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Beyond the mean reaction time: Trial-by-trial reaction time reveals the distraction effect on perceptual-motor sequence learning

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ABSTRACT

Perceptual-motor sequences can be learned quickly under distraction, often demonstrated by the mean reaction time (RT) change in a serial reaction time (SRT) task. However, any arbitrary mean RT can arise from one of many distinct trial-by-trial RT patterns. It is surprising that previous sequence learning studies have hinged only on the mean RT metrics while little is known about the distraction effect on its trial-by-trial processes. In an SRT task with or without distraction, we found that initially learning a fixed repeating sequence without distraction was expressed by a micro-online learning process where reaction time (RT) progressively improved within learning blocks as adults continuously performed the SRT task. Such online RT improvements, however, vanished when the SRT task was performed under distraction. Despite the detrimental effect of distraction on micro-online RT improvements, we observed offline enhancements in RT following rest intervals of 3 min that emerged to secure sequence learning under distraction. We reasoned that distraction may exert influence on the micro-online and offline learning by mediating the engagement of explicit and implicit memory. Given the offline RT change under distraction, a short rest between learning blocks may be a key player in early perceptual-motor sequence learning under distraction. We thus suggest that future studies investigating the distraction effect on sequence learning need to control the length of rest between learning blocks, while previous research with equivocal interpretations of the distraction effect failed to do so.

1. Introduction

Our parents tell us not to watch TV while we study. Their rationale is simple: distraction is bad for learning. The effect of distraction, however, is paradoxical on learning incidental perceptual-motor sequences, where leaners are unaware of the sequential pattern prior to learning, though they often gain explicit knowledge of the sequence through repetitive practice. Thus, learning a perceptual-motor sequence typically arises from an uncertain blend of implicit and explicit memory. Previous research suggested that distraction attenuates or impairs incidental perceptual-motor sequence learning by taxing attentional resources (e.g., Cohen, Ivry, & Keele, 1990; Nissen & Bullemer, 1987), blocking the explicit memory system (e.g., Curran & Keele, 1993; Jimenez & Mendez, 1999), or disrupting sequence temporal structure and thus interfering with the learning of stimulus associations (Schmidtke & Heuer, 1997; Stadler, 1995). In contrast, distractions may not impede sequence learning but only suppress its behavioral expression (e.g., Frensch, Lin, & Buchner, 1998; Frensch, Wenke, & Runger, 1999). These divergent explanations make it clear that our understanding of distraction effects on perceptual-motor sequence learning remains elusive. One limitation of these conceptual accounts is that inference was simply built on the overall level of learning outcome (e.g., the mean reaction time of hundreds of trials). However, it has been argued that analyzing the mean reaction time (RT) may fail to reveal important learning effects (Nemeth et al., 2013; Rickard, Cai, Rieth, Jones, & Ard, 2008). Indeed, several recent sequence learning studies have begun to report that the same learning outcome could arise from remarkably different trial-by-trial RT patterns (Du & Clark, 2016; Du, Prashad, Schoenbrun, & Clark, 2016; Du, Valentini, Kim, Whitall, & Clark, 2017). We propose that taking a

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careful examination beyond the mean RT could open a new window to better understand the distraction effect on sequence learning. This study, therefore in addition to the mean RT, examined the progressive RT changes during perceptual-motor sequence learning to elaborate the distraction effect.

Incidental sequence learning has been commonly studied in the serial reaction time (SRT) task (Nissen & Bullemer, 1987). Participants respond as fast and accurately as possible to a stream of visual cues that follows a fixed repeating sequence. Despite the lack of explicit awareness of the sequence before performing the SRT task, adults are able to rapidly learn the sequence over a few learning blocks of about 100 trials (Nissen & Bullemer, 1987; Willingham, Nissen, & Bullemer, 1989) and may acquire explicit knowledge of the sequence (e.g., Destrebecqz & Cleeremans, 2001). This initial rapid acquisition, forming a mixture of explicit and implicit memories, appears to arise from online learning. In existing research, online learning was defined as the change in mean performance (average of 100 trials) across multiple blocks (Dayan & Cohen, 2011), which in fact consists of short offline periods between learning blocks. In the current study, however, we quantified online learning by the trial-by-trial improvements in individual RT within learning blocks as an experimental participant continuously responds to visual stimuli (Bornstein & Daw, 2012, 2013; Du et al., 2016, 2017; Verstynen et al., 2012). Such online changes in RT has recently been renamed as "micro-online learning" to emphasize the temporal time-scale of learning (Bönstrup et al., 2019). Our first goal, therefore, was to understand the effect of distraction on micro-online learning and examine possible underlying mechanisms. Conceptually, micro-online learning requires iterative mental computations and thus is expected to be vulnerable to distraction, where distraction may either, 1) divert attention (e.g., Nissen & Bullemer, 1987; Shanks & Channon, 2002); 2) block the acquisition of explicit sequence knowledge (e.g., Curran & Keele, 1993; Jimenez & Mendez, 1999) that can speed up micro-online learning (Du et al., 2016; Malone & Bastian, 2010); or, 3) interfere with learning sequence structures (Schmidtke & Heuer, 1997; Stadler, 1995). In addition, distraction may not impair online learning but suppress its behavioral expression (e.g., Frensch et al., 1999; Frensch et al., 1998). For example, the greater attentional demand imposed by distraction would induce an accumulation of fatigue that worsens performance during continuous training (c.f., Eysenck & Frith, 1977). Such performance deterioration could wash out the improvement in performance arising from online learning and thus leave online learning behaviorally invisible.

As for the possible detrimental effect of distraction on online learning, early incidental sequence acquisition appears to be susceptible to distraction. However, learning perceptual-motor sequences is rarely an outcome of a single learning process (Bornstein & Daw, 2012, 2013; Brown & Robertson, 2007a; Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Nemeth, Janacsek, Polner, & Kovacs, 2013). In the SRT task literature, neuroimaging evidence demonstrates that distinct memory systems and neural substrates are involved in learning sequences with or without distraction, suggesting the operation of multiple learning processes (Grafton, Hazeltine, & Ivry, 1995; Hazeltine, Grafton, & Ivry, 1997; Rauch et al., 1995; Seidler et al., 2002). Indeed, recent studies have reported that, in addition to micro-online learning, initial sequence learning may also be behaviorally reflected by a micro-offline process,[3] where RT improves following a short rest between learning blocks under certain circumstances (Bönstrup et al., 2019; Du et al., 2016, 2017). Note that the micro-offline process develops during the initial acquisition stage. At least before a concrete relationship is identified, it should be distinguished from the offline boost, offline learning or memory consolidation that serves to stabilize or enhance memory of sequences after initial acquisition (Censor, Sagi, & Cohen, 2012; Hotermans, Peigneux, Maertens, Moonen, & Maquet, 2006; Robertson, Pascual-Leone, & Miall, 2004). During the fast/initial learning stage, the rest interval itself and what may develop following the rest has often been ignored in previous research on sequence learning, especially for studies on the effects of distraction. For example, it is unclear in some studies whether there was a break between learning blocks and, if so, how long the break was (e.g., Cohen et al., 1990; Shanks & Channon, 2002; Stadler, 1995), while in other studies the length of breaks was dictated by the individual participants (e.g., Curran & Keele, 1993; Shanks, Rowland, & Ranger, 2005). Thus, the second puzzling aspect we aimed to understand is whether distraction affects the micro-offline process. Since distraction may block explicit awareness (e.g., A. Cohen et al., 1990) and engage greater implicit memory (Foerde, Knowlton, & Poldrack, 2006), the offline process is expected to arise under distraction because it is commonly observed when the SRT task is more implicit (Du et al., 2016, 2017).

Here, we examined the micro-online learning and micro-offline processes in a foot-stepping SRT task. The foot-stepping SRT task was used because of its ability in decomposing response time used in classic finger tapping SRT task into reaction time and movement time that may reflect distinct learning effects (Du & Clark, 2016; Moisello et al., 2009). In addition, the performance change in the foot-stepping SRT task is primarily driven by sequence learning and less contaminated by general motor improvement (Du & Clark, 2016, 2018). Participants were asked to perform the foot-stepping SRT task alone (i.e., single-task group) or concurrently with distraction (i.e., dual-task group). To confirm whether distraction impairs micro-online learning or only suppresses its behavioral expression (e.g., by accumulative fatigue under distraction), the online performance change was further examined during an expression phase where both groups performed the SRT task without distraction. If micro-online learning takes place but fails to be expressed under distraction, online RT changes in the dual-task group would reappear during the expression phase with a magnitude comparable to that in the single-task group. Furthermore, to seek an answer as to whether distraction impacts micro-online learning by distorting temporal structures of sequences and thus hampering the learning of stimulus associations, we examined the statistical dependence among RTs that approximates the cognitive representation of stimulus contingencies (Du & Clark, 2016; Gilden, 1997; Gilden, Thornton, & Mallon, 1995). Inferior learning in terms of the statistical dependence in the dual-task group would echo the structure-disruption hypothesis. Finally, to test the hypothesis that distraction blocks the development of explicit memory, we compared the amount of acquired explicit knowledge between two groups after the SRT task.

2. Methods

2.1. Participants

Twenty-two non-musician adults (20.48 ± 0.37 years old, 14 females), without neurological disorders, participated in our study that was approved by the Institutional Review Board at the University of

[3] We chose the term "micro-offline process" rather than similar terms, such as "reminiscense" and "micro-offline learning" for two reasons. First, reminiscence is a broader term used to describe an offline performance change, regardless of when and why such a change takes place. For example, reminiscence may result from fatigue, learning, or both and may take place during or after initial acquisition (Eysenck, 1965; Eysenck & Frith, 1977). Second, we did not use the term "learning" here as it is unclear whether the offline change is purely attributed to learning or a result of blended factors, such as fatigue (Du et al., 2016, 2017; Torok et al., 2017). Although it has been found that the micro-offline performance change signifies certain learning mechanisms in simple sequence learning tasks (Bönstrup et al., 2019) and rotary-pursuit tasks (Eysenck & Frith, 1977), the same conclusion remains to be determined in the SRT task, as these different types of learning tasks tackle different components of motor skill learning (Krakauer et al., 2019).

(*footnote continued*)

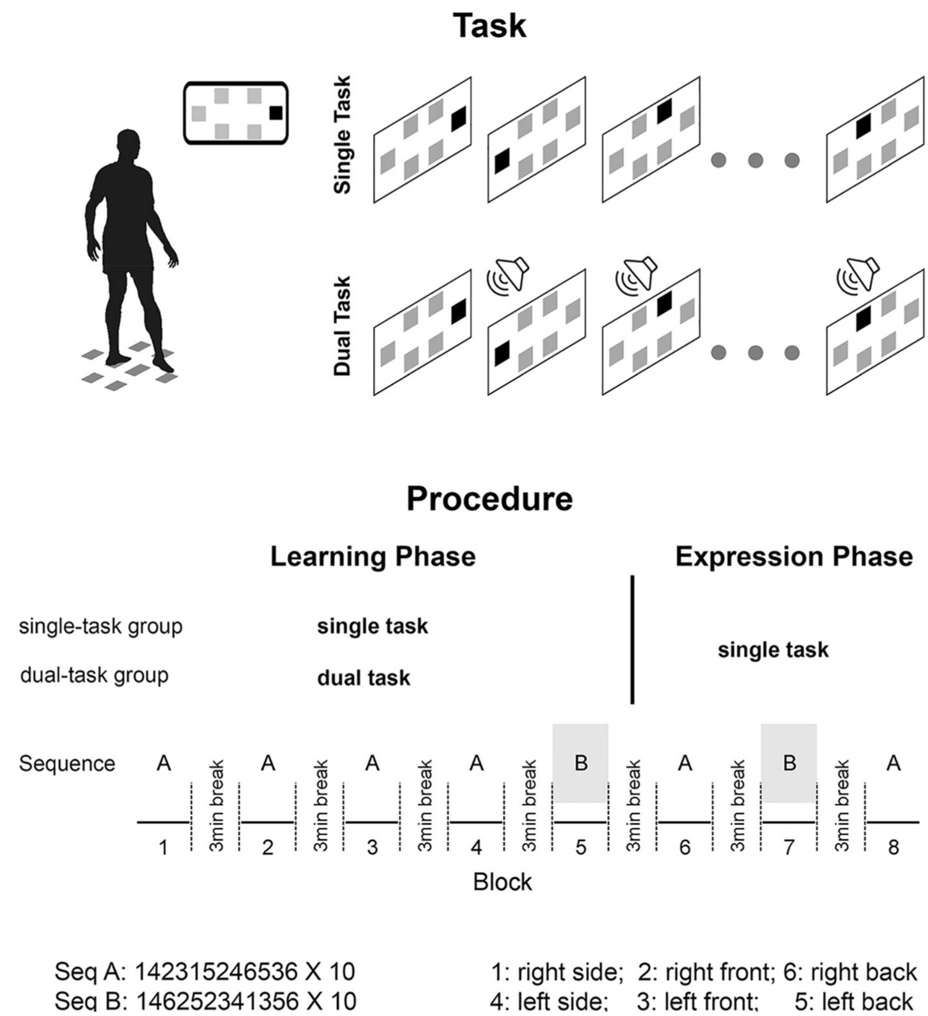

Fig. 1. Participants performed a modified serial reaction time (SRT) task. In block 1–5 (the learning phase), the single-task group performed the SRT task only. The dual-task group performed the SRT task under the distraction imposed by a tone-counting task. The tone-counting task was removed and both groups performed the SRT task only in block 6–8 (the expression phase). In all blocks, visual stimuli followed either sequence A or B which were unknown to participants.

Maryland, College Park. Participants were screened for their experience with the video game, Dance Dance Revolution, given its similarity to the foot-stepping task. All participants signed consent forms prior to their participation and received $15 upon the completion of the experiment.

2.2. Methods and procedure

Participants performed a modified SRT task (Fig. 1). There was a home position surrounded by six stepping targets. The distance from the home position to each target was determined prior to the SRT task for each individual. In particular, participants were asked to step to each target several times as comfortably as they could. The mean position of these steps was then set as the location of each target. During the SRT task, when one of six stimuli appeared on the computer monitor, participants stepped in the direction of the spatially-matched target as quickly and accurately as possible and then returned to the home position. An accurate hit on the target mat was encouraged, but not strictly required to avoid participants unnecessarily lowering their heads to look for the target on the floor. The light-target mapping included stepping with the right foot to the three right targets: 1 (i.e., right side), 2 (i.e., right front), and 6 (i.e., right back); and, stepping with the left foot to three left targets: 3 (i.e., left front), 4 (i.e., left side), and 5 (i.e., left back). These numbers were not displayed to participants until they completed the whole task. The stimulus was presented on the monitor for 700 ms despite the speed of stepping. After a 600 ms delay following the stimulus disappearance, another stimulus appeared on the screen, leading to a fixed 1300 ms inter-stimulus interval. The visual stimuli were controlled by a laptop computer with a customized Labview (National Instruments, Austin, TX, USA) routine. Reflective markers were attached to the participants' big toes, heels, and the 5th metatarsal on both feet. The three-dimensional movement trajectories of these reflective markers were recorded by a Vicon motion capture system (Oxford Metrics, Oxford, UK) with a sampling frequency of 200 Hz. The Vicon motion capture system was time-locked to the Labview program.

The SRT task consisted of eight blocks of 120 steps with a mandatory 3-minute break between blocks. During the learning phase (block 1–5), one group performed the SRT task only (single-task group). The other group (dual-task group) performed the SRT task under the distraction imposed by a tone-counting task (See details below; A. Cohen et al., 1990; Nissen & Bullemer, 1987). Following the learning phase, there was an expression phase that comprised blocks 6–8 where the tone-counting task was removed and both groups performed only the SRT task. Before each block, participants were reminded to respond to stimuli as quickly and accurately as possible. Unknown to participants, in blocks 1 to 4, 6, and 8, the order in which visual stimuli appeared one after another followed sequence A (Fig. 1), while it was replaced by sequence B in blocks 5 and 7. These two sequences were both ambiguous sequences in which there were no unique 1st-order stimulus associations (A. Cohen et al., 1990). After the SRT task, the explicit knowledge of sequence A was accessed by the process dissociation procedure (Destrebecqz & Cleeremans, 2001; Jacoby, 1991). Specifically, participants wrote down 60 steps of the sequence they performed in the SRT task (i.e., inclusion condition) and they created another 60-step sequence in which they were asked to avoid the sequence they experienced during the SRT task (i.e., exclusion condition).

A tone-counting task was imposed when the dual-task group performed the SRT task from blocks 1 to 5 (i.e., the learning phase). In the tone-counting task (A. Cohen et al., 1990; Curran & Keele, 1993; Nissen & Bullemer, 1987), either a high- (1000 Hz) or low-pitch tone (440 Hz) was played after the appearance of each stimulus. The elapsed time from the visual stimulus and the tone was generated randomly between 700 ms and 1150 ms for each trial. Each tone lasted 100 ms so that the tone was played after the current stimulus disappeared and vanished before the next stimulus appeared. Participants were asked to pay equal attention to the SRT and tone-counting tasks and count how many high-pitch tones they heard when they performed the SRT task. Participants reported the number of high-pitch tones they heard and the correct number was then displayed on the monitor after each block. The number of high-pitch tones was randomly selected from the uniform distribution on the integer interval between 30 and 90 (out of 120 trials) so that participants could not easily guess the number. Prior to block 1, both tones were played to participants in the dual-task group. Block 1 did not start until participants stated that they were able to differentiate the high-pitch tone from the low-pitch one. We used the 90% accuracy threshold in the secondary tone-counting task that has been commonly used in the literature (A. Cohen et al., 1990; Curran & Keele, 1993; Shanks & Channon, 2002) to determine whether an individual paid adequate attention to the tone-counting task. Two participants failed to reach this accuracy so their data were excluded from further data analyses.

2.3. Data analysis

Sequence learning is typically indicated by a faster response time to a learned sequence than a novel sequence (Nissen & Bullemer, 1987; Willingham et al., 1989). Here, we decomposed the response time into reaction time (RT) and movement time (MT), which may have different roles in incidental sequence learning (Du et al., 2017; Du & Clark, 2016; Moisello et al., 2009). RT was defined as the time between the onset of visual stimulus and the onset of a foot movement. MT was the time interval between the onset and the termination of the foot movement. To derive these variables, the starting and end points of foot movement were identified from the three-dimension trajectory (filtered by an eighth-order Butterworth filter with a cutoff frequency of 10 Hz) of the foot markers using a customized MATLAB™ (MathWorks, Naticks, MA, USA) script. The onset of each stepping response was set at the first sample when the foot (i.e., represented by either the big toe, heel, or the 5th metatarsal marker whichever reached the threshold at the earliest time) reached 10% maximum movement height. The end point of each stepping response was defined at the time when the foot moved to the target and dropped to the same height as the onset. Thus, for trials where the foot failed to drop to the same height as the onset, MT was considered missing. In addition, RTs and MTs that corresponded to other error steps (i.e., stepping to a wrong target or initially moving to a wrong target followed by rapid correction) were also discarded (please see accuracy results below). Within each learning block, RT or MT that was longer or shorter than 2.5 standard deviations from the individual's mean RT or MT in that block were considered as outliers and were excluded from further analyses. For the last block (block 8) of one participant in the dual-task group, the movement trajectory information was not successfully collected due to technical issues with the Vicon motion capture system, the RT and MT could not be derived. Thus, this participant's data from block 8 were not included in further analyses. After RT and MT were derived for individual steps, we calculated the mean RT/MT of 120 steps in each block. The mean RT/MT difference between blocks 4 and 5 (block 5 minus block 4) as well as that between blocks 6 and 7 (block 7 minus block 6) was then computed to assess sequence learning during the learning and expression phases, respectively.

The behavioral processes underlying early sequence learning were measured by RT changes within and between blocks when participants learned sequence A during the learning phase (blocks 1–4). Specifically, the online process, reflecting RT changes within a block, was computed as the difference in the mean RTs between the first and last 12 steps (i.e., the length of sequence A) in the same block. Offline process represented the RT change after a short rest and was computed as the difference between the mean RT of the last 12 steps in one block and mean RT of the first 12 steps in the succeeding block. In addition, we measured the online changes in blocks 6 and 8 during the expression phase where the tone-counting task was removed. The mean online and offline changes across blocks 1–4 and mean online change between blocks 6 and 8 were used for statistical analyses. A negative value of online and offline RT change indicated that RT became faster.

We fitted the RT time series within each block with a 2nd-order seasonal autoregressive model. The seasonal component was included to account for pre-existing repeated RT patterns originated from biomechanical constraints (Du & Clark, 2016). The estimated 1st- and 2nd-order autoregression coefficients represent the statistical dependence of RT. Learning effects in terms of the statistical dependence were computed as the difference between blocks 4 and 5 (block 5 minus block 4) and that between blocks 6 and 7 (block 7 minus block 6).

To quantify the amount of explicit knowledge that participants acquired, a recall score was calculated as the number of correct 3-element chunks in the sequences that participants generated under both inclusion and exclusion conditions. The chance level for a 3-element chunk in the sequence was 5.56% (i.e., given the first element, 33.33% chance for the second element and 16.78% chance for the third element). Since participants recalled 60 steps, there were 58 3-element chunks and thus the chance level for recalling 3-element chunks in a 60-element long sequence written by an individual was 3.25 (i.e., 58×0.056).

2.4. Statistical analysis

We first used mixed-effect ANOVAs (group × block) to examine distraction and block effects on RT, MT, and autoregression coefficients. Given our primary interests in the distraction effect on learning rather than overall performance, mixed-effect ANOVAs (group × practice phase) were used to examine effects of distraction and practice phase on sequence learning in terms of differences in mean RT as well as statistical dependence in RT between blocks 4 and 5 and between blocks 6 and 7. A mixed-effect ANOVA was used to examine the online process and a one-way ANOVA was performed on the offline process in RT. Tukey-Kramer corrected analyses were performed to decompose any significant effects. The estimations of means and standard errors from these ANOVAs were used to examine whether these learning effects differed from zero. Poisson or Poisson mixture models (i.e., negative binomial regression if recall scores were over-dispersed) were used to examine the distraction effect on recall scores that were measured by count data. Since one evident sign of explicit learning is a decreased recall score from the inclusion to exclusion condition (Destrebecqz & Cleeremans, 2001), pre-planned contrasts were designed to test the difference in recall scores between these two conditions for each group. The significance level for statistical analyses was set at $\alpha = 0.05$.

3. Results

3.1. Accuracy

Since we aimed to compare RT and MT between two groups who performed the SRT task under different contexts, it is necessary to

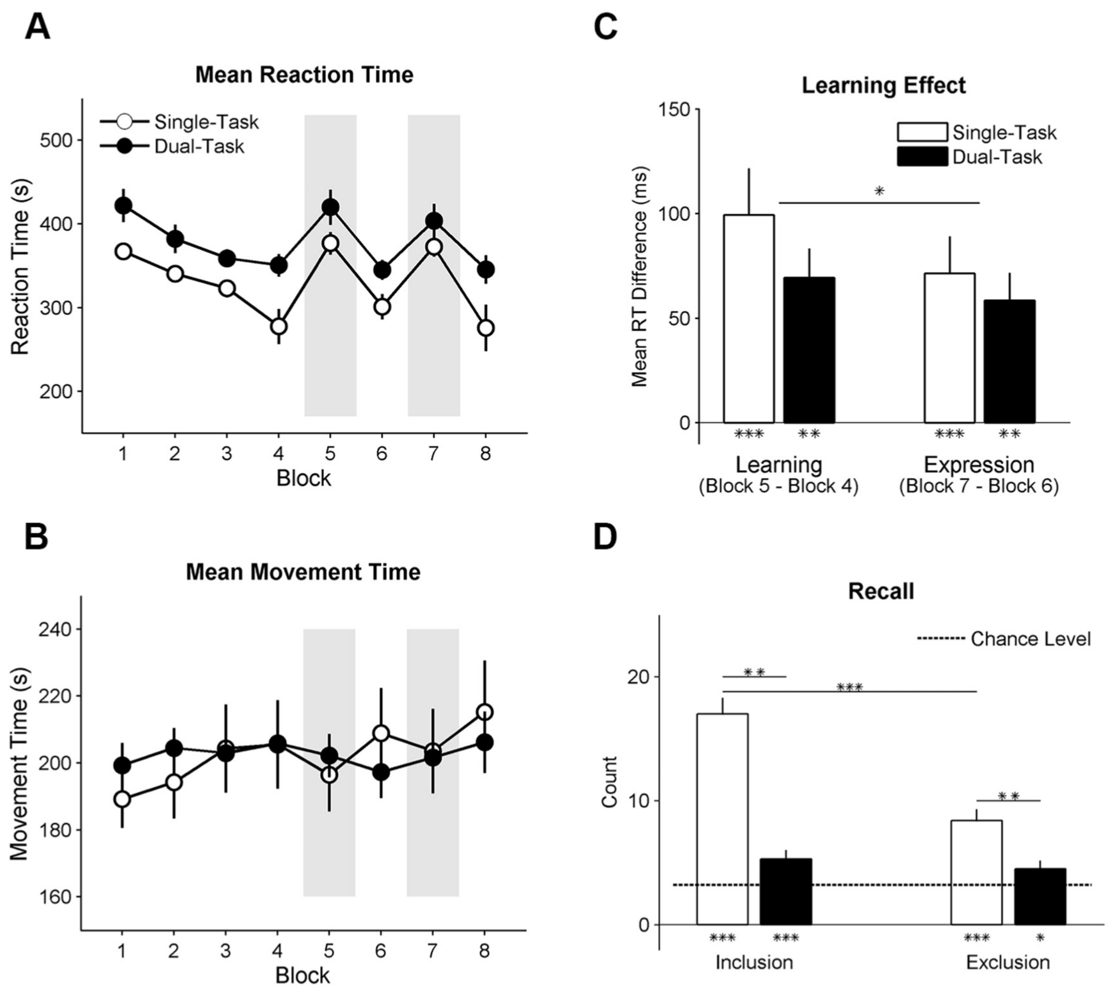

Fig. 2. (A) Mean RT across blocks in both groups. (B) Mean MT across blocks in both groups. (C) Comparable sequence learning (in terms of mean RT of each block) between groups despite practice phase. (D) Higher recall scores in the single-task than the dual-task group and higher recall scores in the inclusion than exclusion condition for the single-task group. Comparable inclusion and exclusion recall scores in the dual-task group. [Error bar - standard error of the mean; * - $p < 0.05$; ** - $p < 0.01$; *** - $p < 0.001$; * near the x-axis – significantly different from zero (C) or chance level (D); * near the error bar – significant difference between experimental conditions].

confirm that any differences in response speed is not caused by a potential speed-accuracy tradeoff. The number of error trials were different when analyzing RT and MT as there were two types of error for RT and three types for MT (see methods). However, consistent with the literature, both response accuracies in the SRT task were typically high. For RT, overall, the stepping accuracy across all 8 blocks was 98.89% ± 0.24% (mean ± standard error) in the single-task group and 99.1% ± 0.3% in the dual-task group. When only the first 5 blocks in the dual-task group, where they performed the SRT task with a distraction, were counted, the accuracy was 99.41% ± 0.22%. When the accuracy was calculated for each block, it was consistently higher than 98% in both groups. Compared to RT, the exact number of error trials was slightly higher for MT, but the accuracy remained to be above 98% across all blocks and for each block in both groups. These results suggest that potential differences in RT or MT between the single- and dual-task groups (see below) are not consequences of distinct speed-accuracy tradeoff strategies used under different contexts.

3.2. Overall learning effects in RT, MT, and explicit sequence knowledge

Mean RT (Fig. 2A) of an individual block was significantly affected by block ($F(7, 125) = 20.23$, $p < 0.001$) and group ($F(1, 18) = 8.16$, $p < 0.05$), but not their interaction ($F(7, 125) = 0.82$, $p = 0.57$). Across all blocks, the single-task group had faster mean RTs than the dual-task group ($p < 0.05$). Despite distraction group, mean RT improved from block 1 to block 4, 6, and 8 (all $p < 0.001$) and remained the same between blocks 1, 5, and, 7 ($p > 0.95$). Importantly, mean RT became slower from block 4 to block 5 as well as from block 6 to block 7 (both $p < 0.001$). Unlike RT, mean MT (Fig. 2B) was significantly affected by block ($F(7, 125) = 3.41$, $p < 0.01$) and its interaction with group ($F(7, 125) = 2.28$, $p < 0.05$). There was no significant effect of group ($F(1, 18) < 0.01$, $p = 0.98$). Post hoc analyses revealed that the single-task group became slower from block 1 to blocks 6 ($p < 0.05$) and 8 ($p < 0.001$). Importantly, there were no differences in mean MTs between blocks 4 and 5 as well as between blocks 6 and 7 for both groups. This MT result is consistent with the idea that MT reflects the execution ability of individual sequence elements (Krakauer, Hadjiosif, Xu, Wong, & Haith, 2019). In our study, the individual sequence elements involve foot stepping to different locations, which is presumably well developed in healthy adults. Taken together, these results suggest that RT, but not MT, represents sequence-specific learning and thus we included RT only for further analyses.

When we focused on the overall learning effect in RT as quantified by the mean RT difference between blocks 4 and 5 (learning phase) as well as between blocks 6 and 7 (expression phase; Fig. 2C), we found that both groups demonstrated sequence learning during the learning phase (single-task: 99.37 ± 22.29 ms, mean ± s.e.m.; $p < 0.001$; dual-task: 69.40 ± 13.84 ms, $p < 0.01$) and expression phase (single-task: 71.48 ± 17.63 ms, $p < 0.001$; dual-task: 58.58 ± 13.07 ms, $p < 0.01$). A mixed-effect ANOVA revealed no significant effects of distraction ($F_{1,18} = 0.92$, $p = 0.35$) and its interaction with practice phase, but the effect of practice phase was found ($F_{1,18} = 4.75$, $p < 0.05$). One caveat of above analyses is that these two groups have different baseline RTs. Thus, the same magnitude of RT improvement may not reflect the same extent of sequence learning (Janacsek, Fiser, & Nemeth, 2012). To address this issue, the same statistical analyses were performed after we transformed each individual RT to a z-score. The results remained qualitatively the same, confirming no difference in two groups in terms of the overall sequence learning effect.

Despite the two groups' comparable learning effects as measured by mean RT, these two groups demonstrated differences in their explicit sequence knowledge (Fig. 2D). Recall scores were higher in the single-task group than the dual-task group (${\chi_{df=1}}^2 = 9.58$, $p < 0.01$) regardless of recall conditions. Although both inclusion (single-task: $p < 0.001$; dual-task: $p < 0.001$) and exclusion recall scores (single-task: $p < 0.001$; dual-task: $p < 0.05$) were higher than chance, pre-planned contrasts revealed that the inclusion recall score was higher than the exclusion recall scores in the single-task group ($p < 0.001$), while they were comparable in the dual-task group. These results are consistent with the literature and suggest that distraction disrupts explicit learning (Curran & Keele, 1993; Grafton et al., 1995).

3.3. Progressive changes in RT

Details of RT changes for both single- and dual-task groups across all blocks and interposed breaks are shown in Fig. 3A. As we hypothesized, the mean online RT change (Fig. 3B) was significantly affected by group ($F_{1,18} = 4.89$, $p < 0.05$), while there were no effects of practice phase ($F_{1,18} = 2.61$, $p = 0.12$) and its interaction with group ($F_{1,18} = 1.06$, $p = 0.32$). RT significantly improved online in the single-task group during both learning (−24.60 ± 11.46 ms, $p < 0.05$) and expression phases (−52.82 ± 23.75 ms, $p < 0.01$). In the dual-task group, however, RT online improvement approximated zero during the learning phase (2.06 ± 8.94 ms, $p = 0.83$). Importantly, online RT changes remained close to zero during the expression phase (−4.18 ± 11.01 ms, $p = 0.81$), suggesting that distraction impairs online learning rather than suppressing its behavioral expression (e.g., by fatigue).

Distraction also significantly affected the mean offline change in RT ($F_{1,18} = 5.05$, $p < 0.05$; Fig. 3C). In particular, there were significant offline RT changes in the dual-task group (−36.60 ± 10.49 ms, $p < 0.01$) and not in the single-task group (−5.23 ± 10.32 ms, $p = 0.60$). Since both online and offline changes in RT were computed based on the first 12 trials in blocks, the measurement may arguably be contaminated by a well-known warm-up effect whereby performance is typically low when participants re-start the same task after a rest (Eysenck & Frith, 1977). This, however, is not an issue in our data. The same results were found when online and offline changes in RT were calculated without the first 3 trials in each block. Taken together, these results support our hypothesis that distraction disrupts online learning and facilitates offline process during early sequence learning.

3.4. Statistical dependence in RT

Model fitting on the RT time series revealed no effects of distraction group ($F_{1,18} = 0.3$, $p = 0.59$), block ($F_{7,125} = 0.95$, $p = 0.47$), and their interaction ($F_{7,125} = 0.39$, $p = 0.91$) on the 2nd-order statistical dependence within RT (Fig. 4A). Most importantly, the autoregression coefficient magnitudes were not significantly different from zero in all blocks for both groups (all $p > 0.95$), suggesting that RT did not demonstrate 2nd-order statistical dependence. Thus, no further analyses of the 2nd-order coefficients were conducted.

In contrast, 1st-order statistical dependence in RT was found in both groups (Fig. 4B). Specifically, A two-way mixed-effect ANOVA revealed no significant interaction between distraction group and block ($F_{7,125} = 1.25$, $p = 0.28$). However, the single-task group exhibited stronger 1st-order statistical dependence than the dual-task group ($F_{1,18} = 3.81$, $p = 0.07$; approached significance). It was also found that the 1st-order statistical dependence was relied on blocks ($F_{7,125} = 6.89$, $p < 0.001$). Specifically, the coefficient magnitude increased from block 1 to blocks 6 ($p < 0.01$) and 8 ($p < 0.001$), suggesting that the 1st-order statistical dependence shown in RT was a result of learning rather than preexisting cognitive dynamics. Learning of the statistical dependence was also revealed by decreased coefficient magnitudes from block 4 to 5 ($p < 0.05$) as well as from block 6 to 7 ($p < 0.05$). The estimations of means and standard errors from the main ANOVA were used to examine whether the coefficient in each block was significantly different from zero. In the single-task group, the 1st-order coefficient was close to zero in blocks 1 (0.1 ± 0.04 ms, $p = 0.38$) and became significantly larger than zero in blocks 4 (0.25 ± 0.06 ms, $p < 0.01$), 6 (0.23 ± 0.08 ms, $p < 0.001$), and 8 (0.30 ± 0.06 ms, $p < 0.001$). These significant coefficients returned to zero in blocks 5 (0.06 ± 0.03 ms, $p > 0.95$) and 7 (0.08 ± 0.04 ms, $p > 0.95$) where sequence B was presented. However, we did not find significant 1st-order statistical dependence in block 1 to 5 in the dual-task group (all magnitudes < 0.09; $p > 0.95$).

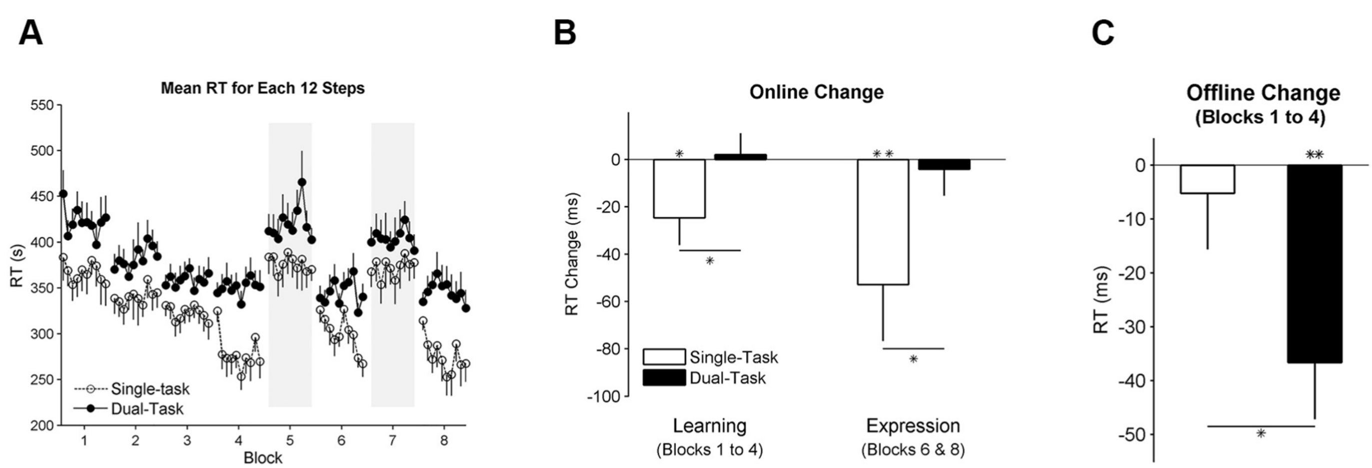

Fig. 3. (A) Visualization of distinct patterns in progressive RT changes (mean RT of every 12 steps). (B) Significant online RT changes in the single-task group and no online improvements in the dual-task group regardless of practice phase. Negative value indicates RT improvement. (C) Significant offline RT changes in the dual-task group and no offline improvements in the single-task group. Negative value indicates RT improvement. [Error bar - standard error of the mean; * - $p < 0.05$; ** - $p < 0.01$; *** - $p < 0.001$; * near the x-axis – significantly different from zero; * near the error bar – significant difference between experimental conditions].

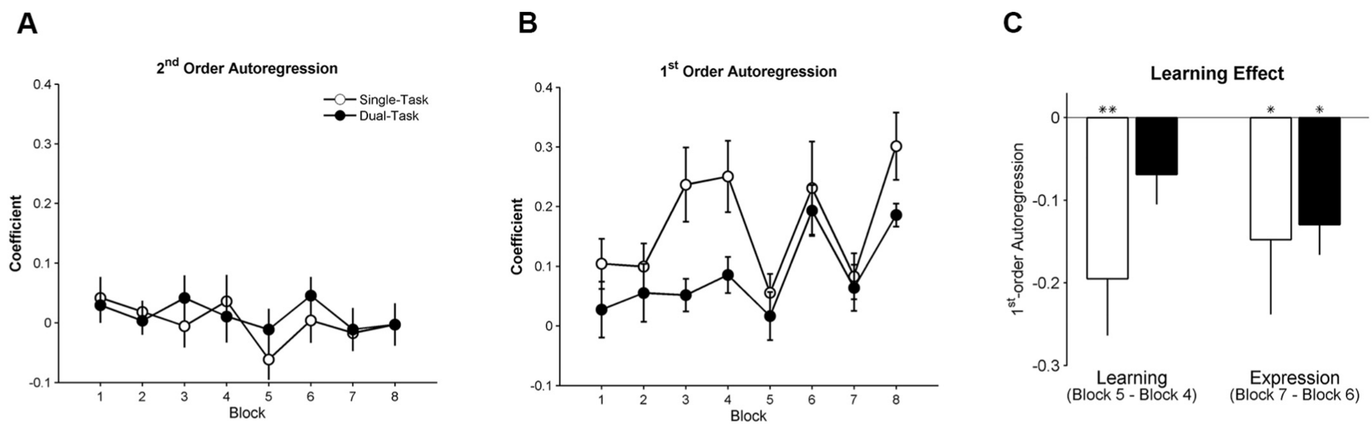

Fig. 4. (A) Coefficients of the 2nd-order autoregression across blocks in both groups. (B) Coefficients of the 1st -order autoregression across blocks in both groups. (C) Comparable sequence learning in terms of the 1st-order autoregression in RT between groups during the expression phase. [Error bar - standard error of the mean; * - $p < 0.05$; ** - $p < 0.01$; *** - $p < 0.001$; * near the x-axis – significantly different from zero; * near the error bar – significant difference between experimental conditions].

After the removal of distraction, significant 1st-order autoregression coefficients were observed in blocks 6 (0.19 ± 0.04 ms, $p < 0.001$) and 8 (0.19 ± 0.02 ms, $p < 0.001$) and not in block 7 (0.06 ± 0.04 ms, $p > 0.95$). When analyzing learning effects (differences between blocks 4 and 5 and between blocks 6 and 7; Fig. 4C) in terms of the 1st-order autoregression coefficient, we found no significant effects of distraction ($F_{1,18} = 1.23$, $p = 0.28$), practice phase ($F_{1,18} = 0.02$, $p = 0.88$), and their interaction ($F_{1,18} = 1.58$, $p = 0.22$). These results show that distraction does not interfere with learning stimulus associations although this learning effect might only be visible in the absence of distraction.

4. Discussion

Using the mean RT metrics, we have replicated previous studies which demonstrated that individuals can learn perceptual-motor sequences under distraction and we have verified multiple accounts proposed to explain the distraction effect on sequence learning. In addition, the trial-by-trial patterns behind the mean RT led to a novel finding that distraction may impair micro-online learning, a typical process involved in initial sequence acquisition. Instead of micro-online learning, sequence acquisition with distraction was accommodated with a micro-offline process. It is worth noting that these RT differences were not caused by different response accuracies between two groups (e.g., speed-accuracy tradeoff) as both groups maintained high accuracies throughout the whole task. Though further evidence is necessary to rule out alternative explanations, we reason that the offline RT change caused by the presence of distraction reflects micro-offline learning rather than a fatigue effect. Importantly, distraction may mediate micro-online and offline learning by modulating implicit and explicit memory involved in sequence learning.

There are two key contributions from this study. By examining the mean and temporal dependency of RT, we provided evidence either supporting or not the previously-hypothesized explanations of the distraction effect on early sequence learning. First, our results do not support the behavioral-suppression interpretation that claims intact sequence learning without complete behavioral expressions under distraction (e.g., Frensch et al., 1999; Frensch et al., 1998). The mean RT cost when switching to a novel sequence was comparable between two groups regardless of the presence of distraction (i.e., both learning and expression phases). The second common view of the distraction effect holds that it disrupts sequence structures. That is, distraction may add random noises into a sequence so the sequence becomes no longer well-structured (Schmidtke & Heuer, 1997), or vary inter-stimulus intervals (Frensch & Miner, 1994; Stadler, 1995), making it hard to learn stimulus associations. Despite their unique features, these interference accounts all predict inferior learning of stimulus contingencies under distraction. This prediction, however, was not supported by our direct measures on the learning of stimulus associations. We found comparable learning effects in terms of the 1st-order autoregression in RT between sequence learning that developed with or without a secondary task, suggesting intact structure learning under distraction. Third, distraction may impair the learning of certain types of sequences (e.g., ambiguous sequences) by diverting attentional resources (A. Cohen et al., 1990). Our results are incompatible with this interpretation as we demonstrated no impairments in learning an ambiguous sequence. In fact, compelling evidence suggests that learning even more complex sequences (i.e., a probabilistic sequence) could be more likely immune from distraction (Jimenez & Mendez, 1999; Schvaneveldt & Gomez, 1998).

Finally, like previous studies (A. Cohen et al., 1990; Grafton et al., 1995), we found that the development of explicit memory was prevented as revealed by chance-level verbal recalls in participants who learned the sequence under distraction, suggesting that distraction may block explicit learning. Given that the explicit knowledge was measured after the expression phase when all participants performed the SRT task alone, the chance-level recalls implies the failure to acquire explicit sequence knowledge even when distraction was absent if participants initially learned the sequence under distraction. Interestingly, despite the absence of explicit memory, we observed intact sequence learning, suggesting that implicit memory was not only preserved, but may also be strengthened to compensate the impaired explicit learning. This interplay between explicit and implicit systems is consistent with a range of empirical findings in sequence learning (Borragán, Slama, Destrebecqz, & Peigneux, 2016; Brown & Robertson, 2007a, 2007b; D. A. Cohen & Robertson, 2011; Galea, Albert, Ditye, & Miall, 2010; Nemeth, Janacsek, Polner, & Kovacs, 2013) as well as falls under the general framework of the competition between multiple memory systems: the frontal/medial temporal lobe-dependent declarative process and striatum-mediated procedural learning (Poldrack et al., 2001; Poldrack & Packard, 2003). It is worth noting that the aforementioned findings may be restricted to the distraction imposed by a tone-counting task, because different types of distraction that involve similar or distinct learning mechanisms (Nemeth et al., 2011) as well as those that require similar or distinct cognitive resources with sequence acquisition (Hemond, Brown, & Robertson, 2010) could give rise to remarkably different learning effects.

Beyond the findings that are primarily built on the mean RT, the novel contribution we made stems from the observations of distinct micro-online offline changes in RT caused by distraction. In the literature, paradoxical distraction effects have largely been reported based on the overall level (e.g., measured by mean RT) of sequence learning (see, Hsiao & Reber, 1998, for a review). Here, analyses on the progressive RT changes help us identify a possible culprit that resulted in these previously-reported inconsistent results on the distraction effect. In particular, our results show that early incidental sequence learning without distraction was driven by micro-online learning, which is consistent with previous empirical (Du et al., 2016, 2017), computational (Cleeremans & McClelland, 1991; Verstynen et al., 2012), and neuroimaging studies (Bornstein & Daw, 2012, 2013), as well as findings in other sequence learning paradigms (Bönstrup et al., 2019). The micro-online learning, however, was not behaviorally observed when distraction was present. Instead, sequence acquisition developed through short breaks interposed between learning blocks, which we referred to as a micro-offline process. The emergence of such an offline gain under distraction, regardless of whether it is caused by fatigue (Rickard et al., 2008; Torok, Janacsek, Nagy, Orban, & Nemeth, 2017) or micro-offline learning (Bönstrup et al., 2019; Du et al., 2016), suggests that the equivocal results for the distraction effect may be caused by varying break lengths used in previous studies. In fact, it is unclear in many studies what the availability and length of the rest intervals were (e.g., Cohen et al., 1990; Frensch et al., 1999; Shanks & Channon, 2002) while in other studies short rests were provided but the rest length was chosen by the individual participants (e.g., Curran & Keele, 1993; Shanks et al., 2005). Our observations highlight that in order to further elucidate the effects of distraction, it is necessary to systematically investigate how RT changes after the short rests between learning blocks.

Our data demonstrate that the micro-online and offline processes are two behavioral signatures when people learn sequences under distraction or not. The micro-online RT gain has been widely known to be driven by incremental online learning (Bornstein & Daw, 2012, 2013; Cleeremans & McClelland, 1991; Verstynen et al., 2012), while the underlying causes of the micro-offline process are unclear. Clearly, to unravel the micro-offline processes is a critical step toward better understanding sequence learning as this early learning stage is where the most substantial improvements in performance occur and what happens during long-term learning (i.e., slow learning, memory consolidation, and retention, etc.) likely relies on how the memory is initially encoded. Here, we discuss three possible interpretations.

First, we suggest that the online and offline RT changes are not related to general motor improvement. In the classic SRT task that involves finger tapping movement, RT typically encompasses general motor improvement (e.g., improving motor execution by strengthening the stimulus-response contigency; see Robertson, 2007, for a review), which is evidenced by improved RT from block 1 to block 5 (e.g., A. Cohen et al., 1990; Nissen & Bullemer, 1987). However, this is not the case in the foot-stepping SRT task wherby RTs in blocks 1 and 5 are comparable (Du et al., 2017; Fig. 2A; see also, Du & Clark, 2016). This is perhaps because unlike rapidly pressing multiple fingers in a sequential order that demands practice to better differentiate and coordinate individual finger movements, the foot-stepping task is more natural to our daily locomotor actions and thus little RT improvement results from learning how to execute the foot stepping action. Therefore, RT improved from block 1 to 4 largely represents sequence-specific learning, so does the online and offline gains measured across these first four blocks. In addition, recent direct evidence supporting the specific-sequence learning argument demonstrated no offline process when people practiced a random sequence where sequence-specific learning, but not general motor improvement, failed to develop (Du & Clark, 2017), confirming that the offline process is not associated with general motor learning. These observations suggest that the online and offline gains observed during the early acquisition stage are not attributed to general motor improvement, at least in the foot-stepping SRT task.

Second, we argue that our results cannot be fully explained by fatigue (Du & Clark, 2017), which is commonly thought as the culprit preventing the behavioral expression of online learning and consequently inducing the deceptive emergence of an offline RT gain (Rieth, Cai, McDevitt, & Mednick, 2010; Torok et al., 2017). That is, distraction does not really impair micro-online learning and biases toward micro-offline learning. Instead, a greater and faster accumulation of fatigue induced by distraction slows down RT when an individual is practicing the task. A short rest allows the reactive inhibition effect to dissipate, recovering RT and thus yielding a misleading offline enhancement effect (Brawn, Fenn, Nusbaum, & Margoliash, 2010; Pan & Rickard, 2015; Rickard et al., 2008; Rieth et al., 2010). With this being said, one would expect the reappearance of the online gain in RT after the distraction was removed, which failed to appear in our data, suggesting that the flat online learning curve and thus the subsequent offline process under distraction are likely not artifacts of fatigue. However, it appears arguable that the persistent flat online RT curve after the removal of distraction may be subjected to a use-dependent bias. That is, repetitions of an action with particular movement parameters, such as speed, direction, or RT bias future movements in favor of these same parameters (Diedrichsen, White, Newman, & Lally, 2010; Hammerbeck, Yousif, Greenwood, Rothwell, & Diedrichsen, 2013; Huang, Haith, Mazzoni, & Krakauer, 2011; Wong, Goldsmith, Forrence, Haith, & Krakauer, 2017). Although future studies are certainly needed to clarify this argument, one clue may render this use-dependent account unlikely. The habitual tendency to adopt an experience-dependent movement parameter requires extensive practice of over 500 trials on actions with that particular parameter (e.g., Wong et al., 2017), while in our study, participants kept changing the RT over practice from block 1 to block 4 and had an equal amount (e.g., one block) of experience on different RTs. It is thus not justified as to why they habitually chose one of these RTs after distraction was removed.

Finally, an alternative or complement to the fatigue account is that the offline RT changes mark learning-related mechanisms. Learning-based offline gain after a short rest has been commonly acknowledged in the simple sequence learning task (Bönstrup et al., 2019) and the rotary-pursuit task (Eysenck & Frith, 1977; Irion, 1949; Kimble & Horenstein, 1948). However, these tasks tap into distinct components of motor skill learning (Krakauer et al., 2019); for example, learning to better execute an already known sequence in the simple sequence learning task and improving feedback control in the rotary-pursuit task or in general tracking tasks. It is unclear whether the learning-based account is true in the SRT task that tackles the acquisition of a sequential order or temporal relationship of individual responses. On the one hand, distraction has been found to block explicit awareness (e.g., A. Cohen et al., 1990) and engage greater implicit memory (Foerde et al., 2006). Recent converging evidence demonstrates that micro-online learning is linked with explicit memory (Du et al., 2016; Malone & Bastian, 2010) and that micro-offline learning overrides online learning when sequences are learned in an implicit manner (Du et al., 2016; Du et al., 2017). Thus, bias toward implicit memory under distraction may attenuate micro-online learning and enhance micro-offline learning. In line with this memory engagement account, the offline gain could reflect a function that strengthens the implicit memory of a partial sequence acquired in the immediately preceding block and thus it may be related to memory consolidation (Censor et al., 2012; Robertson et al., 2004). On the other hand, distraction imposed by the tone-counting task may not only impose attentional demands, but also exerts working memory to retain the number of tones. Since working memory plays a critical role in trial-by-trial learning (Collins & Frank, 2012), engaging working memory by distraction may prevent the sequence being processed and computed incrementally online. Rather, the sequence information may be reassembled or learned in a batch mode during a rest, yielding an micro-offline gain in RT.

In sum, our results, together with previous evidence, incline us to the learning accounts rather than the fatigue-based explanation, although more empirical evidence is needed to warrant such a conclusion. However, no matter whether the observed offline gain in RT is driven by learning or an artifact of fatigue, one thing is for sure: future studies about the distraction effect on sequence learning need to control well the length of rest between learning blocks. Varied lengths of rest could lead to different degrees of offline learning or recovery of fatigue, consequently yielding inconsistent results for the distraction effect on sequence learning.

5. Conclusion

Distraction changes the way perceptual-motor sequences are initially learned. Early learning under no distraction arises from micro-online learning, while it reverts to micro-offline learning when a distraction is present. The interactive operation of an online or offline learning may parallel the competition between explicit and implicit memory that is modulated by distraction. The emergence of an offline process also demonstrates the important role of short rests interposed between learning blocks in early sequence learning under distraction. Thus, the unequivocal and unifying explanation of distraction effects on sequence learning cannot be reached unless the break interposed between learning blocks is controlled and systematically examined. In addition, we urge that, to better understand perceptual-motor sequence learning, future studies should examine the trial-by-trial RT changes, in addition to the analysis of the mean RT data.

Author contribution

Yue Du: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization. **Jane E. Clark**: Conceptualization, Supervision, Writing – Review & Editing.

Declaration of competing interest

The authors declare no competing financial interests.

References

Bönstrup, M., Iturrate, I., Thompson, R., Cruciani, G., Censor, N., & Cohen, L. G. (2019). A rapid form of offline consolidation in skill learning. *Current Biology, 29*, 1346–1351.e4.

Bornstein, A. M., & Daw, N. D. (2012). Dissociating hippocampal and striatal contributions to sequential prediction learning. *European Journal of Neuroscience, 35*, 1011–1023.

Bornstein, A. M., & Daw, N. D. (2013). Cortical and hippocampal correlates of deliberation during model-based decisions for rewards in humans. *PLoS Computational Biology, 9*, e1003387. https://doi.org/10.1371/journal.pcbi.1003387.

Borragán, G., Slama, H., Destrebecqz, A., & Peigneux, P. (2016). Cognitive fatigue facilitates procedural sequence learning. *Frontiers in Human Neuroscience, 10*. https://doi.org/10.3389/fnhum.2016.00086.

Brawn, T. P., Fenn, K. M., Nusbaum, H. C., & Margoliash, D. (2010). Consolidating the effects of waking and sleep on motor-sequence learning. *Journal of Neuroscience, 30*, 13977–13982.

Brown, R. M., & Robertson, E. M. (2007a). Inducing motor skill improvements with a declarative task. *Nature Neuroscience, 10*, 148–149.

Brown, R. M., & Robertson, E. M. (2007b). Off-line processing: Reciprocal interactions between declarative and procedural memories. *Journal of Neuroscience, 27*, 10468–10475.

Censor, N., Sagi, D., & Cohen, L. G. (2012). Common mechanisms of human perceptual and motor learning. *Nature Reviews Neuroscience, 13*, 658–664.

Cleeremans, A., & McClelland, J. L. (1991). Learning the structure of event sequences. *Journal of Experimental Psychology-General, 120*, 235–253.

Cohen, A., Ivry, R. I., & Keele, S. W. (1990). Attention and structure in sequence learning. *Journal of Experimental Psychology-Learning Memory and Cognition, 16*, 17–30.

Cohen, D. A., & Robertson, E. M. (2011). Preventing interference between different memory tasks. *Nature Neuroscience, 14*, 953–955.

Collins, A. G., & Frank, M. J. (2012). How much of reinforcement learning is working memory, not reinforcement learning? A behavioral, computational, and neurogenetic analysis. *European Journal of Neuroscience, 35*(7), 1024–1035.

Curran, T., & Keele, S. W. (1993). Attentional and nonattentional forms of sequence learning. *Journal of Experimental Psychology-Learning Memory and Cognition, 19*, 189–202.

Dayan, E., & Cohen, L. G. (2011). Neuroplasticity subserving motor skill learning. *Neuron, 72*, 443–454. https://doi.org/10.1016/j.neuron.2011.10.008.

Destrebecqz, A., & Cleeremans, A. (2001). Can sequence learning be implicit? New evidence with the process dissociation procedure. *Psychonomic Bulletin & Review, 8*, 343–350.

Diedrichsen, J., White, O., Newman, D., & Lally, N. (2010). Use-dependent and error-based learning of motor behaviors. *The Journal of Neuroscience, 30*(15), 5159–5166.

Du, Y., & Clark, J. E. (2016). New insights into statistical learning and chunk learning in implicit sequence acquisition. *Psychonomic Bulletin & Review,* 1–9. https://doi.org/10.3758/s13423-016-1193-4.

Du, Y., & Clark, J. E. (2017). Offline process during initial acquisition of motor sequences is not an artifact of fatigue. *North American Society for Psychology of Sport and Physical Activity Conference*.

Du, Y., & Clark, J. E. (2018). The “motor” in implicit motor sequence learning: A foot-stepping serial reaction time task. *Journal of Visualized Experiments: JoVE,* 135.

Du, Y., Prashad, S., Schoenbrun, I., & Clark, J. E. (2016). Probabilistic motor sequence yields greater offline and less online learning than fixed sequence. *Frontiers in Human Neuroscience,* 10. https://doi.org/10.3389/fnhum.2016.00087.

Du, Y., Valentini, N. C., Kim, M. J., Whitall, J., & Clark, J. E. (2017). Children and adults both learn motor sequences quickly, but do so differently. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.00158.

Eysenck, H. J. (1965). A three-factor theory of reminiscence. *British Journal of Psychology, 56*, 163–182.

Eysenck, H. J., & Frith, C. D. (1977). *Reminiscence, motivation, and personality.* Springer Science & Business Media.

Foerde, K., Knowlton, B. J., & Poldrack, R. A. (2006). Modulation of competing memory systems by distraction. *Proceedings of the National Academy of Sciences of the United States of America, 103*, 11778–11783.

Frensch, P. A., Lin, J., & Buchner, A. (1998). Learning versus behavioral expression of the learned: The effects of a secondary tone-counting task on implicit learning in the serial reaction task. *Psychological Research, 61*, 83–98.

Frensch, P. A., & Miner, C. S. (1994). Effects of presentation rate and individual differences in short-term memory capacity on an indirect measure of serial learning. *Memory & Cognition, 22*, 95–110.

Frensch, P. A., Wenke, D., & Runger, D. (1999). A secondary tone-counting task suppresses expression of knowledge in the serial reaction task. *Journal of Experimental Psychology-Learning Memory and Cognition, 25*, 260–274.

Galea, J. M., Albert, N. B., Ditye, T., & Miall, R. C. (2010). Disruption of the dorsolateral prefrontal cortex facilitates the consolidation of procedural skills. *Journal of Cognitive Neuroscience, 22*, 1158–1164. https://doi.org/10.1162/jocn.2009.21259.

Gilden, D. L. (1997). Fluctuations in the time required for elementary decisions. *Psychological Science, 8*, 296–301.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science, 267*, 1837–1839. https://doi.org/10.1126/science.7892611.

Grafton, S. T., Hazeltine, E., & Ivry, R. (1995). Functional mapping of sequence learning in normal humans. *Journal of Cognitive Neuroscience, 7*, 497–510.

Hammerbeck, U., Yousif, N., Greenwood, R., Rothwell, J. C., & Diedrichsen, J. (2013). Movement speed is biased by prior experience. Journal of Neurophysiology, 111(1), 128–134.

Hazeltine, E., Grafton, S. T., & Ivry, R. (1997). Attention and stimulus characteristics determine the locus of motor-sequence encoding—A PET study. *Brain, 120*, 123–140.

Hemond, C., Brown, R. M., & Robertson, E. M. (2010). A distraction can impair or enhance motor performance. *Journal of Neuroscience, 30*(2), 650–654.

Hotermans, C., Peigneux, P., Maertens, N. A., Moonen, G., & Maquet, P. (2006). Early boost and slow consolidation in motor skill learning. *Learning & Memory, 13*, 580–583.

Hsiao, A. T., & Reber, A. S. (1998). The role of attention in implicit sequence learning: Exploring the limits of the cognitive unconscious. In M. A. Stadler, & P. A. Frensch (Eds.). *Handbook of implicit learning* (pp. 471–494). Sage.

Huang, V. S., Haith, A., Mazzoni, P., & Krakauer, J. W. (2011). Rethinking motor learning and savings in adaptation paradigms: Model-free memory for successful actions combines with internal models. *Neuron, 70*(4), 787–801.

Irion, A. L. (1949). Reminiscence in pursuit-rotor learning as a function of length of rest and of amount of pre-rest practice. *Journal of Experimental Psychology, 39*(4), 492–499.

Jacoby, L. L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory and Language, 30*(5), 513–541.

Janacsek, K., Fiser, J., & Nemeth, D. (2012). The best time to acquire new skills: Age-related differences in implicit sequence learning across the human lifespan. *Developmental Science, 15*(4), 496–505.

Jimenez, L., & Mendez, C. (1999). Which attention is needed for implicit sequence learning? *Journal of Experimental Psychology-Learning Memory and Cognition, 25*, 236–259. https://doi.org/10.1037//0278-7393.25.1.236.

Keele, S. W., Ivry, R., Mayr, U., Hazeltine, E., & Heuer, H. (2003). The cognitive and neural architecture of sequence representation. *Psychological Review, 110*, 316–339. https://doi.org/10.1037/0033-295x.110.2.316.

Kimble, G. A., & Horenstein, B. R. (1948). Reminiscence in motor learning as a function of length of interpolated rest. *Journal of Experimental Psychology, 38*(3), 239–244.

Krakauer, J. W., Hadjiosif, A. M., Xu, J., Wong, A. L., & Haith, A. M. (2019). Motor learning. *Comprehensive Physiology, 9*, 613–663.

Malone, L. A., & Bastian, A. J. (2010). Thinking about walking: Effects of conscious correction versus distraction on locomotor adaptation. *Journal of Neurophysiology, 103*, 1954–1962. https://doi.org/10.1152/jn.00832.2009.

Moisello, C., Crupi, D., Tunik, E., Quartarone, A., Bove, M., Tononi, G., & Ghilardi, M. F. (2009). The serial reaction time task revisited: A study on motor sequence learning with an arm-reaching task. *Experimental Brain Research, 194*, 143–155.

Nemeth, D., Janacsek, K., Csifcsak, G., Szvoboda, G., Howard, J. H., & Howard, D. V. (2011). Interference between sentence processing and probabilistic implicit sequence learning. *PLoS One, 6*(3), https://doi.org/10.1371/journal.pone.0017577.

Nemeth, D., Janacsek, K., Kiraly, K., Londe, Z., Nemeth, K., Fazekas, K., ... Csanyi, A. (2013). Probabilistic sequence learning in mild cognitive impairment. *Frontiers in Human Neuroscience, 7* (//000321193900001).
Nemeth, D., Janacsek, K., Polner, B., & Kovacs, Z. A. (2013). Boosting human learning by hypnosis. *Cerebral Cortex, 23*, 801–805.
Nissen, M. J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cognitive Psychology, 19*, 1–32.
Pan, S. C., & Rickard, T. C. (2015). Sleep and motor learning: Is there room for consolidation? *Psychological Bulletin, 141*, 812–834. https://doi.org/10.1037/bul0000009.
Poldrack, R. A., Clark, J., Pare-Blagoev, E. J., Shohamy, D., Moyano, J. C., Myers, C., & Gluck, M. A. (2001). Interactive memory systems in the human brain. *Nature, 414*, 546–550. https://doi.org/10.1038/35107080.
Poldrack, R. A., & Packard, M. G. (2003). Competition among multiple memory systems: Converging evidence from animal and human brain studies. *Neuropsychologia, 41*, 245–251. https://doi.org/10.1016/S0028-3932(02)00157-4.
Rauch, S. L., Savage, C. R., Brown, H. D., Curran, T., Alpert, N. M., Kendrick, A., ... Kosslyn, S. M. (1995). A PET investigation of implicit and explicit sequence learning. *Human Brain Mapping, 3*, 271–286. https://doi.org/10.1002/hbm.460030403.
Rickard, T. C., Cai, D. J., Rieth, C. A., Jones, J., & Ard, M. C. (2008). Sleep does not enhance motor sequence learning. *Journal of Experimental Psychology-Learning Memory and Cognition, 34*, 834–842.
Rieth, C. A., Cai, D. J., McDevitt, E. A., & Mednick, S. C. (2010). The role of sleep and practice in implicit and explicit motor learning. *Behavioural Brain Research, 214*, 470–474. https://doi.org/10.1016/j.bbr.2010.05.052.
Robertson, E. M. (2007). The serial reaction time task: Implicit motor skill learning? *Journal of Neuroscience, 27*, 10073–10075.
Robertson, E. M., Pascual-Leone, A., & Miall, R. C. (2004). Current concepts in procedural consolidation. *Nature Reviews Neuroscience, 5*, 576–582.
Schmidtke, V., & Heuer, H. (1997). Task integration as a factor in secondary task effects on sequence learning. *Psychological Research, 60*, 53–71. https://doi.org/10.1007/Bf00419680.
Schvaneveldt, R. W., & Gomez, R. L. (1998). Attention and probabilistic sequence learning. *Psychological Research, 61*, 175–190.
Seidler, R., Purushotham, A., Kim, S. G., Uğurbil, K., Willingham, D., & Ashe, J. (2002). Cerebellum activation associated with performance change but not motor learning. *Science, 296*, 2043–2046.
Shanks, D. R., & Channon, S. (2002). Effects of a secondary task on “implicit” sequence learning: Learning or performance? *Psychological Research, 66*, 99–109.
Shanks, D. R., Rowland, L. A., & Ranger, M. S. (2005). Attentional load and implicit sequence learning. *Psychological Research, 69*, 369–382. https://doi.org/10.1007/s00426-004-0211-8.
Stadler, M. A. (1995). Role of attention in implicit learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*, 674–685.
Torok, B., Janacsek, K., Nagy, D. G., Orban, G., & Nemeth, D. (2017). Measuring and filtering reactive inhibition is essential for assessing serial decision making and learning. *Journal of Experimental Psychology-General, 146*, 529–542. https://doi.org/10.1037/xge0000288.
Verstynen, T., Phillips, J., Braun, E., Workman, B., Schunn, C., & Schneider, W. (2012). Dynamic sensorimotor planning during long-term sequence learning: The role of variability, response chunking and planning errors. *PLoS One, 7*, e47336. https://doi.org/10.1371/journal.pone.0047336.
Willingham, D. B., Nissen, M. J., & Bullemer, P. (1989). On the development of procedural knowledge. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15*, 1047–1060.
Wong, A. L., Goldsmith, J., Forrence, A. D., Haith, A. M., & Krakauer, J. W. (2017). Reaction times can reflect habits rather than computations. *Elife, 6*, e28075.