

RESEARCH ARTICLE

Control of Movement

Cognitive load suppresses explicit learning while sparing implicit learning in visuomotor adaptation

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Abstract

Limiting cognitive resources negatively impacts motor learning, but its cognitive mechanism is still unclear. Previous studies failed to differentiate its effect on explicit (or cognitive) and implicit (or procedural) aspects of motor learning. Here, we designed a dual-task paradigm requiring participants to simultaneously perform a visual working memory task and a visuomotor rotation adaptation task to investigate how cognitive load differentially impacted explicit and implicit motor learning. Over the three consecutive learning days, the control group without the dual task showed an increase in explicit learning and a decrease in implicit learning. In contrast, cognitive load, implemented by the dual task in the experimental group, selectively impaired explicit learning but spared implicit motor learning. Individual analysis uncovered a negative correlation between explicit learning and working memory performance, suggesting a trade-off between motor and cognitive tasks that compete for cognitive resources. Importantly, moderation analysis revealed that the relative increase in implicit learning was not directly influenced by cognitive load but rather indirectly by the changes in explicit learning. Specifically, individuals with more suppression in explicit learning from the dual task exhibited higher implicit learning. Our findings provide new insights into how cognitive load differentially affects explicit and implicit motor learning, as well as the interaction between explicit and implicit learning systems.

NEW & NOTEWORTHY Motor skill acquisition is ubiquitously accompanied by cognitive load, yet its effects on motor learning remain understudied. Using a dual-task paradigm combining visual working memory and visuomotor adaptation, we found a striking dissociation: cognitive load suppresses explicit learning while paradoxically enhancing implicit learning. This enhancement can be explained by the compensatory relationship between explicit and implicit systems, rather than direct facilitation. Our findings revealed how the motor learning system adaptively reorganized under cognitive constraints.

cognitive load; explicit learning; implicit learning; motor learning; working memory

INTRODUCTION

The intricate interplay between cognitive and procedural systems represents one of the most fundamental aspects of human behavior. In daily life, motor learning is often accompanied by cognitively demanding tasks. For your first driving lesson, when you are practicing how to coordinate the control of pedals and the steering wheel, the coach simultaneously urges you to memorize the functionalities of various dials and buttons around the driver's seat. This extra cognitive load challenges our motor learning of the driving action

itself. Understanding how cognitive load influences motor learning is crucial for elucidating the mechanisms underlying the acquisition of procedural knowledge. Previous research has found that additional cognitive load impairs sensorimotor adaptation (1–4) and motor skill learning (5). However, these studies regarded motor learning as a single procedural or implicit learning process, without dissociating the cognitive and procedural aspects of motor learning that may respond differently to cognitive demands (6).

Motor learning itself comprises dissociable explicit (cognitive) and implicit (procedural) systems operating in parallel.



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Submitted 29 May 2025 / Revised 2 July 2025 / Accepted 2 September 2025



For instance, musicians deliberately recall musical notation (explicit) while simultaneously automating finger sequential movements through practice (implicit). Explicit learning involves conscious strategies and deliberate adjustments that rely on cognitive resources (e.g., visual working memory) (7–9) and exhibits reaction time dependence (10–13). In contrast, implicit learning has been widely characterized as an unconscious calibration of the sensorimotor system, largely independent of cognitive resource demands (6). These divergent processes likely exhibit differential susceptibility to cognitive load, yet previous studies conflated their contributions.

Motor adaptation paradigms offer a unique opportunity to dissociate explicit and implicit learning components, which might be distinctly affected by cognitive loads. One classical adaptation paradigm is the visuomotor rotation (VMR) paradigm. Participants adapt their movements to compensate for a rotated hand representation, and their adaptation can be decomposed into an explicit learning component, manifested as deliberate reaiming from the original target (14), and an implicit learning component, manifested as hand deviation beyond the reaiming direction without participants' awareness. Previous studies combined the VMR paradigm with a cognitive dual task and found that additional attentional demands suppressed initial learning (15) and reduced savings (15, 16). Although not distinguished by these researchers, initial learning and savings depend heavily on explicit learning (12, 17, 18), although the implicit system could also contribute to savings (10, 19). Thus, their observed dual-task effects may reflect a selective detrimental effect of cognitive load on explicit learning, although this remains unexplored. On the contrary, the impact of cognitive load on implicit learning remains controversial. Previous studies found that explicit VMR adaptation, but not implicit adaptation, depended on visual working memory based on individual analyses (7, 8), hinting that implicit learning might be immune to cognitive load. However, dual-task manipulation narrowed the directional generalization of VMR adaptation (20, 21) and degraded the overall adaptation for force-field perturbations (4). Given that directional generalization and force-field adaptation largely reflect implicit learning, although explicit strategy also plays a role in force-field adaptation (22), these results suggest that implicit learning could be impaired by cognitive load. Currently, there has been no effort to examine how explicit and implicit learning are simultaneously affected by cognitive load in a unified experimental framework.

Here, we used a dual memory task to impose cognitive load on visuomotor adaptation and examined how explicit and implicit learning components co-evolve across three training days. The memory task specifically involved visual working memory, whose capacity has been shown to correlate with explicit learning of VMR (7, 8) and is crucial for early skill acquisition (23, 24). We expected that cognitive load would suppress explicit learning. At the same time, theories advocating a compensatory or competing role of implicit learning to explicit learning (10, 25–27) would predict that implicit learning would increase relatively to the control condition without the dual task. Conversely, theories advocating that implicit learning was stagnant against task variations (14, 28, 29) would predict a null effect of cognitive load on implicit learning. Testing participants across three executive days would enable us to examine how the relative contributions of explicit and

implicit learning changed as the detrimental effect of cognitive load decreased with practice (30, 31).

METHODS

Participants

We recruited 32 college students from Peking University and randomly assigned them to either the experimental ($n = 16$, 7 females, 22.75 ± 2.49 yr) or the control group ($n = 16$, 8 females, 20.25 ± 1.91 yr). All participants were right-handed and had normal or corrected-to-normal vision. Participants were naive to the purpose of the experiment.

Ethics Statement

The study was approved by the Ethical Committee of the School of Psychological and Cognitive Sciences at Peking University. All participants provided written informed consent to participate in the study and received monetary compensation upon completion of the experiment.

Experimental Setup

Participants sat in front of a vertically placed LCD screen (29.6×52.7 cm, Dell, Round Rock, TX) and performed reaching movements on a horizontally placed digitizing tablet (26.4×20 cm, Wacom Intuos M, Saitama, Japan) using a stylus with their right hand (Fig. 1A). The visibility of their arms and hands was occluded by an opaque fabric. The sampling rate of the tablet was 200 Hz. Procedures and data acquisition were coded in MATLAB 2022b with Psychtoolbox-3-3.0.19.2.

Task Protocol

In the motor task, participants were instructed to perform rapid, straight-line reaching movements to slice through the target with the visual cursor. Each trial began with participants moving the cursor (a 2-mm radius green dot) to the starting position (a 3-mm radius white circle). After they held the cursor in the starting position for 800 ms, a target would appear at one of four possible locations (45° , 135° , 225° , and 315° , 6 cm from the central starting position) in a pseudorandom order in a four-trial cycle. After their movement exceeded the target distance, the positions of the cursor and target were frozen and present for 500 ms. Both the experimental and control groups experienced three consecutive phases (Fig. 1B): a baseline phase with veridical visual feedback (80 trials), an adaptation phase with a 30° visuomotor rotation perturbation (80 trials), and a washout phase without visual feedback (20 trials). During the baseline and adaptation phases, participants were instructed to make the cursor hit the target and experienced continuous feedback. During the washout phase, participants were instructed to move directly to the target without visual feedback and not to use any strategy.

The dual-task manipulation was conducted during the adaptation phase, with distinct task requirements for the experimental and control groups. For the experimental group, participants need to concurrently perform the motor task with VMR and a visual working memory task. Each dual-task adaptation trial proceeded as follows (Fig. 1C): 1) participants returned their right hand to the starting

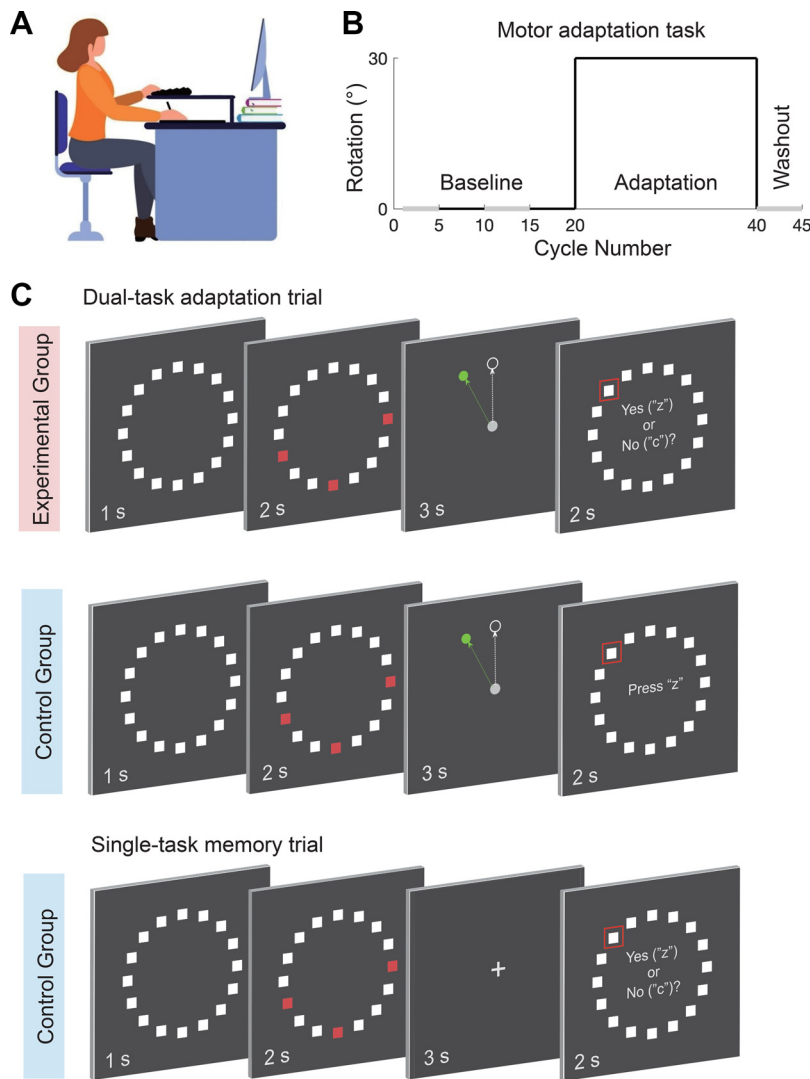


Figure 1. Experimental design. **A:** experimental setup. Participants performed reaching movements using a stylus held by their right hands and performed the memory task using a keyboard operated by their left hand. **B:** experimental procedure. For VMR adaptation, both the experimental and control groups experienced three phases of trials: a baseline phase, an adaptation phase with VMR, and a washout phase without visual feedback. Black lines represent the cycles with visual feedback, and gray lines represent the cycles without visual feedback. **C:** illustration for different trial types. The experimental group experienced dual-task adaptation trials during the adaptation phase (the first row). In each trial, participants needed to memorize the locations of 2–6 random red squares and then completed a reaching movement with a 30° visuomotor rotation. After the reaching movement, they needed to judge whether the indicated square was red before. In the adaptation trials for the control group (the second row), they viewed the same visual stimuli as the experimental group but were not required to memorize the locations. They just needed to press the “z” key after the reaching movement to proceed to the next trial. Participants in the control group additionally performed a single working memory task in a separate session after they completed the adaptation task. In a single-task memory trial (the last row), the procedures of the memory task remained the same, but the reaching movement was replaced by looking at the fixation for 3 s. VMR, visuomotor rotation.

position and held for 800 ms; 2) 16 white squares appeared, evenly distributed on a 9-mm radius circumference, and were present for 1 s; 3) a subset of squares (2–6 randomly selected) turned red and were present for 2 s (memorization phase). Participants need to memorize the locations of the red squares; 4) although keeping the memory, participants performed a reaching movement under visuomotor rotation; 5) upon movement completion, the white squares reappeared, with one square indicated (judgment phase). Participants need to judge whether the indicated square had turned red during the memory phase by pressing “z” for yes or “c” for no. The response time limit of 2 s was enforced, with a “reacting too slow” text warning appearing if participants exceeded this limit.

For the control group, to isolate the effects of cognitive load while controlling for potential confounds (e.g., intertrial intervals, visual stimulation, and key-press responses), control participants experienced an identical procedure to the experimental group with one critical exception: they were not required to memorize the locations of red squares. During the judgment phase, they were instructed to simply press the “z” key indiscriminately on all trials. Therefore, the group differences in motor learning could only be caused by

the cognitive load induced by the memory task. In addition, to examine the dual-task cost on the working memory task, control participants completed a single working memory task in a separate session after the adaptation experiment. This session replicated the dual-task protocol’s temporal structure, except that the period of reaching movements was replaced by a 3-s fixation period (Fig. 1C).

Data Analysis

The kinematic data were recorded from the tablet at a sampling rate of 125 Hz. The movement direction was determined by the deviation of two lines, one from the start position to the target and the other from the start position to the hand position at the peak outward velocity. We defined the direction of hand deviation to counter the perturbation as the positive direction. The movement direction for each movement cycle was calculated by averaging the movement direction of all four trials in a cycle, one for each of the different target locations.

Early learning was defined as the average hand deviation from the target in the first five cycles, and late learning, as well as total learning, was defined as the average hand deviation in the last five cycles. To isolate explicit and implicit

learning components, we used no-feedback trials in the washout phase to measure implicit learning. Implicit learning was quantified as the hand deviation in the first cycle of the washout phase. Explicit learning was calculated by subtracting implicit learning from total learning. We used the hand deviation in the last cycle of the washout phase to quantify the time-stable component of implicit learning (10). To investigate whether the decay rate of implicit learning differed between the experimental and control groups, we estimated the retention factor (A), ranging from 0 to 1, using a state-space model. In the absence of motor error during the washout phase, the implicit state decays with its retention rate A :

$$x_{t+1} = Ax_t \quad (1)$$

where x_{t+1} and x_t represent implicit learning on trials $t+1$ and t , respectively.

For the reaching task, we excluded trials with movement time exceeding 400 ms as well as trials with systematic movements to the incorrect direction (i.e., movement direction less than -20° or exceeded 120°). These criteria resulted in the removal of $<1\%$ of trials.

Statistical Analyses

Statistical analyses were carried out in R (v. 4.2.2). We used mixed ANOVAs to examine the effects of dual-task manipulation (between-group) and training days (within-group) on different learning metrics. The F test degrees of freedom were adjusted using the Greenhouse–Geisser correction if the sphericity assumption was violated.

We used general linear models rather than simple correlations to examine the relationship among explicit learning, implicit learning, and working memory performance. This was because each participant contributed data across 3 days, involving a within-subject effect that needed to be controlled. To examine the relationship between explicit and implicit learning, we used a linear model:

$$x_{\text{Implicit}} = \beta_0 + \beta_1 \times x_{\text{Explicit}} + \beta_2 \times x_{\text{Day}} + \beta_3 \times (x_{\text{Explicit}} \times x_{\text{Day}}) + \beta_4 \times x_{\text{subject}} + \varepsilon,$$

where x_{Implicit} is the magnitude of implicit learning measured by the first cycle in the washout phase, x_{Explicit} is the magnitude of explicit learning estimated at the same time, x_{Day} is the learning day, $x_{\text{Explicit}} \times x_{\text{Day}}$ is the interaction between the two factors, x_{subject} is the random factor of subject, and ε is the residual error. The estimate β_1 and corresponding t test P value indicate the correlation between explicit and implicit learning. We further examined the relationship among working memory performance, explicit learning, and implicit learning. The working memory performance was represented by memory accuracy within a testing session on a particular training day. To test whether working memory accuracy can predict explicit learning, we used a linear model:

$$x_{\text{Explicit}} = \beta_0 + \beta_1 \times x_{\text{Acc}} + \beta_2 \times x_{\text{Day}} + \beta_3 \times (x_{\text{Acc}} \times x_{\text{Day}}) + \beta_4 \times x_{\text{subject}} + \varepsilon,$$

where x_{Explicit} is the magnitude of explicit learning, x_{Acc} is working-memory accuracy, x_{Day} is the learning day, $x_{\text{Acc}} \times x_{\text{Day}}$ is the interaction between the two factors, x_{subject} is the

random factor of subject, and ε is the residual error. The estimate β_1 and corresponding t test P value indicate the prediction relationship between accuracy and explicit learning. We used a similar model to test the relationship between working memory performance and the magnitude of implicit learning, replacing x_{Explicit} with x_{Implicit} .

Furthermore, we conducted moderation analyses to answer two specific questions. First, our unique dataset, using cognitive load as an intervention for adaptation, enables us to examine the relationship between explicit and implicit learning, specifically the direction of their interaction. In the literature, some researchers have advocated that explicit learning drives implicit learning (10, 26), whereas others have advocated that implicit learning could develop spontaneously, with explicit learning subsequently compensating for it (32). We thus conducted the moderation analyses to test these two contrasting hypotheses. Second, we investigated whether cognitive load could modulate the relationship between explicit and implicit learning. Here, we used working-memory (WM) accuracy as a measure of cognitive load. To test the hypothesis that explicit learning drives implicit learning and the relationship is modulated by WM accuracy, we used a linear model:

$$x_{\text{Implicit}} = \beta_0 + \beta_1 \times x_{\text{Explicit}} + \beta_2 \times x_{\text{Acc}} + \beta_3 \times (x_{\text{Explicit}} \times x_{\text{Acc}}) + \beta_4 \times x_{\text{Day}} + \beta_5 \times x_{\text{subject}} + \varepsilon,$$

where the estimate β_3 and corresponding P value represent the moderation effect. To test another hypothesis that implicit learning drives explicit learning, we used a similar linear model with reversing x_{Explicit} and x_{Implicit} variables. We also conducted the same moderation analysis but used reaction time of working memory task to replace x_{Acc} . Although reaction time (RT) is a less sensitive performance variable for working memory investigated here, we explored its potential effect on the interaction between explicit and implicit learning.

RESULTS

To investigate the effect of cognitive load on explicit and implicit learning components, we designed a dual-task adaptation paradigm combining a visual working memory task with the classical visuomotor rotation adaptation paradigm (Fig. 1). We recruited 32 participants who were randomly assigned to either the experimental or control group ($n = 16$ each). Both groups experienced a baseline phase, an adaptation phase, and a washout phase (Fig. 1B). During the adaptation phase, the experimental group was required to concurrently perform both the visual working memory and VMR reaching tasks, whereas the control group performed only the VMR reaching tasks without memorization. The working memory task required participants to memorize the locations of 2–6 randomly selected red squares from a circular array of 16 white squares, maintain the memory while performing the reaching movement, and then judge whether a highlighted square was one of the memorized squares after the movement (Fig. 1C). The participants completed the same three-phase learning session on each of the three consecutive days.

First, on the motor task, as we expected, the experimental group showed lower overall learning and slower initial learning

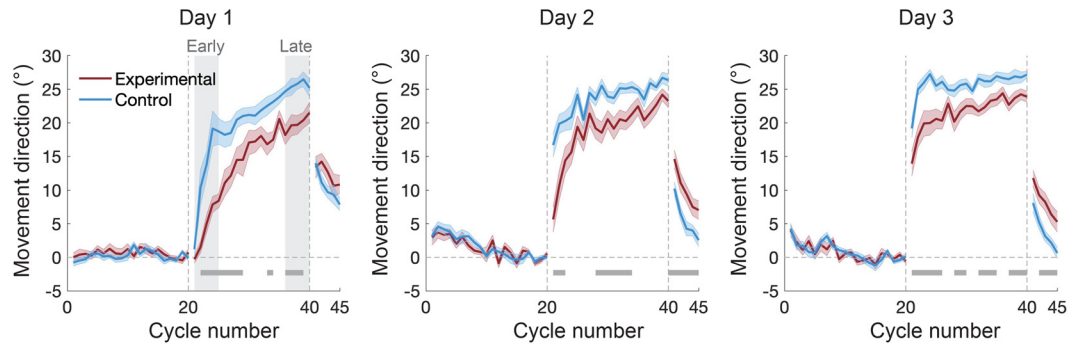


Figure 2. Motor learning across the 3 days (red lines for the experimental group and blue lines for the control group), from left to right. Participants experienced a baseline phase (the 1st–20th cycles), an adaptation phase (the 21st–40th cycles), and a washout phase (the 41st–45th cycles). The washout phase was used to measure implicit learning. Solid lines depict the mean, and shaded areas depict the standard error (SE) for each group. The dark gray lines represent the clusters where the movement directions significantly differed between the two groups ($P < 0.05$). The light gray areas represent the defined early (the 1st–5th cycles) and late (the 36th–40th cycles) learning phases, operationally defined for statistical analyses.

compared with the control group (Fig. 2), suggesting that motor learning was impaired by the dual-task manipulation. Mixed ANOVAs revealed a significant main effect of group: the learning of the experimental group was lower than that of the control group for both early [Fig. 3A; $F(1,30) = 32.603$, $P < 0.001$] and late learning phases [Fig. 3B; $F(1,30) = 18.422$, $P < 0.001$]. Both groups exhibited increased early learning across days [$F(2,60) = 103.789$, $P < 0.001$], revealing the savings effect. Total learning, measured during the late learning phase, showed a significant interaction between group and day

[$F(2,60) = 3.241$, $P = 0.046$]. The control group did not show a significant difference across days [$F(2,30) = 1.171$, $P = 0.197$], whereas the experimental group significantly increased their total learning across days [$F(2,30) = 10.281$, $P < 0.001$; day 2 vs. day 1: $t = 3.015$, $P = 0.016$; day 3 vs. day 1: $t = 4.525$, $P < 0.001$]. However, the experimental group's total learning was lower than that of the control group on each day [day 1: $t = 4.074$, $P < 0.001$; day 2: $t = 3.000$, $P = 0.005$; day 3: $t = 3.308$, $P = 0.002$], suggesting that additional cognitive load impedes visuomotor rotation learning even after 3 days of training.

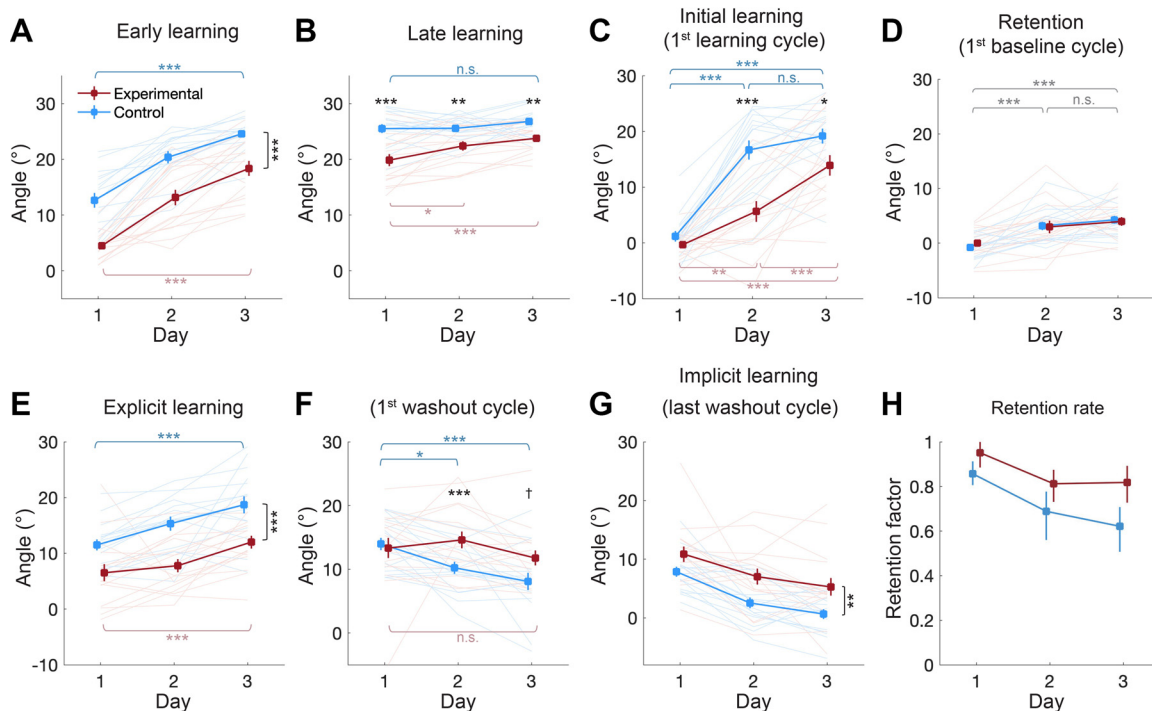


Figure 3. Learning measures are compared between groups and across days. **A:** early learning (the 1st–5th cycles during the adaptation phase). **B:** late learning (the 16th–20th cycles during the adaptation phase). **C:** the first learning cycle on each day. **D:** learning retention as revealed by the first baseline cycle. Explicit learning is calculated by subtracting implicit learning, measured by the first washout cycle, from total learning (**E**); implicit learning is measured by the first washout cycle (**F**); implicit learning is measured by the last washout cycle (**G**). Red and blue lines are for the experimental and control groups, respectively. Data are shown as means $\pm$ SE. The light lines represent individual data. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$, †marginally significant ($P = 0.055$), and n.s. $P > 0.05$. Blue symbols represent statistics for the control group, pink symbols represent statistics for the experimental group, and black symbols represent group differences. **H:** the retention rate of implicit learning during the washout phase estimated from state-space model fitting. Data are shown as median and 95% confidence intervals, both estimated by bootstrap resampling (resampling size = 5,000).

Learning from the previous day was retained across days, as shown by the difference in the first-cycle adaptation (termed initial learning, distinct from early learning above) on each day (Fig. 3C). A mixed ANOVA revealed significant main effects of group [$F(1,30) = 14.520$, $P < 0.001$] and day [$F(2,60) = 83.315$, $P < 0.001$] on initial learning, as well as a significant interaction between group and day [$F(2,60) = 7.174$, $P = 0.002$]. The experimental group showed smaller initial learning than the control group on both *day 2* ($t = 4.203$, $P < 0.001$) and *day 3* ($t = 2.233$, $P = 0.033$). The group difference in initial learning could be attributed to reduced recall of explicit strategies [Coltman et al. (33); Haith et al. (12); Huberdeau et al. (17); Morehead et al. (18)]. Distinct temporal patterns of initial learning emerged between groups. For the control group, initial learning saturated across days as no further improvements between *day 2* and *day 3* ($t = 1.304$, $P = 0.606$), after a significant *day 2* improvement over *day 1* ($P < 0.001$). In contrast, the experimental group showed further improvement in initial learning on *day 3* (*day 2* vs. *day 1*: $t = 3.398$, $P = 0.006$; *day 3* vs. *day 2*: $t = 4.330$, $P < 0.001$), suggesting cognitive load prevented them from reaching the learning ceiling. We also found significant offline learning retention across days (Fig. 3D), as indicated by the significantly deviated movement direction of the first baseline cycle on *day 2* ($t = 5.282$, $P < 0.001$; experimental group: $2.96 \pm 1.14^\circ$; control group: $3.16 \pm 0.77^\circ$) and *day 3* ($t = 5.789$, $P < 0.001$; experimental group: $3.99 \pm 0.80^\circ$; control group: $4.28 \pm 0.74^\circ$) compared with that on *day 1*, implying the implicit learning from previous days was not completely washed out. However, there was no significant group difference [$F(1,30) = 0.019$, $P = 0.890$].

We dissociated the explicit and implicit learning components to examine their respective susceptibility to cognitive load. Implicit learning was measured by exclusion trials (i.e., the first cycle of the washout phase), where participants were instructed to reach directly to the target without visual feedback. Explicit learning was calculated by subtracting implicit learning from total learning. Under cognitive load induced by the visual working memory task, the experimental group exhibited smaller explicit learning than the control group (Fig. 3E), as revealed by a significant main effect of group on explicit learning [$F(1,30) = 20.013$, $P < 0.001$]. Explicit learning of both groups improved across days [$F(2,60) = 18.453$, $P < 0.001$] without group-by-day interaction [$F(2,60) = 0.762$, $P = 0.471$]. Thus, cognitive load appeared to suppress explicit strategic learning, and repetitive learning of the dual task did not alleviate this effect. Interestingly, for implicit learning, we found a significant interaction between group and day [Fig. 3F; $F(2,60) = 4.136$, $P = 0.021$], suggesting that the implicit learning of the two groups exhibited divergent changes across days. On the first day, implicit learning did not significantly differ between the two groups ($t = 0.334$, $P = 0.740$). However, implicit learning showed a drastically different changing pattern: it decreased across 3 days for the control group [$F(2,30) = 9.224$, $P < 0.001$; post hoc comparison: *day 2* vs. *day 1*: $t = -2.717$, $P = 0.032$; *day 3* vs. *day 1*: $t = 4.289$, $P < 0.001$], consistent with previous studies suggesting an attenuation effect of implicit learning across learning sessions (34–36). In contrast, implicit learning remained unchanged across days for the experimental group [$F(2,30) = 2.593$, $P = 0.091$].

As a result, the experimental group had significantly larger implicit learning than the control group on *day 2* ($t = 2.599$, $P = 0.014$), although the group difference was reduced on *day 3* ($t = 1.995$, $P = 0.055$). Besides using the first-cycle washout, the conventional measure of implicit learning, we also assessed the implicit learning by using the average learning over all the washout trials. Again, we found a significant main effect of group [$F(1,30) = 9.061$, $P = 0.005$], with the experimental group showing higher implicit learning than the control group. There was a significant main effect of day [$F(1.6,47.9) = 27.847$, $P < 0.001$], but there was no significant interaction [$F(1.6,47.9) = 1.848$, $P = 0.175$]. Taken together, these results indicate that the additional cognitive load suppressed explicit learning and relatively promoted implicit learning.

For assessing the stability of implicit learning, we estimated the retention rate of implicit learning during the washout phase by fitting a state-space model (see METHODS). The retention rates between groups were compared on each day with bootstrap resampling (Fig. 3H). On *days 1* and *2*, the experimental group had larger retention factors than the control group, but their 95% confidence intervals overlapped [*day 1*: (0.88, 1.00) vs. (0.81, 0.91); *day 2*: (0.73, 0.87) vs. (0.56, 0.78)]. On *day 3*, the experimental group showed significantly larger retention factors [(0.73, 0.89) vs. (0.51, 0.71)]. It appears that cognitive loading improved the retention of implicit learning, and the effect was incremental over days. The retention rates also differed across days, with significantly lower retention factors on *days 2* and *3* than on *day 1*, suggesting that implicit learning decays faster over days. However, these results on the decay of implicit learning should be viewed with a grain of salt since we only had five washout trial cycles for estimating the decay rate. Recent studies have revealed that implicit learning comprises a volatile (fast-changing) component and a stable (slow-changing) component (37, 38). The last washout cycle can possibly reflect the stable component, and we thus compared it across conditions. The same mixed ANOVA revealed significant main effects of group [Fig. 3G; $F(1,30) = 10.394$, $P = 0.003$] and day [$F(2,60) = 21.641$, $P < 0.001$], whereas the interaction was not significant [$F(2,60) = 0.417$, $P = 0.661$]. Taken together, we found that implicit learning was relatively enhanced with cognitive loading, as shown by the amplitude of implicit learning, its retention rate, and its stable components.

Reaction time (RT) of reaching movements provides another index of explicit strategic learning since long reaction times are needed for explicit learning, especially during early learning (10–13). Indeed, RT increased dramatically during early learning when the perturbation was turned on for both groups on each day (Fig. 4A). RT decreased across days for both groups, as revealed by a significant main effect of day for both early [Fig. 4B; $F(2,60) = 6.240$, $P = 0.003$] and late learning phases [Fig. 4C; $F(1.42,42.64) = 13.390$, $P < 0.001$]. There was not a significant group difference in RT during the early phase [$F(1,30) = 1.371$, $P = 0.251$], whereas the experimental group exhibited higher RT during the late learning phase than the control group, as revealed by a marginally significant main effect of group [$F(1,30) = 3.970$, $P = 0.055$], suggesting the higher difficulty for the experimental group to form explicit motor learning.

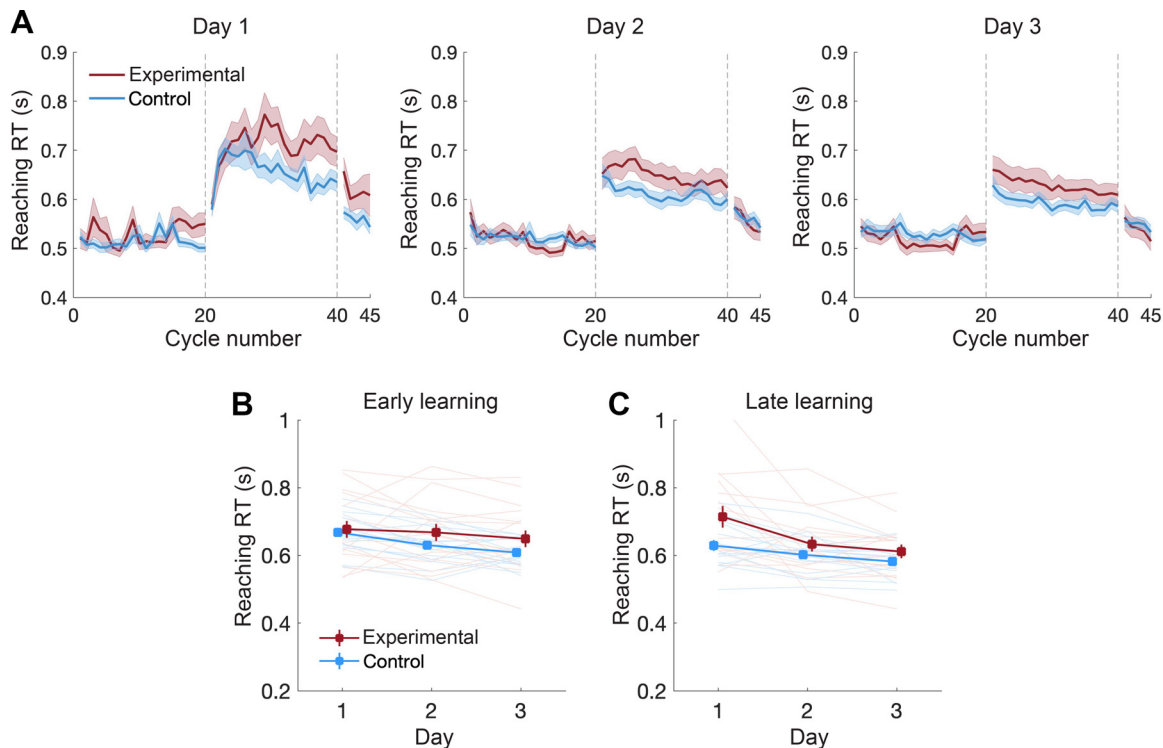


Figure 4. Reaction time results. **A:** reaching reaction time as a function of trial cycles, with three learning days plotted separately. Red and blue lines for the experimental group and control group, respectively. Shades denote SE across participants. **B** and **C:** average RT during early (the 1st–5th cycles) and late (the 16th–20th cycles) learning. Red lines represent the experimental group, and blue lines represent the control group. Data are shown as means $\pm$ SE. The light lines represent individual data. RT, reaction time.

The aforementioned results have shown that the dual-task manipulation affected motor learning. We further investigated how the dual-task manipulation affected participants' memory performance, which was quantified by reaction time and accuracy. To examine the dual-task cost on working memory performance, we additionally assessed the control group's performance on the working-memory task alone in a separate session after the dual task on each day. We compared the dual-task working memory performance for the experimental group with the single-task working memory performance for the control group. For RT during the early phase (Fig. 5B), a mixed ANOVA revealed significant main effects of group [$F(1,30) = 13.806$, $P < 0.001$] and day [$F(2,60) = 39.125$, $P < 0.001$], as well as a significant interaction between group and day [$F(2,60) = 7.593$, $P = 0.001$]. RT was significantly higher in the dual-task condition than in the single-task condition on *day 1* ($t = 5.068$, $P < 0.001$) and *2* ($t = 2.496$, $P = 0.018$), but not *day 3* ($t = 1.561$, $P = 0.129$), reflecting a dual-task cost for the memory task, evidenced during early learning decreased over time [$F(1.67,50.18) = 1.054$, $P = 0.346$]. For RT during the late phase (the last 10 trials; Fig. 5C), we did not observe the same interaction effect, although the main effect of time was significant [$F(1.67,50.18) = 22.790$, $P < 0.001$] with a marginal main effect of group [$F(1,30) = 3.354$, $P = 0.077$]. Taken together, the dual-task cost for the memory task was reduced over trials within a learning session and across days, and its effect was most salient during early learning on *day 1*.

For memory accuracy (Fig. 5D), a mixed ANOVA revealed significant main effects of group [$F(1,30) = 141.277$, $P < 0.001$]

and day [$F(2,60) = 20.452$, $P < 0.001$], and a significant interaction [$F(2,60) = 4.131$, $P = 0.021$]. Participants' single-task accuracy achieved relatively high levels on each day (*day 1*: $90.94 \pm 1.10\%$, *day 2*: $91.80 \pm 1.23\%$, *day 3*: $95.00 \pm 1.02\%$), without significant improvements across days (post hoc comparisons: *day 1* vs. *day 2*: $t = 0.538$, $P = 1.000$; *day 2* vs. *day 3*: $t = 2.514$, $P = 0.053$), whereas the accuracy under dual-task condition improved across days (*day 1* vs. *day 2*: $t = 3.716$, $P = 0.002$; *day 2* vs. *day 3*: $t = 2.881$, $P = 0.022$), although it remained substantially below single-task performance (*day 1*: $65.39 \pm 1.58\%$, *day 2*: $71.33 \pm 2.06\%$, *day 3*: $75.00 \pm 2.10\%$). The accuracy under dual-task conditions was lower than under single-task conditions on each day ($P < 0.001$), suggesting that the dual task affected the working memory performance even after 3-day training. Considering that late-phase RTs became similar between the two conditions, the affected memory accuracy ($<80\%$ at the end of 3-day training) appears to be a more sensitive metric than RT for assessing the effect of cognitive load during the dual task.

Two possible mechanisms can explain the effect of cognitive load, that is, the reduction in explicit learning and the relative increase in implicit learning (Fig. 3, E and F). The first is an independent-effect hypothesis that occupied working memory independently affects both learning components (Fig. 6A). The second is a moderation hypothesis that occupied working memory upregulates the existing negative correlation between explicit and implicit learning (Fig. 6, D and E). For testing the independent-effect hypothesis, we correlated working memory performance with implicit and explicit learning using a generalized linear model (details in

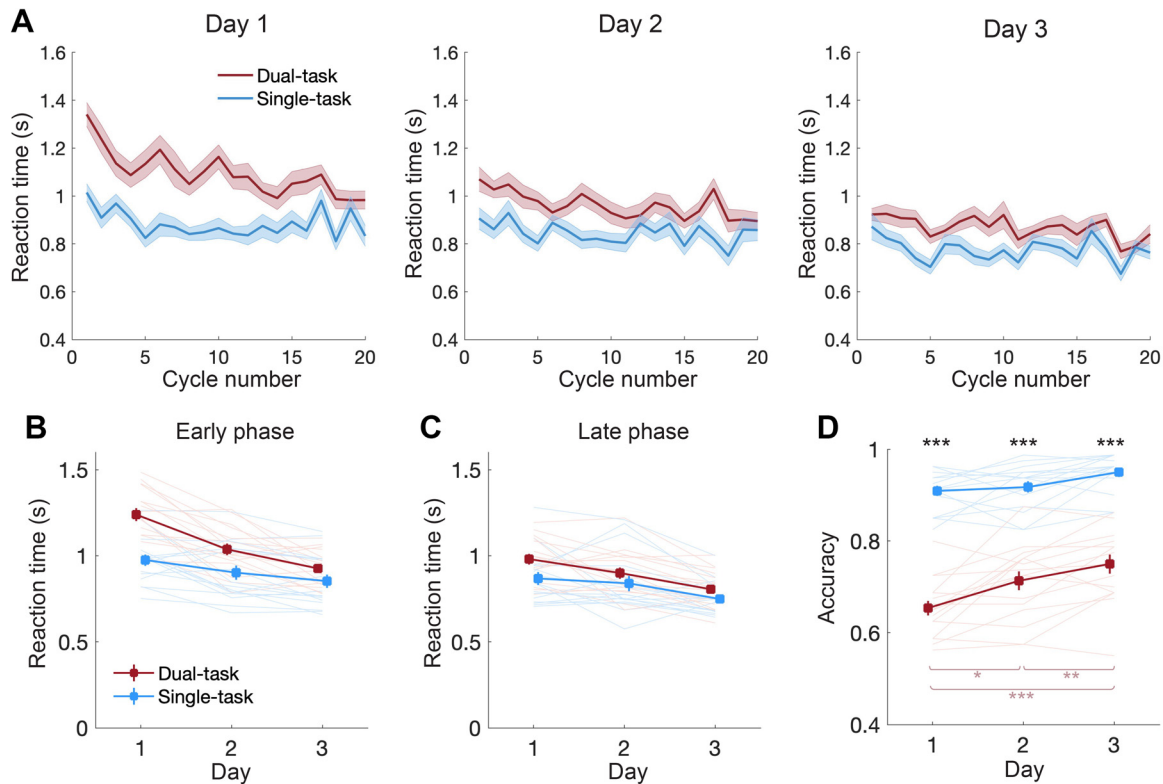


Figure 5. Performance of the working memory task. **A:** reaction time as a function of trial cycles. Three learning days are plotted in separate panels. Red and blue lines for the experimental group (dual-task) and control group (single-task), respectively. Shades denote SEM across participants. **B** and **C:** average RT during early (the 1st–5th cycles) and late (the 16th–20th cycles) learning. **D:** average memory accuracy. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$, and n.s. $P > 0.05$ (black for group difference and pink for day differences in the experimental group). Red lines represent the experimental group, and blue lines represent the control group. Data are shown as means $\pm$ SE. The light lines represent individual data. RT, reaction time.

METHODS). We found that the working-memory accuracy could negatively predict explicit learning (Fig. 6B; $\beta = -29.438$, $t = -2.184$, $P = 0.035$) but not implicit learning (Fig. 6C; $\beta = 18.531$, $t = 1.452$, $P = 0.156$). Thus, the relative increase in implicit learning with the concurrent working memory task was unlikely to be caused by independent influence from working memory itself. The negative correlation between working memory performance and explicit learning suggested that participants traded off between the two tasks, given the limited cognitive resources and the difficulty of the task. For experimental participants, their working memory task performance remained below ceiling across the 3 days, with accuracy below 80% even on the final day.

For the moderation hypothesis, we first confirmed the widely reported negative correlation between explicit and implicit learning (Fig. 6F; linear regression: $\beta = -0.755$, $t = -7.178$, $P < 0.001$) (10, 26, 39). Using working memory performance as a moderator, we evaluated two possible hypotheses: explicit learning drives implicit learning (Fig. 6D) or the reverse (Fig. 6E). Moderation analysis revealed that only the former case showed a significant moderation effect ($\beta = 1.399$, $t = 2.300$, $P = 0.029$), whereas the latter did not ($\beta = 0.826$, $t = 1.052$, $P = 0.299$). The positive estimate β indicated that worse working memory performance strengthened the negative correlation between explicit and implicit learning. These results suggested that cognitive load induced by the dual-task manipulation primarily influenced explicit learning, and the change in implicit learning was secondary. The

explicit learning was derived by subtracting the implicit learning (the first washout cycle) from the total learning (the last adaptation cycles); thus, this temporal contingency might render the two learning components somewhat interdependent. We conducted a control analysis using more independent quantifications of explicit and implicit learning. Specifically, we quantified explicit learning by using trials 1 and 3 of the first washout cycle (subtracting them from the total learning) and implicit learning by using trials 2 and 4 of this cycle. We then repeated the moderation analysis and found that the moderation effect remained significant ($\beta = 2.425$, $t = 2.461$, $P = 0.020$), confirming that our findings were robust against possible methodological confounds. We also used reaction time as the working memory performance variable, replacing working memory accuracy, to perform the moderation analysis. We did not find a significant moderation effect of RT on the relationship between explicit and implicit learning ($\beta = -0.282$, $t = -0.610$, $P = 0.545$), as expected given that RT was a less sensitive measure of working memory performance than accuracy (Fig. 5C).

DISCUSSION

In this study, we investigated the influence of cognitive load on motor learning, specifically its differential impacts on explicit and implicit learning processes. As expected, we found that the concurrent visual working memory task reduced visuomotor rotation learning, and this reduction

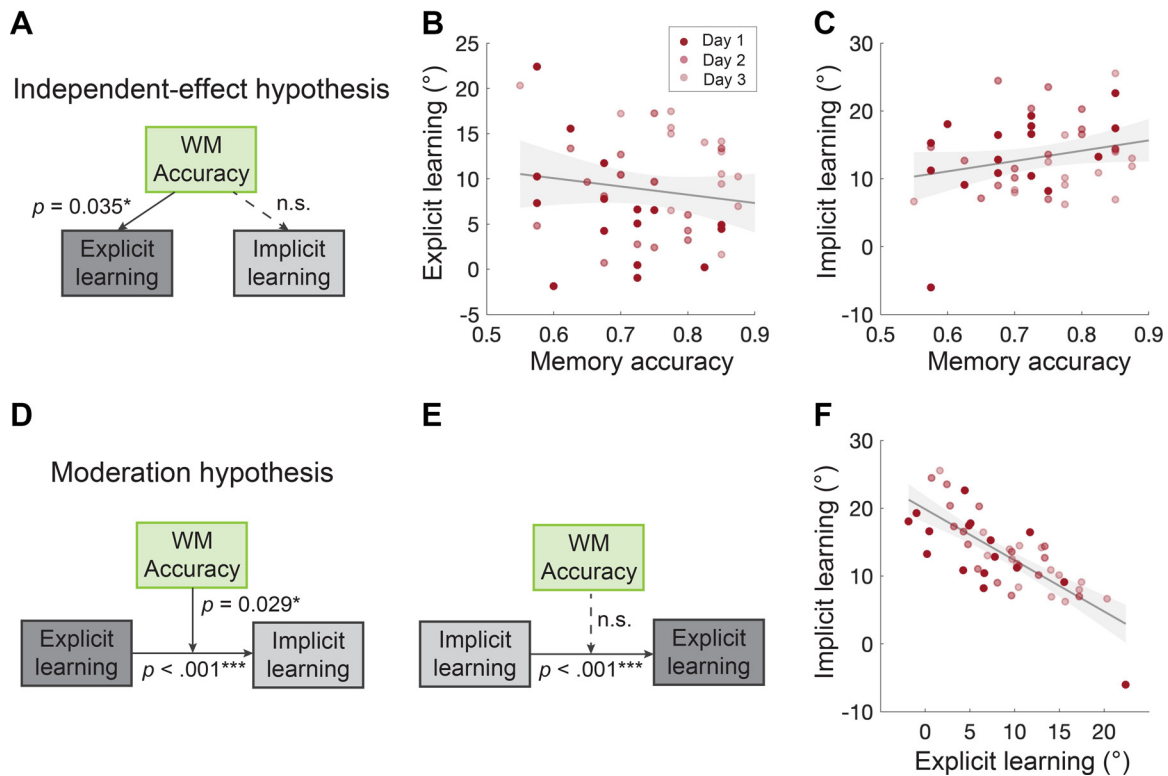


Figure 6. Correlational analyses. *A*: illustration of the independent-effect hypothesis: working memory performance affects both explicit and implicit learning components directly. *B*: working memory accuracy negatively predicts explicit learning. *C*: WM accuracy is not correlated with implicit learning. *D* and *E*: illustration of the moderation hypothesis: working memory performance modulates the effect of explicit learning on implicit learning (*D*), or working memory performance modulates the effect of implicit learning on explicit learning (*E*). *F*: implicit and explicit learning were negatively correlated. * $P < 0.05$, *** $P < 0.001$, and n.s. $P > 0.05$. For data presentation, the dark, medium, and light red dots represent the learning data on days 1–3, respectively. The lines denote simple linear regression fits. WM, working memory.

was primarily attributable to impaired explicit learning. Notably, contrary to previous reports of either null (7, 8) or detrimental effects (4, 20, 21) of cognitive load on implicit learning, we found that implicit learning was enhanced relatively when compared with the performance of the control group, who did not perform the dual task. Specifically, for the implicit learning magnitude assessed by the first wash-out cycle, the control group exhibited a decreasing trend of implicit learning over the three training days, whereas the experimental group maintained their implicit learning magnitude. Other implicit learning measures, including the decay rate and stable component, also indicated that extra cognitive load enhanced implicit learning. Moderation analyses revealed that this relative increase in implicit learning was not caused by a direct effect of cognitive load, but rather by its moderation effect on the negative association between these two learning processes.

Dual-Task Effects on Motor Adaptation

Our findings shed new light on how cognitive load affects motor learning. Vandevorde et al. (40) used a nearly identical visual working memory task as a dual-task manipulation for visuomotor rotation learning but restricted its administration to the baseline phase when no perturbation was applied. As expected, this preadaptation cognitive load did not affect subsequent motor adaptation. Keisler and Shadmehr (41) found that a declarative memory task administered after force-field adaptation selectively disrupted the consolidation

of the fast learning component while sparing the slow learning component. Given that the fast and slow components in force-field adaptation have been associated with explicit and implicit learning components, respectively (22), these results likely suggest that postlearning cognitive load may specifically interfere with the consolidation of explicit learning.

Our study, instead, suggests that concurrent cognitive load induced by a dual task affects adaptation itself, particularly impairing explicit learning while paradoxically enhancing implicit learning. These results departed from a series of studies by Song and colleagues (15, 16, 21), in which a rapid serial visual presentation (RSVP) task was performed concurrently with visuomotor rotation adaptation. Their RSVP task required participants to report the number of target items appearing in a random sequence of target and foil items. They found that this attention-demanding task slowed down initial VMR learning (15), reduced savings (15, 16), and generalization (21) after initial learning. Hence, their dual task appears to reduce both explicit and implicit learning since initial learning and savings largely reflect explicit learning (12, 17–19, 34), and generalization reflects implicit learning (42–44). However, their dual task might affect learning by factors other than cognitive loading. The RSVP task necessitated sustained fixation near the starting position of center-out reaching movements, whereas VMR adaptation requires peripheral target localization followed by strategic reaiming—a sign of explicit learning (45–47). In fact, implicit learning is also developed based on a perceptual error

anchoring around the reaiming direction (42, 43, 48). The fixation constraints imposed by the RSVP task thus likely prevent normal feedback processing in visuomotor adaptation, introducing interfering artifacts unrelated to cognitive load. Our dual task circumvented these limitations by asking participants to memorize the visual items before reaching movement, thus leaving their natural fixation patterns unaffected during adaptation. Our findings show the pure effect of cognitive loading on visuomotor rotation without the confounds of fixation changes.

Competition for Shared Cognitive Resources and Trade-offs between Dual Tasks

When concurrent tasks compete for limited cognitive resources, dual-task costs emerge—a performance decrement relative to single-task conditions (40, 49, 50). In our study, we observed the dual-task costs in both motor (Figs. 2, 3, and 4) and memory tasks (Fig. 5). For the motor task, motor adaptation exhibited reduced learning rate and magnitude under dual-task conditions; for the memory task, concurrent adaptation led to higher reaction time and lower accuracy. Although dual-task costs attenuated across training days, residual deficits persisted even on the third day, evidenced by lower adaptation and memory accuracy in the dual-task group compared with the control group. Notably, a performance trade-off emerged between tasks, as shown by a negative correlation between explicit motor learning and working memory accuracy (Fig. 6B). Individuals with better memory performance showed lower explicit learning, suggesting differential prioritization of tasks during sustained cognitive demand. Even on day 3, the dual-task group's memory accuracy remained below 80% (Fig. 5D). In this cognitively demanding situation, individuals' choices of resource allocation would be reflected in dual-task performance.

The selective impairment of explicit learning by the visual working memory task suggests a competition for shared cognitive resources. The extent of explicit learning in visuomotor rotation has been associated with capacities in mental rotation (7, 13, 51, 52) and visual working memory (7, 8, 53). Individuals with higher visual working memory capacity showed better explicit learning (7, 8, 53). Also, neuroimaging studies have identified overlapping neural substrates between these two tasks: visual working memory tasks engage the right prefrontal cortex, specifically the right dorsolateral prefrontal cortex (DLPFC), along with the right premotor and parietal cortices (7, 54–57). These regions are also engaged during the early stage of VM adaptation (58–62), where explicit learning dominates. Thus, we postulate that the competition of common cognitive and neural resources underlies the detrimental effect of the visual working memory task on explicit learning.

The absence of a direct effect of cognitive load on implicit learning suggests that visual working memory and implicit VM adaptation might depend on dissociable cognitive resources. Implicit adaptation is insensitive to various manipulations that impact cognitive processing. Changes of awareness of upcoming perturbations did not change implicit adaptation (14, 63). Shortening preparation time, whereas reducing explicit learning, did not affect implicit learning (10, 12). On the individual level, the visual working memory capacity was not correlated with implicit learning (8). Neuroimaging and neurophysiological studies identify the cerebellum as a crucial neural

substrate underlying implicit adaptation (64–68). Notably, recent computational modeling studies have shown that implicit adaptation to visuomotor rotation perturbation is driven by the prediction error of localizing one's effector (48, 69, 70). This prediction error results from a combination of visual, proprioceptive, and motor-prediction cues, a multisensory integration process that presumably resides in the cerebellum. In contrast, the visual working memory task here predominantly involves working in frontoparietal regions (7, 54–57). Thus, the lack of detrimental effect of our dual task on implicit adaptation supports the relative independence of cognitive and neural underpinnings of the two tasks involved.

Interactions between Explicit and Implicit Motor Adaptation

Our findings shed new light on the debate about the interplay between explicit and implicit processes during motor learning. Some researchers proposed that these two processes compete for the same motor error signals (10) and complement each other for successful adaptation (10, 26, 27). This complementary relationship is corroborated by negative correlations between explicit and implicit learning on the individual level (10, 26, 39). However, some other studies failed to find the negative correlation (63, 71), leading to the proposition that they operated independently (71). Our study provides converging evidence for the negative relationship between explicit and implicit learning across multiple levels of analysis: 1) at the group level, the experimental group showed higher explicit learning and lower implicit learning compared with the control group (Fig. 3, E–G); 2) across training days, the control group showed increasing explicit learning while decreasing implicit learning (Fig. 3, E–G); 3) at the individual level, implicit and explicit learning were negatively correlated (Fig. 6F). Importantly, our moderation analysis showed that cognitive load upregulated the negative correlation between implicit learning and explicit learning (Fig. 6D), indicating that individuals more affected by the dual task in terms of explicit learning adapted more implicitly. In addition, the moderation analysis showed that implicit learning compensated for explicit learning, rather than the other way around. We postulate that cognitive load challenges explicit learning and forces implicit learning to increase its role for successful adaptation. This compensatory role of implicit learning is consistent with a previous study (26). The compensatory role could be more salient when the task is cognitively challenging, such as being forced to move with limited preparation time (10), random perturbations (26), or the dual-task scenario in our study. Together, these findings underscore that human motor adaptation is, by itself, adaptive, flexibly accommodating varying task demands by adjusting the relative roles of explicit and implicit processes.

Distinct Relearning Effects of Explicit and Implicit Motor Adaptation

Motor learning, just like other learning systems (e.g., the verbal learning domain) (72, 73), exhibits a saving effect in that relearning of previous content is faster than the original learning (6, 12, 17, 19, 33, 74, 75). However, recent studies revealed a paradoxical attenuation of implicit adaptation

during relearning, that is, its contribution to accommodating the perturbation is slower and smaller when the same perturbation is experienced a second time (34–36), although the overall adaptation is still faster with the savings effect. Our control group replicated this phenomenon with the overall adaptation increased (Fig. 3B), but the implicit adaptation decreased (Fig. 3F) over three consecutive days. The mechanism of the decrease in implicit readaptation is still under debate (34–36). Some studies attributed it to a decrease in sensitivity to perturbation-elicited motor errors, that is, the error history (33, 76, 77) could desensitize the implicit learning system and decrease its learning rate. Specifically, people experienced an extended period of nearly zero performance error on the learning asymptote during initial adaptation, and this error history reduced error sensitivity and thus reduced the readaptation. Other studies attributed the slower readaptation to the difficulty of recalling motor memory associated with movements with the original perturbation (34–36). This recall difficulty stems from interference from similar motor memories associated with movements with different feedback, that is, reaching with veridical feedback at baseline and reaching without feedback at washout (35, 36, 78). The decline of implicit learning across days in the control group could be explained by either the desensitization or the interference account. Specifically, between two learning sessions (across days), our participants experienced no-feedback washout and veridical feedback baseline trials, which might serve as a source of motor memory interference. However, our findings of unchanged implicit adaptation across learning sessions in the experimental group are more consistent with the desensitization account than with the interference account. Compared with the control group, our experimental group had large performance errors even late into their learning session on each day. According to the error sensitivity account, these sustained motor errors might prevent desensitization, thereby preserving implicit readaptation. On the contrary, our experimental group performed the memory dual task, which arguably acted as additional interference to memory recall on top of the existing interference from competing motor memories, according to the interference account. Thus, the interference account should predict a further decrease in implicit readaptation when comparing the experimental group to the control group. However, we observed the opposite. Notably, our findings cannot rule out the interference account, as cognitive interference from the memory dual task may operate independently of motor interference. Further studies are needed to tease apart these potential factors that affect implicit adaptation.

In conclusion, extra cognitive loading impacts initial sensorimotor adaptation, with a direct detrimental effect on explicit processes and an indirect enhancing effect on implicit processes, highlighting that cognitive and procedural systems work in a complementary manner with their relative contributions flexibly altered by resource constraints.

DATA AVAILABILITY

Data and code are available at the Open Science Framework (<https://osf.io/rsx8v/>).

GRANTS

This work was supported by the Space Medical Experiment Project of China Manned Space Program Grant HYZHXMRO1001, the STI2030-Major Projects Grant 2021ZD0202600, and the National Natural Science Foundation of China Grants 32471099 and 6206113600 (to K.W.).

DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the authors.

AUTHOR CONTRIBUTIONS

X.Z. and K.W. conceived and designed research; X.Z. and T.Z. performed experiments; X.Z. analyzed data; X.Z. and K.W. interpreted results of experiments; X.Z. prepared figures; X.Z. and K.W. drafted manuscript; X.Z. and K.W. edited and revised manuscript; X.Z., T.Z., and K.W. approved final version of manuscript.

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