2 = .167$) at Oz of the occipital region. The training group had a larger difference (N1: $M = -3.17$, $SD = 2.69$; N2: $M = -3.25$, $SD = 2.70$; P1: $M = 3.93$, $SD = 8.63$; P3: $M = 3.21$, $SD = 6.31$) than the control group (N1: $M = -1.29$, $SD = 3.11$; N2: $M = -0.73$, $SD = 3.54$; P1: $M = -0.02$, $SD = 7.37$; P3: $M = -1.00$, $SD = 5.22$) on these amplitudes.

In addition, the N2 effect was analyzed in the go/no-go task (the mean amplitude in no-go trials minus that in go trials between 310 and 410 ms), and the waveforms are shown in Fig. 5. The N2 effect was not observed in the pre-test in both groups (all *t*s < 0.813, all *p*s > .420). In the post-test, a greater N2 was found in the training group for the no-go condition than for the go condition, $t(48) = 2.858$, $p = .006$, but no significant amplitude difference was found in the control group, $t(46) = 1.028$, $p = .309$.

Table 2
Descriptive behavioral and EEG statistics of the go/no-go task (*M* ± *SD*).

	Training group (n = 25)		Control group (n = 24)	
	Pre-test	Post-test	Pre-test	Post-test
Behavioral data				
Accuracy (go and no-go)	0.86 ± 0.07	0.85 ± 0.07	0.81 ± 0.07	0.83 ± 0.09
Reaction time (go)	717.32 ± 86.12	691.44 ± 87.48	711.01 ± 101.84	671.16 ± 75.92
Accuracy (go)	0.86 ± 0.06	0.84 ± 0.09	0.81 ± 0.09	0.82 ± 0.11
Accuracy (no-go)	0.84 ± 0.13	0.89 ± 0.08	0.78 ± 0.14	0.84 ± 0.11
EEG data				
N1 amplitude	−3.28 ± 2.25	−6.45 ± 3.12	−3.19 ± 2.78	−4.48 ± 2.52
N2 amplitude	−3.59 ± 2.39	−6.84 ± 2.52	−3.71 ± 3.18	−4.44 ± 3.02
P1 amplitude	7.62 ± 6.99	11.54 ± 8.45	7.05 ± 6.13	7.03 ± 5.31
P3 amplitude	7.46 ± 5.65	10.66 ± 6.87	7.06 ± 5.18	6.06 ± 4.01

Note. EEG, electroencephalographic.

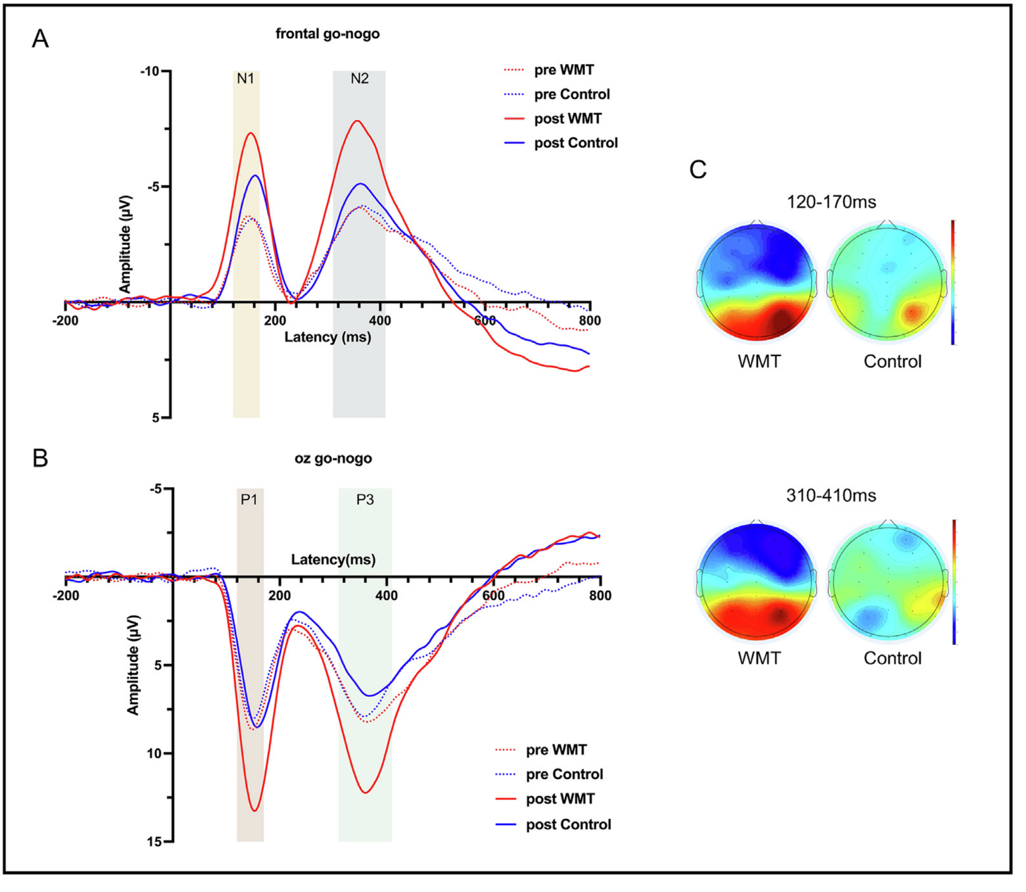

Fig. 4. Waveforms and topographical maps in the go/no-go task. (A) Waveforms at the frontal region for the average of FZ, FCZ, F3, F4, FC3, and FC4. (B) Waveforms at Oz of the occipital region. (C) Topographical maps for the differences (post-test minus pre-test) in the two groups and between the two time windows. WMT, working memory training.

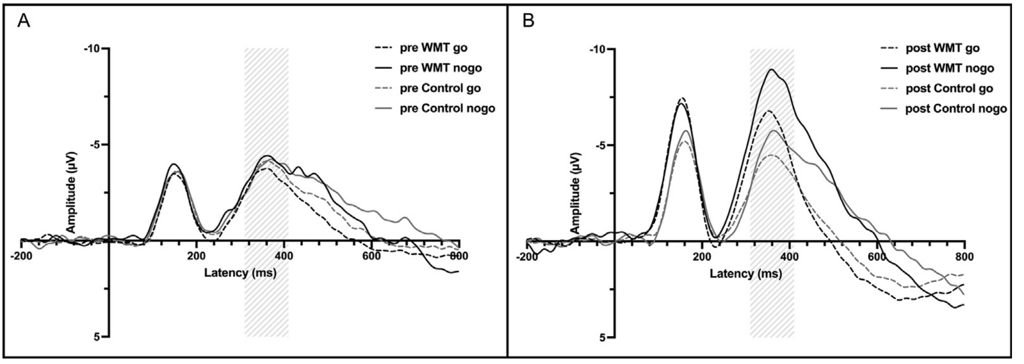

Fig. 5. N2 effect of the go/no-go task. (A,B) The training group and the control group were in the pre-test (A) and in the post-test (B). The time window of the N2 waveforms was 310 to 410 ms. WMT, working memory training.

Table 3
Scores of Raven's Coloured Progressive Matrices ($M \pm SD$).

	Training group (n = 26)		Control group (n = 24)	
	Pre-test	Post-test	Pre-test	Post-test
Behavioral data scores	10.96 ± 3.23	11.31 ± 3.11	9.04 ± 4.28	9.33 ± 3.59

The scores of Raven's Coloured Progressive Matrices: No significant effects

Results of scores of Raven's Coloured Progressive Matrices are shown in Table 3. The ANCOVA on scores in Raven's Coloured Progressive Matrices revealed no significant effect of the group, $F(1, 48) = 1.271$, $p = .265$. The difference score in the training group was 0.35 ($SD = 2.59$) and in the control group was 0.29 ($SD = 3.21$).

Discussion

We investigated whether computerized WMT in typically developing preschool children can transfer to other cognitive domains. We found that the running memory training transferred to preschool children's WM and inhibitory control, as indicated by changes in the amplitude of their endogenous and exogenous ERP components and the performance of the WM task. However, the training failed to enhance their inhibitory control behavior performance and fluid intelligence scores.

WMT enhanced WMC at both behavioral and neural levels

The current study assessed the near and far transfer effects after an adaptive running memory training task in a sample of preschool children. We found that the transfer effect of WMT to an untrained 1-back task occurred at both the behavioral level (e.g., accuracy) and the neural response level (e.g., ERP amplitudes). Our results are consistent with the results of previous preschool intervention studies (Bergman Nutley et al., 2011; Thorell et al., 2009), suggesting that WMT is an effective way to enhance cognitive functioning in preschoolers, as reflected in both behavioral and neural indicators.

The P3 component of the *n*-back task is considered to be a valid indicator of WM updating ability given that the P3 amplitude is positively correlated with *d*-prime (Ren et al., 2023) and lower accuracies in behavioral performance are associated with an attenuated P3b amplitude in children with cognitive disabilities (Evans et al., 2011). P3 appears when the brain is engaged in monitoring a constantly changing environment, reflecting the updating process (Lenartowicz et al., 2010). We detected that after training the average amplitude of P3 in the post-training test was significantly higher in the training group than in the control group. This result suggests that our training paradigm improved preschoolers' updating ability, which is consistent with previous findings that WMT could enhance the amplitude of P3 with *n*-back task in adults (Zhao et al., 2013), in middle school students with learning difficulties (Zhang et al., 2018), and in children aged 7 to 12 years with dyslexia (Lotfi et al., 2020).

The P2 component evoked from the frontal regions reflects the inhibition of irrelevant information and the ability to attend to the target stimulus (Zhao et al., 2013). In the post-test, the average amplitude of the P2 component was increased in the training group, indicating that children devoted more resources to attend to the target stimulus in order to achieve better task performance (Carretié et al., 2001). The prefrontal region N1 and the parietal region P1 components were also increased in the post-test in the training group. The N1 and P1 components represent the early stage of attentional processing of external stimuli by the brain (Vogel & Luck, 2000). The increase in the mean amplitude of these two waveforms illustrates that the effects of training on the children have already begun to appear from the perceptual stage.

WMT enhanced neural signals strongly associated with inhibitory control

WM and inhibitory control are highly correlated functions. Inhibitory control requires the support of certain WMC, and only by keeping the target in mind and focusing on it can information-guided behavior be correctly expressed and the likelihood of incorrect responses be reduced (Diamond, 2013). Previous WMT studies often chose inhibitory control tasks as an important measure of transfer effects (Thorell et al., 2009; Wang et al., 2022; Zhang et al., 2019). The current study did not observe any improvement in the behavioral measurements of inhibitory control tasks in preschoolers. This is not surprising given that previous studies also failed to find such an effect (Thorell et al., 2009; Zhang et al., 2019). However, we did notice some changes in the ERP results. After training, there was a significant increase in the N1 and N2 mean amplitudes in the prefrontal region and a significant increase in the P1 and P3 mean amplitudes in the occipital region in the training group as well as the appearance of the N2 effect. These results have not been reported before, suggesting that these ERP components might be more sensitive than behavioral measures to detect the WMT effects (Thomas et al., 2022).

The N2 component is considered a marker for conflict monitoring and attentional control and is an important indicator of inhibitory control (e.g., Larson et al., 2014; Lo, 2018). In this study, the N2 component was observed in the frontal regions of the go/no-go task in preschoolers, and the mean amplitude increased after training. Although a majority of studies in adolescents and adults observed better task performance with smaller N2 amplitudes (Lo, 2018), a decrease in N2 is usually interpreted as an increase in cognitive efficiency. However, given the continuing development of prefrontal cortical areas in young children and adolescents, larger N2 amplitude may indicate enhanced cognitive resources to support task performance (Buss et al., 2011). Our result that children after training showed a higher mean N2 amplitude may imply that trained children were able to exert a higher cognitive effort and top-down control to complete the task. Their goal-keeping ability and goal-directed behavior might have been improved after training.

The P3 amplitude reflects the process of allocating attention, which increases as the brain matures (Downes et al., 2017). Children with larger P3 amplitude are shown to have higher levels of learning in the go/no-go tasks, and the P3 amplitude can predict an improvement in academic achievement between kindergarten and first grade (Willner et al., 2015). Our finding that WMT induced an increase in the P3 amplitude in the go/no-go task may suggest an improvement in attentional allocation ability as a result of WMT. This result is slightly different from what has been reported in the literature given that we observed that the P3 amplitude changes occurred at a more posterior location than previously reported for the parietal region (e.g., St. John et al., 2019). This may be due to the immaturity of the prefrontal–parietal cortical network or the employment of different task strategies (Ciesielski et al., 2004). We also did not find anterior shifts in the distribution of brain regions after the intervention, reflecting the limited effect of the month-long cognitive training on the transfer of this task. Because we observed an increase in the mean amplitudes of the anterior N1 and posterior P1 components in both the *n*-back task and the go/no-go task, the training-induced improvement in exogenous attention is not task-specific.

There are two possible explanations for the absence of changes in behavioral indicators and the changes in ERP indicators. First, the ERP results indicate enhanced controlled processing that has not yet shifted from controlled to automatic processing in the post-test, failing to conserve cognitive resources to cope with other problems to improve behavioral performance. Second, although inhibitory control and WM share cognitive processes, they also have many unshared components. Changes in ERP results reflect alterations in the same cognitive processes, whereas behavioral results suggest that there may be other modulatory mechanisms that have not been revealed. For example, subcortical areas may have a key role in modulating the relocation effect of updating after training on untrained task performance, with a close relation to the striatum (Dahlin et al., 2008). Berger et al. (2022) found that changes in inhibitory control ability are associated with structural indicators of maturation in the cognitive control network.

Our results also indicate that one possible reason that previous WMT studies in preschoolers failed to find a transfer to inhibitory control tasks may be their choice of the training task and chosen indicators. Although the current study also did not find improved behavioral performance, certain improvements in neural responses were observed. This improvement in neural responses reflects the enhanced controlled processing after preschoolers' training. Our result also supports the notion that updating and inhibition are cognitively and neurologically correlated, but they are not the same entity. As McKenna et al. (2017) pointed out in a *meta*-analysis study, updating, inhibition, and switching are separable but partially overlapping at the neural level in children aged 6 to 18 years. The current study identified this relation between updating and inhibition in younger children.

WMT failed to cause a transfer to fluid intelligence in preschool children

In the current study, scores on the Raven's Coloured Progressive Matrices were used to assess fluid intelligence. Given that no significant group differences were observed, it appeared that the running memory task training was not successful in increasing fluid intelligence. A similar result was reported before on WMT in preschoolers (Bergman Nutley et al., 2011; Thorell et al., 2009; Zhang et al., 2019). Based on this result, it can be argued that the updating component might not be crucial for the ability of preschool WMT to transfer to fluid intelligence. However, Peng et al., (2017) did report a transfer effect with intervention targeting the updating component. This transfer effect might be due to the specific training effect of the *n*-back paradigm. Although both the *n*-back task and the running memory task primarily involve an updating component in WM, they also differ in other aspects. First, the running memory task primarily targets the updating component (Pappa et al., 2020), whereas the *n*-back task also targets storage, monitoring, and maintenance in addition to targeting the updating process. Second, they have different higher-order structures (Gathercole et al., 2019). The *n*-back task requires a comparison of each successive stimulus with the most recently presented stimulus, whereas the running memory task requires a fully sequential recall of updated stimulus sets after unpredictable endings of sequences. Third, they involve different neural systems, with the running memory task activating neural changes in the striatum (Dahlin et al., 2008) and the *n*-back task more likely generating neural changes in the prefrontal–parietal connectivity network (Owen et al., 2005).

In addition, there may be other reasons for the failure to see the improvement in fluid intelligence in the WMT group. The 1-back related P2 amplitude and the go/no-go related N2 amplitude reveal an increase in the top-down attentional control and allocation of attentional resources in response to distractors in this age of children. This is different from the findings of others in older children and adults, who tend to show a decrease in invested attentional resources and an increase in neurological efficiency (Lo, 2018), whereas effective processing of information in attentional networks appears to be a brain marker of intelligence (Rueda, 2018). It should be noted that participants in the training group had higher baseline scores on the pre-test, which may have limited their potential to benefit from the cognitive intervention (the compensation effect; Karbach & Unger, 2014; Swanson & McMurran, 2018).

Limitations and future directions

First, the current study is limited by the small sample size due to the difficulty of recruiting younger children and the high workload of intervention and testing. In addition, we only controlled for age, gender, and grade between groups; other factors were not considered, such as socioeconomic status, which is known to be a factor influencing WM and inhibitory control (Ben-Asher et al., 2024; Farah, 2017; St. John et al., 2019). Because all the participants came from the same kindergarten, they likely came from a similar socioeconomic background, which is the middle of the range in China. Future studies could consider expanding this work to a larger sample size with more diverse socioeconomic backgrounds.

Second, the difficulty of the task could affect the findings or mask potential training-related benefits. Some of the findings, such as the lack of significant improvement in fluid intelligence and the lack of observed behavioral changes in inhibitory control, may have been influenced by the difficulty of the task set in this study. We also expect that future studies could use different training and measurement tasks that are more child-friendly and more sensitive to detecting training-related benefits to replicate the findings of this study or to find a comparison of differences.

Third, the ERP recording saline device, although more friendly to young children, it is less stable and has a lower signal-to-noise ratio than the gel electrodes during data collection and analysis (Luck & Kappenman, 2017). Although the ERP technique has a high temporal resolution, it has a relatively low spatial resolution and is limited in the observation of subcortical areas (e.g., striatum, cingulate gyrus) and in understanding changes in brain activation patterns in typically developing children. Future research could choose other imaging methods, such as functional near-infrared and functional magnetic resonance, to further validate our findings on the neural mechanisms of preschool WMT transfer to inhibitory control and to explore the changes in neural mechanisms brought about by cognitive interventions.

Conclusions

The current study makes several important contributions to the literature on the efficacy of WMT. First, it demonstrates that WMT in preschool children could achieve a near transfer effect, although its far transfer effect to inhibitory control might be limited, at least at the behavioral level. At the neural level, we did observe the training-induced neurophysiological changes during the WM and inhibitory control tasks, including increases in the mean amplitudes of endogenous and exogenous components. Future research could further examine this issue. Second, although the transfer to fluid intelligence by targeting the updating component was not observed, our study suggests that the transfer to fluid intelligence through WMT in preschoolers may depend on the use of *n*-back tasks compared with previous research.

The results of this study have important implications for theory development and training practice. Theoretically, they can help us to better understand the neural mechanisms of WMT in preschoolers and to better identify the critical links between WM and other cognitive abilities. Practically, the study provides an evidence-based approach to evaluate the efficacy of WMT in preschool children and helps to develop proper and effective cognitive training programs for young children.

CRediT authorship contribution statement

Yan Hong: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ting Zhang:** Data curation. **Cong Pang:** Data curation. **Ling Zou:** Validation, Methodology. **Ming Li:** Writing – review & editing. **Renlai Zhou:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability

The data to reproduce the analyses presented here are available from the corresponding author (rlzhou@nju.edu.cn) upon reasonable request, as are the materials necessary to attempt to replicate the findings.

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References

Baddeley, A. D. (1992). Working memory. *Science, 255*(5044), 556–559. https://doi.org/10.1126/science.1736359.
Baddeley, A. D. (2012). Working memory: theories, models, and controversies. *Annual Review of Psychology, 63*(1), 1–29. https://doi.org/10.1146/annurev-psych-120710-100422.
Ben-Asher, E., Porter, B. M., & Church, J. A. (2024). Distinct constellations of common risk factors differentially relate to executive-function ability in children. *Psychological Science, 35*(5), 489–503. https://doi.org/10.1177/09567976241235931.
Berger, P., Friederici, A. D., & Grosse Wiesmann, C. (2022). Maturational indices of the cognitive control network are associated with inhibitory control in early childhood. *Journal of Neuroscience, 42*(32), 6258–6266. https://doi.org/10.1523/JNEUROSCI.2235-21.2022.
Bergman Nutley, S., Söderqvist, S., Bryde, S., Thorell, L. B., Humphreys, K., & Klingberg, T. (2011). Gains in fluid intelligence after training non-verbal reasoning in 4-year-old children: A controlled, randomized study. *Developmental Science, 14*(3), 591–601. https://doi.org/10.1111/j.1467-7687.2010.01022.x.
Blacker, K. J., Negoita, S., Ewen, J. B., & Courtney, S. M. (2017). N-back versus complex span working memory training. *Journal of Cognitive Enhancement, 1*(4), 434–454. https://doi.org/10.1007/s41465-017-0044-1.
Buss, K. A., Dennis, T. A., Brooker, R. J., & Sippel, L. M. (2011). An ERP study of conflict monitoring in 4–8-year old children: Associations with temperament. *Developmental Cognitive Neuroscience, 1*(2), 131–140. https://doi.org/10.1016/j.dcn.2010.12.003.
Carretié, L., Martín-Loeches, M., Hinojosa, J. A., & Mercado, F. (2001). Emotion and attention interaction studied through event-related potentials. *Journal of Cognitive Neuroscience, 13*(8), 1109–1128. https://doi.org/10.1162/089892901753294400.
Cheng, C., & Kibbe, M. M. (2022). Development of updating in working memory in 4–7-year-old children. *Developmental Psychology, 58*(5), 902–912. https://doi.org/10.1037/dev0001337.
Ciesielski, K. T., Harris, R. J., & Cofer, L. F. (2004). Posterior brain ERP patterns related to the go/no-go task in children. *Psychophysiology, 41*(6), 882–892. https://doi.org/10.1111/j.1469-8986.2004.00250.x.
Covey, T. J., Shucard, J. L., & Shucard, D. W. (2019). Working memory training and perceptual discrimination training impact overlapping and distinct neurocognitive processes: Evidence from event-related potentials and transfer of training gains. *Cognition, 182*, 50–72. https://doi.org/10.1016/j.cognition.2018.08.012.
Dahlin, E., Neely, A. S., Larsson, A., Bäckman, L., & Nyberg, L. (2008). Transfer of learning after updating training mediated by the striatum. *Science, 320*(5882), 1510–1512. https://doi.org/10.1126/science.1155466.
Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009.
Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*(1), 135–168. https://doi.org/10.1146/annurev-psych-113011-143750.
Dimitrov, D. M., & Rumrill, J. P. D. (2003). Pretest–posttest designs and measurement of change. *Work, 20*, 159–165 https://content.iospress.com/download/work/wor00285?id=work%2Fwor00285.
Downes, M., Bathelt, J., & De Haan, M. (2017). Event-related potential measures of executive functioning from preschool to adolescence. *Developmental Medicine & Child Neurology, 59*(6), 581–590. https://doi.org/10.1111/dmcn.13395.
Engel de Abreu, P. M. J., Conway, A. R. A., & Gathercole, S. E. (2010). Working memory and fluid intelligence in young children. *Intelligence, 38*(6), 552–561. https://doi.org/10.1016/j.intell.2010.07.003.
Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods, Instruments, & Computers, 28*(1), 1–11. https://doi.org/10.3758/BF03203630.
Evans, J. L., Selinger, C., & Pollak, S. D. (2011). P300 as a measure of processing capacity in auditory and visual domains in specific language impairment. *Brain Research, 1389*, 93–102. https://doi.org/10.1016/j.brainres.2011.02.010.
Farah, M. J. (2017). The neuroscience of socioeconomic status: Correlates, causes, and consequences. *Neuron, 96*(1), 56–71. https://doi.org/10.1016/j.neuron.2017.08.034.
Gathercole, S. E., Dunning, D. L., Holmes, J., & Norris, D. (2019). Working memory training involves learning new skills. *Journal of Memory and Language, 105*, 19–42. https://doi.org/10.1016/j.jml.2018.10.003.
Grammer, J. K., Carrasco, M., Gehring, W. J., & Morrison, F. J. (2014). Age-related changes in error processing in young children: A school-based investigation. *Developmental Cognitive Neuroscience, 9*, 93–105. https://doi.org/10.1016/j.dcn.2014.02.001.
Harms, M. B., Zayas, V., Meltzoff, A. N., & Carlson, S. M. (2014). Stability of executive function and predictions to adaptive behavior from middle childhood to pre-adolescence. *Frontiers in Psychology, 5*, 331. https://doi.org/10.3389/fpsyg.2014.00331.
Harvey, P. O., Le Bastard, G., Pochon, J. B., Levy, R., Allilaire, J. F., Dubois, B., & Fossati, P. (2004). Executive functions and updating of the contents of working memory in unipolar depression. *Journal of Psychiatric Research, 38*(6), 567–576. https://doi.org/10.1016/j.jpsychires.2004.03.003.
Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the United States of America, 105*(19), 6829–6833. https://doi.org/10.1073/pnas.0801268105.

Jaeggi, S. M., Buschkuehl, M., Perrig, W. J., & Meier, B. (2010). The concurrent validity of the N-back task as a working memory measure. *Memory, 18*(4), 394–412. https://doi.org/10.1080/09658211003702171.

Karbach, J., & Unger, K. (2014). Executive control training from middle childhood to adolescence. *Frontiers in Psychology, 5*, 390. https://doi.org/10.3389/fpsyg.2014.00390.

Klingberg, T., Fernell, E., Olesen, P. J., Johnson, M., Gustafsson, P., Dahlström, K., ... Westerberg, H. (2005). Computerized Training of Working Memory in Children With ADHD-A Randomized, Controlled Trial. *Journal of the American Academy of Child & Adolescent Psychiatry, 44*(2), 177–186. https://doi.org/10.1097/00004583-200502000-00010.

Larson, M. J., Clayson, P. E., & Clawson, A. (2014). Making sense of all the conflict: a theoretical review and critique of conflict-related ERPs. *International Journal of Psychophysiology, 93*(3), 283–297. https://doi.org/10.1016/j.ijpsycho.2014.06.007.

Lenartowicz, A., Escobedo-Quiroz, R., & Cohen, J. D. (2010). Updating of context in working memory: an event-related potential study. *Cognitive, Affective, & Behavioral Neuroscience, 10*(2), 298–315. https://doi.org/10.3758/CABN.10.2.298.

Lo, S. L. (2018). A meta-analytic review of the event-related potentials (ERN and N2) in childhood and adolescence: Providing a developmental perspective on the conflict monitoring theory. *Developmental Review, 48*, 82–112. https://doi.org/10.1016/j.dr.2018.03.005.

Lotfi, S., Rostami, R., Shokoohi-Yekta, M., Ward, R. T., Motamed-Yeganeh, N., Mathew, A. S., & Lee, H.-J. (2020). Effects of computerized cognitive training for children with dyslexia: An ERP study. *Journal of Neurolinguistics, 55*, 100904. https://doi.org/10.1016/j.jneuroling.2020.100904.

Luck, S. J., & Kappenman, E. S. (2017). Electroencephalography and event-related brain potentials. In J. T. Cacioppo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (4th ed., pp. 74–100). Cambridge University Press.

McKenna, R., Rushe, T., & Woodcock, K. A. (2017). Informing the structure of executive function in children: A meta-analysis of functional neuroimaging data. *Frontiers in Human Neuroscience, 11*, 154. https://doi.org/10.3389/fnhum.2017.00154.

Melby-Lervåg, M., Redick, T. S., & Hulme, C. (2016). Working memory training does not improve performance on measures of intelligence or other measures of "far transfer": Evidence from a meta-analytic review. *Perspectives on Psychological Science, 11*(4), 512–534. https://doi.org/10.1177/1745691616635612.

Oberauer, K., Lewandowsky, S., Farrell, S., Jarrold, C., & Greaves, M. (2012). Modeling working memory: An interference model of complex span. *Psychonomic Bulletin & Review, 19*(5), 779–819. https://doi.org/10.3758/s13423-012-0272-4.

Owen, A. M., McMillan, K. M., Laird, A. R., & Bullmore, E. (2005). N-back working memory paradigm: a meta-analysis of normative functional neuroimaging studies. *Human Brain Mapping, 25*(1), 46–59. https://doi.org/10.1002/hbm.20131.

Pappa, K., Biswas, V., Flegal, K. E., Evans, J. J., & Baylan, S. (2020). Working memory updating training promotes plasticity & behavioural gains: a systematic review & meta-analysis. *Neuroscience & Biobehavioral Reviews, 118*, 209–235. https://doi.org/10.1016/j.neubiorev.2020.07.027.

Peng, J., Mo, L., Huang, P., & Zhou, Y. (2017). The effects of working memory training on improving fluid intelligence of children during early childhood. *Cognitive Development, 43*, 224–234. https://doi.org/10.1016/j.cogdev.2017.05.006.

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clinical Neurophysiology, 118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019.

Raven, J. C. (1998). *Manual for Raven's Progressive Matrices*. Oxford Psychologists Press.

Redick, T. S., Calvo, A., Gay, C. E., & Engle, R. W. (2011). Working memory capacity and go/no-go task performance: Selective effects of updating, maintenance, and inhibition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*(2), 308–324. https://doi.org/10.1037/a0022216.

Ren, M., Xu, J., Li, Y., Wang, M., Georgiev, G., Shen, L., Zhao, J., Cao, Z., Zhang, S., Wang, W., Xu, S., Zhou, Z., Chen, S., Chen, X., Shi, X., Tang, X., & Shan, C. (2023). Neural signatures for the n-back task with different loads: An event-related potential study. *Biological Psychology, 177*, 108485. https://doi.org/10.1016/j.biopsycho.2023.108485.

Ross-Sheehy, S., Reynolds, E., & Eschman, B. (2021). Unsupervised online assessment of visual working memory in 4- to 10-year-old children: Array size influences capacity estimates and task performance. *Frontiers in Psychology, 12*, 692228. https://doi.org/10.3389/fpsyg.2021.692228.

Rueda, M. R. (2018). Attention in the heart of intelligence. *Trends in Neuroscience and Education, 13*, 26–33. https://doi.org/10.1016/j.tine.2018.11.003.

Rueda, M. R., Rothbart, M. K., McCandliss, B. D., Saccomanno, L., & Posner, M. I. (2005). Training, maturation, and genetic influences on the development of executive attention. *Proceedings of the National Academy of Sciences of the United States of America, 102*(41), 14931–14936. https://doi.org/10.1073/pnas.0506897102.

Salthouse, T. A. (2014). Relations between running memory and fluid intelligence. *Intelligence, 43*, 1–7. https://doi.org/10.1016/j.intell.2013.12.002.

Sedek, G., Krejtz, I., Rydzewska, K., Kaczan, R., & Rycielski, P. (2016). Three functional aspects of working memory as strong predictors of early school achievements: The review and illustrative evidence. *Polish Psychological Bulletin, 47*(1), 103–111. https://doi.org/10.1515/ppb-2016-0011.

Shipstead, Z., Redick, T. S., & Engle, R. W. (2012). Is working memory training effective? *Psychological Bulletin, 138*(4), 628–654. https://doi.org/10.1037/a0027473.

Snyder, H. R., & Munakata, Y. (2010). Becoming self-directed: Abstract representations support endogenous flexibility in children. *Cognition, 116*(2), 155–167. https://doi.org/10.1016/j.cognition.2010.04.007.

St. John, A. M., Finch, K., & Tarullo, A. R. (2019). Socioeconomic status and neural processing of a go/no-go task in preschoolers: An assessment of the P3b. *Developmental Cognitive Neuroscience, 38*, 100677. https://doi.org/10.1016/j.dcn.2019.100677.

Swanson, H. L., & McMurran, M. (2018). The impact of working memory training on near and far transfer measures: Is it all about fluid intelligence? *Child Neuropsychology, 24*(3), 370–395. https://doi.org/10.1080/09297049.2017.1280142.

Thomas, K. S., Birch, R. E., Jones, C. R. G., & Vanderwert, R. E. (2022). Neural correlates of executive functioning in anorexia nervosa and obsessive–compulsive disorder. *Frontiers in Human Neuroscience, 16*, 841633. https://doi.org/10.3389/fnhum.2022.841633.

Thorell, L. B., Lindqvist, S., Bergman Nutley, S., Bohlin, G., & Klingberg, T. (2009). Training and transfer effects of executive functions in preschool children. *Developmental Science, 12*(1), 106–113. https://doi.org/10.1111/j.1467-7687.2008.00745.x.

Vogel, E. K., & Luck, S. J. (2000). The visual N1 component as an index of a discrimination process. *Psychophysiology, 37*(2), 190–203. https://doi.org/10.1111/1469-8986.3720190.

Wang, L., Sheng, A., Chang, L., & Zhou, R. (2022). Improving fluid intelligence of children through working memory training: The role of inhibition control. *Frontiers in Psychology, 13*, 1025036. https://doi.org/10.3389/fpsyg.2022.1025036.

Wang, X., & Covey, T. J. (2020). Neurophysiological indices of the transfer of cognitive training gains to untrained tasks. *Neurobiology of Learning and Memory, 171*, 107205. https://doi.org/10.1016/j.nlm.2020.107205.

Wass, S. V., Scerif, G., & Johnson, M. H. (2012). Training attentional control and working memory—Is younger better? *Developmental Review, 32*(4), 360–387. https://doi.org/10.1016/j.dr.2012.07.001.

Willner, C. J., Gatzke-Kopp, L. M., Bierman, K. L., Greenberg, M. T., & Segalowitz, S. J. (2015). Relevance of a neurophysiological marker of attention allocation for children's learning-related behaviors and academic performance. *Developmental Psychology, 51*(8), 1148–1162. https://doi.org/10.1037/a0039311.

Yu, X., Li, K. Q., Liu, Y., An, X. Y., & Liu, X. P. (2015). Interventional effects of working memory updating training and Cogmed working memory training on children with ADHD. *Chinese Journal of Clinical Psychology, 23*(2), 201–205.

Zhang, H., Chang, L., Chen, X., Ma, L., & Zhou, R. (2018). Working memory updating training improves mathematics performance in middle school students with learning difficulties. *Frontiers in Human Neuroscience, 12*, 154. https://doi.org/10.3389/fnhum.2018.00154.

Zhang, Q., Wang, C., Zhao, Q., Yang, L., Buschkuehl, M., & Jaeggi, S. M. (2019). The malleability of executive function in early childhood: Effects of schooling and targeted training. *Developmental Science, 22*(2)e12748. https://doi.org/10.1111/desc.12748.

Zhao, X., Zhou, R., & Fu, L. (2013). Working memory updating function training influenced brain activity. *PLoS One, 8*(8)e71063. https://doi.org/10.1371/journal.pone.0071063.