Individualized challenge point practice as a method to aid motor sequence learning

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Running head: Individualized practice informs motor learning

Key words: learner-adapted practice, challenge point, motor sequence learning, contextual interference

Wadden, K. P., Hodges, N. J., De Asis, K. L., Neva, J. L., & Boyd, L. A. (2019). Individualized challenge point practice as a method to aid motor sequence learning. *Journal of motor behavior*, *51*(5), 467-485.
https://www.tandfonline.com/doi/abs/10.1080/00222895.2018.1518310

https://doi.org/10.1080/00222895.2018.1518310

Abstract

We conducted two studies to investigate if and how: 1) the rate of skill acquisition was related to motor performance at retention of a serial RT task (Study 1); and 2) whether rate of skill acquisition and baseline performance could be used to design schedules of practice related tocontextual interference (CI) to enhance motor learning (Study 2). In Study 1, a slower rate of skill acquisition of repeating sequences in practice was related to faster response times at retention. Based on performance in Study 1, three levels of individualized CI were created for Study 2. Compared to low and moderate levels of CI, the higher CI practice condition led to faster response times in retention. We conclude that an individualized ‘challenge point’, which generates high CI enhances motor learning by optimizing challenge.

Introduction

Motor sequence learning occurs with repeated practice. Behaviour associated with repeated practice follows a nonlinear rate of improvement [1]. In speed/accuracy–based tasks, individual movement times decrease and accuracy increases with practice. An improvement in motor performance reflects changes in task demands as individuals' skill proficiency increases [2]. The order in which motor skills are practiced affects how they are acquired and, importantly, how well they are retained [2-4]. These practice order effects have been captured through the concept of contextual interference (CI), which relates to the amount of task switching/interference associated with the practice of different motor skills. CI offers one method by which motor task difficulty can be manipulated. However, it has been suggested that task difficulty should be tailored to each individual, based on an optimal "challenge point" [5]. Individuals have different cognitive and motor abilities that, in conjunction with the intrinsic demands of the task, uniquely influence motor skill acquisition [5]. Our aim in the current studies was to operationalize and test the concept of an individual challenge point as a tool to study, and to potentially facilitate, motor sequence learning.

To accomplish this aim, we first examined individual performance curves during an initial acquisition session (Study 1). This allowed us to assess how the rate of skill acquisition, and the duration that individuals spend in various phases of practice, related to measures of motor learning (i.e., retention). In a second study, we used practice parameters from Study 1 to devise individualized practice schedules with respect to the amount of practice within each phase (Study 2). We predicted that a slower rate of acquisition (i.e., more time in a cognitive phase of practice) would lead to better retention. Further, we expected that optimal challenge would be related to a moderate or high degree of task switching (keeping individuals in a cognitive phase of practice for longer).

The challenge point framework (CPF) is a conceptual framework that describes motor learning–related changes in behaviour [5]. The theoretical point at which an individual reaches a maximum potential for motor learning during practice is known as the "optimal challenge point". The challenge point reflects an interaction between the skill level of the individual and task difficulty. Hypothetically, the challenge point can be modified to the skill level of the individual by manipulating task constraints. For example, challenge point can be influenced by the amount of switching between tasks within a practice session (so termed CI). To date, the notion of individualized optimal challenge points has been largely understood at the conceptual level, but has not been specifically studied in human behaviour (cf., Choi, Gordon, Park, & Schweighofer, 2011; Choi et al., 2008). Theoretically, individualizing practice to an optimal challenge point ensures that task processing demands do not exceed, or fall below, cognitive and motor abilities [5].

One task constraint on learning that is related to optimal challenge is the degree of CI experienced during practice of two or more different skills. High CI occurs when multiple variations of a task are practiced under high levels of variability [8]. CI is most easily induced by altering the order in which motor tasks are practiced which increases the amount of switching between tasks [9]. Randomizing the practice order of motor tasks constitutes the highest form of CI. The frequent switching in high CI is thought to affect the cognitive operations involved in evaluating, planning and assembling movements [4, 9-12]. Although the information processing demands associated with frequent switching typically impairs initial performance and slows the rate of skill acquisition, increased processing demands enhance performance at a retention test.

This is in comparison to low CI conditions, where tasks are practiced in a repetitive, blocked order, which requires a small amount of task switching. Blocked practice often speeds the rate of skill acquisition and initial performance, but at a cost of poorer performance at a retention test. These blocked/random dissociations between practice and retention have been termed the CI effect. Random practice paradigms are considered to have “desirable difficulties”, as the high amount of switching increases information processing demands and facilitates retention of motor skills [13]. However, because individuals possess different cognitive and motor abilities, this type of randomized practice can create a level of challenge outside the optimal range for a particular individual [5]. There is evidence that age, level of expertise, and task complexity moderate the efficacy of random practice [14-17].

In learner-adapted practice, the demands of the task are tailored to the unique skills of an individual. By accounting for each individual’s current performance, it is possible to dynamically modulate task difficulty (e.g., task-switching) only after a predetermined performance criteria is met [7]. There are two methodological classifications of learner-adapted practice: learner-controlled and computer-controlled [7]. Learner-controlled practice allows individuals to choose their own practice schedule and tailor the difficulty to their own needs/perceived ability/challenge. When individuals choose how to order practice, rarely do they engage in as much task-switching as would be experienced with a random schedule, yet they show comparable retention benefits [18, 19]. These findings have been demonstrated in keyboard- (Hodges et al., 2014) and mouse-controlled (Keetch & Lee, 2007) sequencing tasks.

Computer-controlled learning uses an algorithm to adjust difficulty during practice. Choi et al. (2008) used a visuomotor adaptation task and showed that those who practiced with computer-controlled difficulty conditions outperformed those who practiced randomly at a delayed retention test [7]. Despite the success of this approach, the computer-controlled method has not received further study. Our current work was designed to test the efficacy of a computer-controlled, learner-adapted practice schedule on the acquisition of a motor sequence task. In contrast to Choi et al. (2008), who used a group mean reference value to adjust difficulty during practice, we employed individual-specific reference values determined from earlier practice of a related task.

In Study 1 we quantitatively distinguished individual phases of learning to provide an indication of the cognitive and motor demands of the task [20, 21]. The information processing demands associated with each phase of skill acquisition are contingent on task performance, which is known as the “performance-resource function” [20]. Thus, in Study 1, we extended previous work that classified individualized practice performance curves with respect to the phases of learning [21], to identify three phases of practice. This resulted in an exponential description of performance during one massed practice session. We then quantified motor performance (response time) and trials spent in each of the three phases to determine their relationship to performance at a delayed retention test, a key index of motor learning [22].

In Study 2, individual practice metrics from Study 1 were used to create three computer-controlled, learner-adapted conditions. The algorithm integrated the learner’s rate of motor skill acquisition and, based on the performance-resource function, the mean response time from each of the three phases of motor skill acquisition. This resulted in three individualized practice schedules of differing challenge (low, medium, and high difficulty). The three practice conditions acted to maintain individual performances near an individualized mean response time extracted from the three phases of practice in Study 1. We were able to use data from Study 1 to account for individual differences in task performance to test optimal challenge points. Thus, in

Study 2, individuals were forced to stay near an individualized reference value through manipulation of task difficulty. Therefore, in our two studies, we evaluated the relationship between rate of skill acquisition and time spent in each practice phase and retention performance (Study 1) and used this individualized information to inform a learner-adapted practice algorithm for the learning of motor sequences, based on individually determined indices of challenge (low, medium, and high difficulty; Study 2).

We tested two hypotheses. In Study 1, we hypothesized that a slower rate of motor skill acquisition and a significant amount of practice spent within the early cognitive phase of practice constituted “optimal” challenge and would result in improved scores on a retention test. This hypothesis was based on the idea that high amounts of switching keep individuals at a cognitively demanding stage of practice (Cross, Schmitt & Grafton, 2007) and enhance long-term retention (Lee & Magill, 1983; Shea & Zimny, 1988; Wright et al., 2016). Indeed, other work showed that individuals with the slowest rates of motor improvements at a semi-immersive virtual reality taskperformed best at a later delayed retention test (Lakhani et al., 2016). In Study 2, we hypothesized that the individualized practice condition, which required participants to perform near a reference value that would keep response times slow and hence on a moderate or high switching schedule, would enhance motor learning. This hypothesis is constructed from CI literature that shows a beneficial learning outcome following more (rather than less) erroneous performance during practice (Magill & Hall, 1990).

Study 1 — Methods

Participants

Fourteen healthy young adults, self-reported as right-handed, participated (mean [M] age = 24.35; standard deviation [SD] = 4.40 years; maximum [max.] = 34 years; 6 = female [F]). Participants were recruited from the University of British Columbia (UBC) campus. All participants provided written informed consent to the experimental procedures that was approved by the UBC Office of Research Ethics under the Clinical Research Ethics' Board.

Discrete pairing task (DPT)

We developed a motor task that required participants to execute multiple motor sequences, with each being of equal difficulty. We designed the discrete pairing task (DPT) to draw upon information processing demands within stages of the motor sequence learning framework [23]. In the DPT, sequences were comprised of three alternating shapes (triangle, circle, and square) displayed at four spatial locations within the centre of the screen (see Figure 1). The type of shape at the four locations differed between sets of stimuli within a sequence. The keyboard letters — V, B, N, M — corresponded to each of the four spatial locations in an ordinal manner from left to right. Within each set of stimuli, one of the shapes appears twice. The participant's task was to make two key presses to move the repeating shapes together, beginning with the most leftward press.

The first key press highlighted the location of the leftward repeating shape (Response 1; Figure 1a2). The second key press moved the first highlighted shape to the location next to the second repeating shape (Response 2; Figure 1a3). Once the pairing was correctly completed, four new stimuli immediately appeared on the screen and the participant was again required to identify the pair and move the shape to a new location.

Each repeating sequence consisted of five sets of stimuli (Figure 1b). Since two key presses were executed during performance of one set of stimuli, 10 key presses were executed during the performance of one full sequence. Participants were instructed to complete each sequence as quickly and accurately as possible. They were also informed that there were three sequences to learn.

Insert Figure 1

The addition of a paired association rule in the DPT, which required individuals to position two repeating shapes side-by-side, added a layer of cognitive complexity beyond that typically present in simple, motor sequence learning, tasks (i.e., the serial reaction time task [SRT]). The rule-based associations place additional demands on cognition (associated with movement decisions and motor planning), allowing us to better manipulate processing demands associated with the task. The DPT requires explicit strategizing early in practice, but with mastery, demands on attention decrease and motor proficiency develops, enabling fast and accurate execution. This expected progression provided our rationale for delineating the three phases of motor sequence learning. Due to the relatively simplistic nature of the task and the constraints on the types of shapes and location, we were able to create comparable sequences of equal difficulty.

Difficulty was controlled by the location of the matched shapes and hence the key response. Sequences containing the same set of locations had a similar difficulty level. Since each set of stimuli was comprised of four shapes, where one shape occurred twice, but never side-by-side to start, there were three possible ways to place the matched shape.

Assuming a “1” represents the matched shape and a “0” is any other shape, the possible shape placements were defined as:

Placement 1 — 1010   *Placement 2 — 0101*   *Placement 3 — 1001*

In the DPT, every sequence had two occurrences of shape placement 1, two occurrences of shape placement 2, and one occurrence of shape placement 3, in differing orders (e.g., 11223, 12312, etc.). Via manipulation of the order of placement, it was possible to create the three sets of sequences (i.e., sequence A, B, and C). Therefore, a sequence — for example, sequence A — might have the following order of locations: 11223. This would require the learner to press the following keys: V, B, V, B, B, N, B, N, V, N.

The DPT was developed and executed in a custom Microsoft Visual Studio 4.0 XNA game studio program (© 2014 Microsoft Corporation, Redmond, WA, USA).

Study protocol

In the task-familiarization session, participants completed 30 minutes of DPT practice, but there were no repeating sequences. This session was designed to familiarize individuals with the task goal and procedures, such that any later learning effects would be a result of the practice conditions and repeating sequences and not of general task understanding or changes in motor control. One week later, participants completed the experimental phase, practicing three different motor sequences (consisting of 10 key-presses each) in a serial, repeating order (e.g., A, B, C, A, B, C, etc.), during a single practice session. During this session, participants performed 30 blocks of the DPT task and each block contained six trials of each 10-movement motor sequence (e.g., sequence A, B, C, A, B, C, etc.). Each sequence (A, B, C) was performed 180 times across the entire practice session (i.e., 540 practice trials which lasted approximately 60 minutes). Participants returned to the laboratory 24 hours after the practice session to complete a delayed retention test that involved them performing one block of the DPT task that contained 10 trials per sequence (A, B, C), again completed in a serial order. Retention tests were completed in approximately 15 minutes.

**Insert Figure 2*

Practice performance curve

The DPT is based on discrete sequencing skill acquisition (Abrahamse et al., 2013), which permits individuals to use explicit trial-and-error discovery. Participants are unable to advance to the next trial until the targets are positioned correctly. Thus, the primary dependent measure was response time total (RTT) (response 1 + response 2) for each set of stimuli. For each sequence, the mean RTT (mRTT) across the five sets of stimuli was calculated. The total mean RTT (tmRTT) is the average mRTT for all three sequences calculated for each respective trial.

To determine the individual rate of motor skill acquisition, an exponential function (performance curve) was fitted to the tmRTT across the practice session using the following equation (equation 1) [1]:

$$1.\quad \boldsymbol{E(tmRTT_N) = A + Be^{-\alpha * N}}$$

$E(tmRTT_N)$ is the expected value of RTT on practice trial N; A is the expected values of RTT after the practice has been completed (asymptote parameter); B is the change in the expected value of RTT from the beginning of the practice to the end of practice (change score parameter); Alpha (α) is the exponential learning rate parameter.

Instead of relying on arbitrary divisions as has occurred in the past [24], we employed slope calculations to delineate three separate phases of practice from each individual’s exponential function. First, we calculated the mean slope (equation 2) of individuals' exponential function (see above, equation 1):

$$2.\quad \frac{rise}{run} = \frac{f(x_n) - f(x_0)}{x_n - x_0}$$

Next, the running average for the slope of the exponential function was determined along the intervals [0, x_1] and [x_2, n]. The first interval, running left to right, delineated the first phase of practice ([0, x_1]; Phase I). The second interval, running right to left, delineated the third phase of practice ([x_2, n]; Phase III). The running average for the slope of the exponential function across these two intervals, [0, x_1] (equation 3) and [x_2, n] (equation 4), are detailed, respectively, below:

$$3.\quad \frac{f(x) - f(0)}{x - 0} = \frac{A + Be^{-\alpha x} - A - B}{x} = \frac{B(e^{-\alpha x} - 1)}{x}$$

$$4.\quad \frac{f(n) - f(x)}{n - x} = \frac{A + Be^{-\alpha n} - A - Be^{-\alpha x}}{n - x} = \frac{B(e^{-\alpha n} - e^{-\alpha x})}{n - x}$$

The points x_1 and x_2 were determined based on the SD of the running average for each interval from the mean slope of the exponential function. Specifically, beginning left to right for the interval [0, x_1], the first point x_1 was determined where the average value of the running slope is no longer greater than three SDs of the mean slope [25, 26]. The second point, x_2, was determined in the same manner but beginning from right to left for the interval [x_2, n]. This bidirectional approach was adopted to enable identification of the extremes (i.e., Phase I and III), based on procedures adopted in similar work [25, 26]. After determining the two division points x_1

and x_2, three phases of practice were identified: Phase I [0, x_1], Phase II [x_1, x_2], and Phase III [x_2, n]. Phase II was represented by trials between Phase I and III (see Figure 3).

**insert Figure 3*

To determine the amount of motor sequence learning at retention, both absolute and relative retention performance indices were used. Absolute retention is not affected by temporary performance factors in practice, such as fatigue or effort; it has been defined as the simplest and most scientifically justifiable measure of learning (Schmidt & Lee, 2011). Relative retention offers some insight into memory and forgetting. Relative retention was the degree of gain or loss in the retention interval as a function of the amount of improvement in practice. Relative retention was calculated by subtracting mean absolute retention from the last block of practice, which was then divided by the performance on the last block of practice minus the performance on the first block of practice (i.e., tmRTT of Block 30 – Retention / tmRTT of Block 30 – tmRTT Block 1) [27]. For both indices (i.e., absolute retention, relative retention), a lower value represents greater retention.

Statistical analysis

Primary analyses: A repeated measures analysis of variance (ANOVA) was performed on tmRTT across the three phases (I, II, III) to determine if the proposed theoretical phases produced significantly different performance and learning outcomes. These phase values were later used in Study 2 as individual-specific reference values for the computer-controlled, learner-adapted algorithm to create the three practice difficulty levels.

The relationship between the motor skill rate of acquisition (α) and the absolute and relative retention tmRTT values were tested using Pearson's correlation analyses (*r*). Pearson's correlation analyses were also performed on the proportion of trials spent in the various practice phases (I, II, III) as a function of the overall amount of practice trials and both absolute and relative retention.

Secondary analyses: Subsequently, to ensure rate of skill acquisition was the primary predictor of absolute retention, a hierarchical multiple regression was performed to predict the absolute retention based on the tmRTT for block 1 and 30, and the rate of skill acquisition (α). tmRTT for block 1 and 30 were first entered in step 1, followed by rate of skill acquisition in step 2. The final model for the hierarchical regression analysis was evaluated for overall significance, and the significance level of the change in R^2 when adding rate of skill acquisition to the model ($p \leq 0.05$).

To further assess the association between practice parameters and performance at retention, and relationships within practice parameters, the relationship between the absolute tmRTT values and tmRTT in the practice phases (I, II, III) were tested using Pearson's correlation analyses (r). Additionally, the relationship between the ratio of trials in the practice phase (I, II, III) and the rate of skill acquisition (α) were tested using Pearson's correlation analyses.

All data were visually inspected for skewness and kurtosis and objectively tested for normality with the Shapiro-Wilk test with a significance level set at $p < 0.001$ [28]. *Post hoc* pairwise comparisons were performed following significant effects. To control for familywise errors associated with multiple statistical tests (i.e., to guard against Type-I errors), Bonferroni corrections were applied ($p_{\text{corrected}}$). Pending the significance of the Mauchly's test of sphericity, a Greenhouse-Geisser correction was used to adjust degrees of freedom. Effect sizes were reported as partial eta-squared (η_ρ^2), where 0.01 is considered a relatively small effect, 0.06 moderate and more than 0.14, a large effect [29]. The 95% confidence intervals (CIs) of the mean difference

(MD) were used to describe the effect of phase on the motor performance. Data are presented in the text as mean (M) plus or minus standard deviation (SD) or standard error (SE). For all statistical tests, significance was set at probability value (p) ≤ 0.05. SPSS 22.0 (SPSS Inc., Chicago, IL, USA) statistical software was used for analyses.

Results

Primary analyses: One subject was excluded from subsequent analyses for reporting they did not hear the pre-practice instruction that explicitly informed individuals of the presence of three repeating sequences. We first determined goodness-of-fit of the data based on the exponential learning rate parameter (α). The average R squared (R^2) for all participants (n = 13) was 0.54 (SD = 0.15; min. = 0.22, max. = 0.70). We considered these values to provide a moderate to good representation of the data [30, 31]. Exemplary data from three participants who showed either a fast, slow, or relatively variable rate of acquisition is shown in Figure 4. Single-subject practice and retention data, and normalized performance curves for Study 1 are displayed in Figures 6 and 7, respectively. Curves were divided by a normalization factor of A + B; A = asymptote value; B = change score.

**insert Figure 4*

To confirm that the practice phases were distinguishable with respect to tmRTT, a repeated measures ANOVA yielded a main effect of phase, $F_{(1.33, 16.01)} = 49.35$, $p < 0.001$, $\eta_\rho^2 = 0.80$, large effect size. *Post hoc* comparisons confirmed that Phase I response times (M = 0.65 seconds [s], SD = 0.09) were on average slower than Phase II (M = 0.47 s, SD = 0.12) (MD = 0.18, 95% CI [0.09, 0.26]) and Phase III (M = 0.39 s, SD = 0.13) (MD = 0.26, 95% CI [0.18, 0.35]). Phase II was also significantly slower than Phase III (MD = 0.083, 95% CI [0.042, 0.12]) (all ps ≤ 0.001). For comparison, tmRTT in retention was 0.41 s (SD = 0.13).

Following Bonferroni correction for multiple comparisons ($p_{\text{corrected}} = 0.025$), the relationship between rate of acquisition (α) and absolute but not relative retention was significant (see Table 1a). As shown by the significant positive relationship, individuals whose performance was worse in retention (i.e., longer response time) more quickly achieved their asymptote value (α) (see also Figure 5). Similar trends were seen for relative retention, but these correlations were not significant (see Table 1b).

**insert Table 1a and b*

**insert Figure 5*

We also examined whether the proportion of trials spent in the various practice phases correlated with absolute and relative retention (Table 1b). The average number of trials for each phase were: Phase I (M = 48.23, SD = 13.45), Phase II (M = 25.69, SD = 2.59), and Phase III (M = 105.15, SD = 11.62). All practice phase durations showed significant correlations with absolute retention ($p_{\text{corrected}} = 0.017$). Importantly, the number of trials spent in Phase I was negatively related to absolute retention (i.e., relatively more time in Phase I was related to faster and lower tmRTT), whereas the reverse was true for Phases II and III. For relative retention, the data mirrored that seen for absolute retention, although the correlations were not significant following Bonferroni corrections.

Secondary analyses: The overall regression model, with tmRTT for block 1 and 30 entered in step one, rate of skill acquisition in step two, achieved significance ($F_{(3,9)} = 6.13$, $p = 0.015$), with an R^2 of 0.67. When only tmRTT_{b1} and $\text{tmRTT}_{\text{b30}}$ were included, the model was not significant ($F_{(2,10)} = 0.09$, $p = 0.92$), with an R^2 of 0.02. The addition of α in the second block significantly improved the model: $\Delta R^2 = 0.65$, $\Delta F_{(1, 9)} = 17.92$, $\Delta p = 0.002$. Thus, start-point and floor effects did not influence the absolute retention performance.

Absolute retention also did not significantly correlate with tmRTT in each phase of practice ($p > 0.05$), although all correlations were small and positive ($r = 0.29$, $r = 0.24$, and $r = 0.32$ for Phases 1 to III, respectively). Ratio of trials in each practice phase was highly correlated with rate of skill acquisition (all rs > ± 0.97). Greater time spent in Phase I was associated with a slower rate of acquisition, while more time spent in Phases II and III was associated with a faster rate of acquisition.

**insert Figure 6*

**insert Figure 7*

Discussion

The goal of Study 1 was to develop a methodological approach to assess individual differences in motor learning. To accomplish this, we developed the DPT and quantified practice metrics with an exponential curve fitting method. Exponential curve fitting characterized individuals' performance during skill acquisition of multi-task practice in a massed single session. This allowed for the calculation for the rate of motor skill acquisition (α) and the proportion of trials in each phase of practice, based on systematic changes in the slope of the performance curve. In accordance with previous data-driven methods that dissociate potential phases of learning [21], we showed that skill acquisition could be meaningfully differentiated into three phases. Moreover, in support of findings in the CI literature (e.g., Schmidt & Bjork, 1992), a slower rate of motor skill acquisition during practice was associated with better delayed retention (i.e., faster response times).

The amount of interpretable information is a factor in determining an optimal challenge point [5]. However, this concept is difficult to operationalize and potentially difficult to measure during practice. We hypothesize that a slower rate of motor skill acquisition, as well as more practice time spent within the early cognitive phase of practice, would be associated increased performance at retention. In Study 1, individuals practiced three sequences in a serial, repeating order. Although the practice schedule task difficulty was consistent, the skill level of the individual increased with each practice trial. Individuals transitioned through the phases at learner-dependent rates (α), signifying their overall motor skill acquisition capability. In Study 2, we used the performance metrics from Study 1 to manipulate task difficulty in the same individuals using a computer-controlled, learner-adapted practice schedule. This allowed us to gain insights about how best to operationalize and optimize individual challenge in practice to facilitate learning.

Study 2 — Methods

CI effects can be influenced by task difficulty, which can be divided into two categories: (1) nominal difficulty; and (2) functional difficulty. Nominal task difficulty relates to the conditions under which the tasks are performed. Functional task difficulty is dependent upon the skill level of the learner [5]. When the nominal difficulty of tasks is low, blocking the order of the practice trials so that all trials for one task are performed before the next, leads to superior short-term performance compared to random ordering of tasks. However, delayed retention testing reveals the reverse effect: random (high CI) practice produces superior retention. Under conditions where the nominal difficulty of the task is relatively high, the benefits of random practice on long-term retention can be negated [32]. Further, experienced performers benefit more from high CI practice than do novices [33]. In Study 2, we created three practice difficulties (low, medium, and high difficulty), based on each individual's practice performance curve from Study 1, to assess the effectiveness of learner-adapted practice schedules in a task that had constant nominal difficulty and relatively easy task difficulty.

A learner-adapted algorithm was used to systematically manipulate task difficulty/cognitive demands during motor sequence learning of multiple sequences. Individual performance curves from Study 1 informed the computer-controlled, learner-adapted practice schedule. Rather than using a generalized challenge point (i.e., mean reference value) across all individuals [7], we used participant-specific, individual challenge points. This was based on motor skill acquisition under the serial practice condition from Study 1, allowing us to determine (and manipulate) motor practice difficulty.

Based on results from Study 1, a slower rate of motor skill acquisition (α), with more time spent in Phase I of practice, was expected to relate to superior performance at retention. Therefore, we hypothesized that a high difficulty practice algorithm, which requires individuals to practice near their Phase I (tmRTT reference value), would result in the best performance at a delayed retention test. Thus, in Phase I, faster response times should promote constant switching between trials because performance quickly surpasses the reference value. This contrasts with a low difficulty practice condition, which would encourage individuals to practice near their Phase III reference value (i.e., low switching between trials). A medium practice difficulty (related to Phase II of practice) and a moderate amount of switching between trials were expected to result in an intermediate level of retention. We implemented a "within-subjects" design that allowed us to compare the efficacy of these three types of practice based on individual performance curves. We did not explicitly compare the effectiveness of adaptive practice schedules with non-adaptive schedules. Rather, our aim was to test the potential usefulness and optimality of practice schedules (comparing low, medium and high challenge) based on individualized reference values extrapolated from a different, yet related practice task.

Participants

Study 2 had the same participants as Study 1 (n = 13).

Practice conditions

Study 2 involved three weeks of learner-adapted practice and delayed retention sessions (see Figure 2). After a one-week washout period from Study 1, participants were randomly assigned to take part in the three learner-adapted practice conditions in counterbalanced order. Individual-specific reference values from Study 1 (tmRTT) were generated from Phases I, II, and III to create practice conditions of high, medium, and low difficulty, respectively. Each learner-adapted condition was separated by a one-week wash-out period. Each week was comprised of one massed practice session and a 24-hour delayed retention test.

Nine sequences were created and randomized across the three practice difficulty conditions. During each practice session, participants practiced three sequences resulting in 30 blocks of the DPT. Each block contained 18 trials of a 10-movement motor sequence. Each sequence was performed 180 times across the entire practice session. Participants returned to the laboratory 24 hours following the practice session to complete a delayed retention test.

To systematically manipulate task difficulty, the mean tmRTT within each of the three phases of testing from Study 1 provided the individual-specific reference values for each of three levels of learner-adapted task difficulty; low (Phase III), medium (Phase II), and high (Phase I). The individualized reference values for Phase I ranged from 0.51 to 0.80 s, for Phase II, from 0.24 to 0.68 s, and for Phase III, from 0.24 s to 0.65 s. These were used to dictate when an individual switched to practice a new sequence. In addition to these values, switching was also based on the rate of motor skill acquisition rate (α) extracted from the exponential function of each individual's practice performance curve. Therefore, these values (i.e., tmRTT_ref and α) were inputted in the equation (equation 5) below:

$$5. \quad \boldsymbol{S(t) = S(t-1) * (1 + \alpha(mRTT(t) - tmRTT\_ref\ ))}$$

The switching function (S(t)), which determined if the participant performed a new sequence or continued with the present sequence, equaled the switching function of the previous trial, S(t-1), multiplied by a number based on the tmRTT of the current trial in comparison with the corresponding reference RTT value (RTT_ref). Before the start of a block, and when switching to a new sequence occurred, the value of S(0), the switching function at trial 0, was set to 1. Sequence switching occurred when the switching function's value went below a specified threshold (based on pilot testing a threshold of 0.90 was set). If the participant had a faster RTT relative to the reference value, the switching function decreased and vice versa.

The individualized motor skill acquisition rate (α, calculated from Study 1) affected how much the switching function changed for a given difference in RTT to the reference tmRTT value. Although this value differed between individuals, it was constant between the three learner-adapted conditions. Thus, if the rate of acquisition was fast in Study 1, the switching function would increase. Conversely, if the rate of acquisition was slow in this previous study, the switching function would decrease (i.e., there was less switching). The average motor skill acquisition rate calculated from Study 1 for all participants was $\alpha = 0.02$ (SD = 0.01; min. = 0.010; max. = 0.034).

The order of each of the three sequences in the block was random. The maximum number of switches between sequences in each block was 17 and the minimum was two. Hence, a hypothetical, fully random condition would result in 510 switches in total.

Due to the known impact of prior explicit knowledge on motor sequence learning, explicit recognition testing was performed at the end of retention [34, 35]. Participants were asked if they recognized a sequence after watching it played on a screen. For each sequence, the five sets of stimuli flashed on the screen for 1.5 s, in the sequential order performed during practice. After the completion of each sequence, participants were asked to indicate recognition by pressing "1" for "Yes" or "2" for "No." Eighteen sequences were randomly "played" during the recognition test. Each of the three sequences performed during practice appeared twice, the remaining were novel. Percentage correct was calculated. If participants' success rate was greater than chance, they were considered to have explicitly recognized the presented sequences (i.e., implicit learning did not occur).

Performance measures

The tmRTTs for each of three practice phases (I, II, III) for each condition were calculated (see Study 1). Both absolute and relative retention measures were used (see Study 1).

Statistical analysis

To provide validation for the learner-adapted algorithm, a repeated measures ANOVA was performed on the number of switches for CONDITION (low, medium, high difficulty). To ensure there was no difference in initial performance across conditions, a repeated measures ANOVA was performed on tmRTT for each sequence during the first block of practice. To evaluate the effect of CONDITION on response time across practice, a two-way repeated-measures ANOVA was performed with CONDITION (low, medium, high difficulty) and PRACTICE PHASE (I, II, III) as variables.

For retention and recognition tests, a one-way, repeated measures ANOVA was performed to test for CONDITION effects (low, medium, high difficulty).

Post hoc pairwise comparisons were performed following significant effects. As in Study 1, Bonferroni corrections were applied to correct for multiple comparisons ($p_{\text{corrected}}$). All data were visually inspected for skewness and kurtosis and objectively tested for normality with the Shapiro-Wilk test with a significance level set at $p < 0.001$ [28]. The number of switches for low and medium conditions were non-normal ($W_{(13)} \leq 0.57$, $p < 0.001$). Following $\log_{10}$ transformation, all switch data were found to be normal ($p > 0.001$). For statistical analyses, $\log_{10}$ transformations were applied to the number of switches for all conditions. Pending the significance of the Mauchly's test of sphericity, Greenhouse-Geisser corrections were implemented to adjust degrees of freedom. Effect sizes were reported as partial eta-squared (η_ρ^2) where 0.01 is considered a relatively small effect, 0.06 moderate and more than 0.14, a large effect [29]. The 95% CIs of the MD were used to describe the effect of learner-adapted practice on the motor performance. Data are presented in the text as M ± SD or SE. For all statistical tests, significance was set at $p \leq 0.05$. SPSS 22.0 (SPSS Inc., Chicago, IL, USA) statistical software was used for statistical analyses.

Results

Practice

The total number of switches between sequences differed statistically across conditions, despite the large between subject variability, $F_{(2, 24)} = 32.15$, $p < 0.001$, $\eta_\rho^2 = 0.728$, large effect size. *Post hoc* tests revealed that the high condition (M = 225.2 switches, SD =108.83, min. =113, max. = 439) had significantly more switches than the medium (M = 141.6 switches, SD = 85.9, min. = 96, max. = 417, $p_{\text{corrected}} = 0.005$) and low (M = 94.8 switches, SD = 76.41, min. = 60, max. = 338, $p_{\text{corrected}} < 0.001$) conditions. There was also a significant difference between the low and medium conditions ($p_{\text{corrected}} < 0.001$) (see Table 2 for individual number of switches).

**insert Table 2*

In accordance with predictions, mean response times co-varied with condition such that the low difficulty condition had the shortest duration (M = 0.38 s; SE = 0.02), followed by medium (M = 0.39 s, SE = 0.02) and high (M = 0.43 s, SE = 0.02). Despite differences between conditions, the main effect of condition was not significant: $F_{(2,24)} = 2.55$, $p = 0.10$, $\eta_\rho^2 = 0.18$, large effect size. There was a practice phase effect, $F_{(1.1,13.16)} = 6.63$, $p = 0.02$, $\eta_\rho^2 = 0.36$, large effect size, but not a significant CONDITION × PRACTICE PHASE interaction, $F_{(1.2,14.0)} = 3.04$, $p = 0.10$, $\eta_\rho^2 = 0.20$, large effect size. Phase I practice (M = 0.46 s, SE = 0.03) had a significantly longer mean response times than Phase II (M = 0.37 s, SE = 0.02) (MD = 0.095, $p_{\text{corrected}} = 0.000003$, 95% CI [0.065, 0.12]), but not Phase III (M = 0.38 s, SE = 0.02) (MD = 0.083, $p_{\text{corrected}} = 0.131$, 95% CI [-0.019, 0.19]). Phase II and Phase III did not significantly differ (MD = -0.12, $p_{\text{corrected}} = 1.00$, 95% CI [-0.098, 0.074]) (see Figure 14a).

Individuals started each condition at a similar level of performance between practice weeks, confirmed by no effect of condition during Block 1, $F < 1$, $p > 0.05$. Single-subject practice and retention data for low, medium, and high difficulty conditions are displayed in Figures 8, 10, and 12, respectively. Normalized performance curves for low, medium, and high difficulty conditions are displayed in Figures 9, 11, and 13, respectively.

**insert Figure 8*

**insert Figure 9*

**insert Figure 10*

**insert Figure 11*

**insert Figure 12*

**insert Figure 13*

Retention

Practice condition significantly affected absolute retention: $F_{(1.29, 15.47)} = 13.16$, $p = 0.001$, $\eta_{\rho}^2 = 0.52$, large effect size. As shown in Figure 14b, the high difficulty condition (M = 0.32, SD = 0.811) resulted in significantly faster response times than the low (M = 0.47, SD = 0.128) (MD = .15 s, $p_{\text{corrected}} = 0.005$, 95% CI [0.046, 0.249]) and medium conditions (M = 0.40, SD = 0.090) (MD = 0.081 s, $p_{\text{corrected}} = 0.001$, 95% CI [0.035, 0.127]). Low and medium did not differ from each other ($p > 0.05$). There was also a CONDITION main effect for relative retention: $F_{(2, 24)} = 3.93$, $p = 0.033$, $\eta_{\rho}^2 = 0.25$, large effect. A significant difference was only observed between the high (M = –0.05, SD = 0.264) and low (M = 0.50, SD = 0.708) (MD = 0.54, $p_{\text{corrected}} = 0.02$, 95% CI [0.085, 1.00]) conditions. There was no significant difference between the high and medium (M = 0.32, SD = 0.564) conditions (MD = -0.32, $p_{\text{corrected}} = 0.13$, 95% CI [–0.086, 0.818]).

**insert Figure 14a and b*

Accuracy was generally high on the explicit recognition test (> 90%), but there was no significant difference between conditions ($F < 1$, $p > 0.05$); high (M = 92.3%, SD = 8.93, min. = 72.2%), medium (M = 93.1%, SD = 8.22, min. = 77.8%) and low (M = 96.2%, SD = 5.24, min. = 88.9%).

General discussion

We used a within-subjects experimental design to investigate individualized-adapted practice schedules and to test whether a high or moderate degree of task challenge is most beneficial for motor learning. The learner-adapted algorithm produced significant differences in the number of total switches between the low and medium, low and high, and medium and high conditions, showing that our algorithm was effective in altering the amount of CI. Differences were noted both on a between-subject level as well as within participants, given that switching was dependent on an assumed performance-resource function based on an earlier practice episode (Study 1). For some individuals, what would be seen as a moderate amount of switching would be classed as "high" switching for others and similarly "low" switching would be classed as medium for others (see Table 2). Indeed, the minimum number of switches for the high condition (113) was less than the average for the medium difficulty condition (142). Despite the individualized nature of the CI conditions, there were significant differences across the three conditions of practice at retention. In accordance with previous CI studies where more random (high CI) conditions of practice resulted in superior retention, we showed that the high condition resulted in faster response times in retention [2, 4, 8]. Keeping individuals in a practice phase representative of the early practice stage, which is thought to be high in cognitive effort, controlled the high level of difficulty during practice, which subsequently benefited retention.

Our high difficulty condition would be considered a type of "hybrid" schedule, characterized by short periods of blocked practice before a switch (in comparison to medium and low CI conditions, which would have medium and long periods of blocked practice, respectively). That is, the algorithm we employed ensured that individuals practiced the same motor sequence until they had achieved a specific level of performance (tmRTT) before moving to the next motor task. Potentially, this hybrid CI scheduling in the high condition, which alternated between blocked and random practice, produced an environment that was relatively high in attentional demands and cognitive effort, thereby enhancing performance compared to the medium and low difficulty conditions. This supports previous studies showing that hybrid practice schedules produced learning effects comparable to random practice, while maintaining a level of performance during practice comparable to blocked practice [36, 37]. However, because we did not test yoked practice conditions (where these individualized switching schedules are imposed on a partner), we are unable to make direct comparisons with past work. Nevertheless, it is positive that our method resulted in long-term learning effectiveness, without apparent costs in practice (i.e., performance differences in acquisition).

In our studies, practice parameters from an earlier learning phase, including rate of motor skill acquisition and average response time in a practice phase, were effective in generating high levels of individualized challenge, which positively impacted delayed retention. However, given the relatively low nominal task difficulty of the current sequence-learning paradigm, task-specific effects should be further probed. When the motor response or task-demands are more complex, a high degree of challenge is unlikely to be the best condition for learning. For example, blocked practice conditions facilitated retention of novel key-press sequences when a task-irrelevant focus (involving verbal identification of the pitch of an auditory tone) was additionally required. This was compared to conditions when a task-relevant focus was required [38]. Similarly, when the motor task involved sensorimotor integration and timing, in comparison to acquisition of stimulus-response associations as required in our task, low-challenging, blocked practice was preferable to high challenge conditions, at least in the initial phase of practice [39]. These task-specific effects in the CI literature marry with the recommendations based on the challenge point framework; that challenge is both a function of the individual’s skills (functional difficulty) and the task-demands (nominal difficulty, Guadagnoli & Lee, 2004).

It is important to investigate, and to begin to quantify, the evolving processes underlying changes in motor performance across practice, as well as how these phenomena relate to or explain longer-term retention and transfer to similar yet novel skills. Our chosen method for doing this was based on deriving an exponential function from three parameters based on an individual's performance curve: *A*, *B*, and α. If individuals do not demonstrate a large change in performance (*y* values) across their entire practice (*x* values), the rate of motor skill acquisition (α) will be high because performance quickly plateaus. Conversely, if individuals do demonstrate a large change in performance (*y* values) across a small number of early practice trials (*x* values), the rate of motor skill acquisition (α) will also be high because performance quickly plateaus. Both situations may indicate that the practice paradigm was either too difficult or too easy, respectively, for individuals (i.e., not at an optimal challenge point), leaving them with no useful information to extract. Inspection of individual performance curves alerted us to both these situations in Study 1. For example, subject 4 and subject 11 had comparable rates ($\alpha = 0.036$ and $\alpha = 0.038$, respectively; Figure 6); however, subject 11 had a change in performance (B value) of 0.12, while subject 4 had a change in performance of 0.85. In addition, there was no association between performance in the phases of practice and retention. In the present sample, both subjects demonstrated faster rates of motor skill acquisition, compared to other individuals, which translated into poorer retention test performance in Study 1. These two subjects show different degrees of improvement in performance with similar rates of skill acquisition, supporting the notion that information processing demands were above or below optimal. However, for subject 4, based on the larger number of switches (low difficulty: 338; medium difficulty: 417; high difficulty: 439) in the learner adaptive practice conditions, that indicates frequently surpassing baseline reference values, external factors, such as motivation and attentional, may have contributed to lack of change in baseline performance [40]. There may be other methods that are equally or more useful in determining task difficulty, based on performance-curve fitting to dictate optimal methods of practice for either multiple or single tasks. This will probably be task-dependent, practice amount-dependent, and of course dependent on the similarity between the initial task where curve fitting was performed and the transfer task.

We chose to fit our data to an exponential function for two reasons: (1) exponential functions are preferred over power functions for individual performance data, whereas the latter provides a better fit for group data (Heathcote & Brown, 2000); and (2) the learner-adapted algorithm in the present paper was based on a model derived from Choi et al. (2008), where it was assumed that motor learning related performance curves are relatively well modelled with exponential functions. Despite these reasons, we were only able to capture just over 30% of the variance in our data through this method, and it may be that there are better model fits than exponential curve fitting which can help describe learning and which can be used to derive parameters for altering learning in future tasks.

In Study 1, participants acquired three different motor tasks in a highly predictable environment (i.e., serial order). In this type of practice, sequence knowledge develops and presumably motor chunks are created in a sequential fashion, progressing from an individual element level to multiple elements within a sequence [2]. We showed advantages associated with a slower rate of motor skill acquisition for later retention. Retention advantages that result from a slower rate of motor skill acquisition presumably stem from to time spent interpreting information and maintaining cognitive effort during practice [34]. This is supported by an fMRI study showing greater activity in motor regions associated with movement planning and response selection during slowed initial performance in random practice [3]. Individuals in the random practice group took more time to plan their movements when acquiring a motor skill, yet showed an enhanced learning effect at a delayed retention test [3]. In our study, it is likely that enhanced retention performance was related to time spent interpreting information and cognitive effort involved in learning the sequence of movements through planning, problem solving, and strategizing.

The results of Study 2 support our expectations that learning could be manipulated through an individualized, computer-controlled, learner-adapted algorithm, and that a condition that necessitated high cognitive effort would best promote learning. The high difficulty condition, which required individuals to be near the performance-resource demands of Phase I (cognitive phase), generated a level of challenge that was superior for learning in comparison to the low and medium difficulty conditions (corresponding to Phases III and II, respectively). In addition, benefits for the high difficulty condition were shown regardless of the method used to assess retention (absolute or relative retention), which suggests this condition was not only effective in producing an enhanced response time at the delayed retention test, but also in maintaining and/or increasing performance at retention. Although we did not make comparisons across generalized or experimenter-determined algorithms in this study (e.g., pure random or blocked practice), nor did we compare learner-adapted to yoked conditions, we did satisfy our aim of showing that our method of determining individual-specific difficulty, based on performance curve analysis and optimizing challenge, can lead to within-subject learning benefits compared to learner-adapted low CI practice. In future work, it will be necessary to probe the effectiveness of this computer-controlled protocol in comparison to practice schedule protocols that are based on a generally high (or low) degree of task difficulty (irrespective of the individual or task). Also, comparisons between the individual challenge points used in our learner-adapted algorithm to the more general challenge points used by Choi et al. (2008) would be helpful.

Performance curves are not new to the field of motor performance and learning [41]; however, the present studies highlight a novel use of performance curves in generalized (Study 1) and learner-adapted (Study 2) practice conditions. While there are known difficulties in the application of performance curves, and potential errors that can be made in their interpretation [42], our study demonstrates that when used methodically, valuable information, such as the rate of skill acquisition, and performance in practice phases, can be obtained to design learner-adapted practice paradigms. Specifically, entry-level abilities and/or prior experience can provide useful information that is often unexamined when assessing and using performance curves to inform future training paradigms [43]. This is a first step towards the use of prior knowledge of individual skill level to improve response to motor training through individualized practice schedules based on rate of skill acquisition.

In conclusion, we provide evidence that a high-difficulty practice condition is optimal for learning of a discrete-pairing, sequence-learning task (DPT). Although this high difficulty condition was characterized by more switching between sequences than the other conditions, it differed from typical high-CI schedules in that small blocks of practice before a switch to a new sequence characterized the schedule of practice, and there was also considerable variability of switching between participants. Moreover, this high-CI schedule did not have the typically shown practice-performance costs seen with "random" schedules when compared to blocked practice (low CI). This was the case even though we used a within-subjects design to assess the effectiveness of these learner-adapted practice schedules (which is an atypical method for assessing and comparing across practice schedule manipulations). We relate our data to the concept of optimal challenge, as introduced by Guadagnoli and Lee (2004). However, the theoretical concept and identification of an "optimal" challenge point requires further investigation. Overall, our results illustrate that performance curve metrics (based on a previous practice episode of a similar task) may facilitate the assignment of a numerical value to the concept of optimal challenge.

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Figure Captions

Figure 1a and b: The discrete pairing task (DPT).
The goal was to spatially pair two repeating shapes. On a computer screen, four white shapes appeared on a black background following the cue "Ready, next sequence!" **a.** Two of the four shapes repeated. Hence the participant must identify the repeating shape and then select that shape (by pressing the spatially compatible key) and then move it next to its partner by selecting the key corresponding to this new location. An example is shown in a1, where the circle shape repeats. The participant presses the spatially-corresponding key (a2) to highlight the most leftward circle ("V"), and then presses a second key, indicating the new location to which the leftward circle will move, in this case switching with the triangle by pressing "N" (a3). Correct pairing of the two repeated shapes will trigger the next set of stimuli. **b.** Each sequence consisted of five sets of stimuli. Because two key presses were executed during performance of one set of stimuli, a total of 10 key presses were executed during the performance of one sequence. In the example shown the sequence order is V, N, V, N, B, N, B, N, V, B.

Figure 2: Outline of design for Studies 1 and 2.
Study 1 was conducted across two weeks, involving serially-ordered practice of the different sequences and a 24-hour delayed retention test. Study 2 involved three additional weeks of testing under three counterbalanced conditions (low, medium, and high difficulty). Each condition was followed by a 24-hour delayed retention test.

Figure 3: The phases of skill acquisition based on performance-resource function.
Total mean response time total (tmRTT) was fit to an exponential function: $\boldsymbol{E}(\boldsymbol{tmRTTN}) = \boldsymbol{A} + \boldsymbol{B} * \boldsymbol{e}^{-\boldsymbol{\alpha} * \boldsymbol{N}}$. E(tmRTTN) is the expected value of tmRTT on practice trial N; A is the expected value of tmRTT after practice (asymptote parameter); B is the change in the expected value of tmRTT from the beginning to the end of practice (change score parameter); alpha (α) is the rate parameter (Heathcote et al., 2000). The three phases (I to III) were identified based on calculation of the change in the slope of curve.

Figure 4: Three examples of performance curves.
Individuals showed a fast (alpha [α] = 0.038; dashed line), slow (alpha [α] = 0.0098; solid line), and variable (alpha [α] = 0.016; dotted line) rate of skill acquisition across 30 blocks of practice.

Figure 5: Scatterplot showing the relation between alpha (α) values extracted from the exponential curve fitting for each participant during practice and absolute retention tmRTT (s).
Higher alpha (α) indicates faster rate of skill acquisition.

Figure 6: Single-subject practice and retention data for Study 1 (baseline).
Additional analysis: A repeated measures analysis of variance (ANOVA) yielded a significant main effect of practice block on mRTT: $F_{(29, 319)} = 27.46$, $p < 0.001$, $\eta_{\rho}^2 = 0.71$, large effect size.

Figure 7: Single-subject normalized curves for practice.
For each participant, curves were divided by a normalization factor of A(i) + B(i); A = asymptote value; B = change score; i = participant number.

Figure 8: Single-subject practice and retention data for low difficulty condition.
Additional analysis: a repeated measures analysis of variance (ANOVA) yielded a significant main effect of practice block: $F_{(29, 319)} = 11.48$, $p < 0.001$, $\eta_\rho^2 = 0.56$, large effect size.

Figure 9: Single-subject normalized performance curves for practice for low difficulty condition.

Figure 10: Single-subject practice and retention data for medium difficulty condition.
Additional analysis: a repeated measures analysis of variance (ANOVA) yielded a significant main effect of practice block: $F_{(29, 319)} = 16.21$, $p < 0.001$, $\eta_\rho^2 = 0.60$, large effect size.

Figure 11: Single-subject normalized performance curves for practice for medium difficulty condition.

Figure 12: Single-subject practice and retention data for high difficulty condition.
Additional analysis: A repeated measures analysis of variance (ANOVA) yielded a significant main effect of practice block: $F_{(29, 319)} = 15.92$, $p < 0.001$, $\eta_\rho^2 = 0.59$, large effect size.

Figure 13: Single-subject normalized performance curves for practice for high difficulty condition.

Figure 14a and b: Practice and retention performance.
a. Practice performance across the three phases of practice (Phase I, II, III) collapsed across learner-adapted difficulty conditions. * = significance at $p_{corrected} < 0.05$ (error bars show standard deviation of the mean). **b.** Retention performance (absolute tmRTT) for each of the three learner-adapted difficulty conditions. * = significance at $p_{corrected} < 0.0167$ (error bars show standard deviation of the mean).

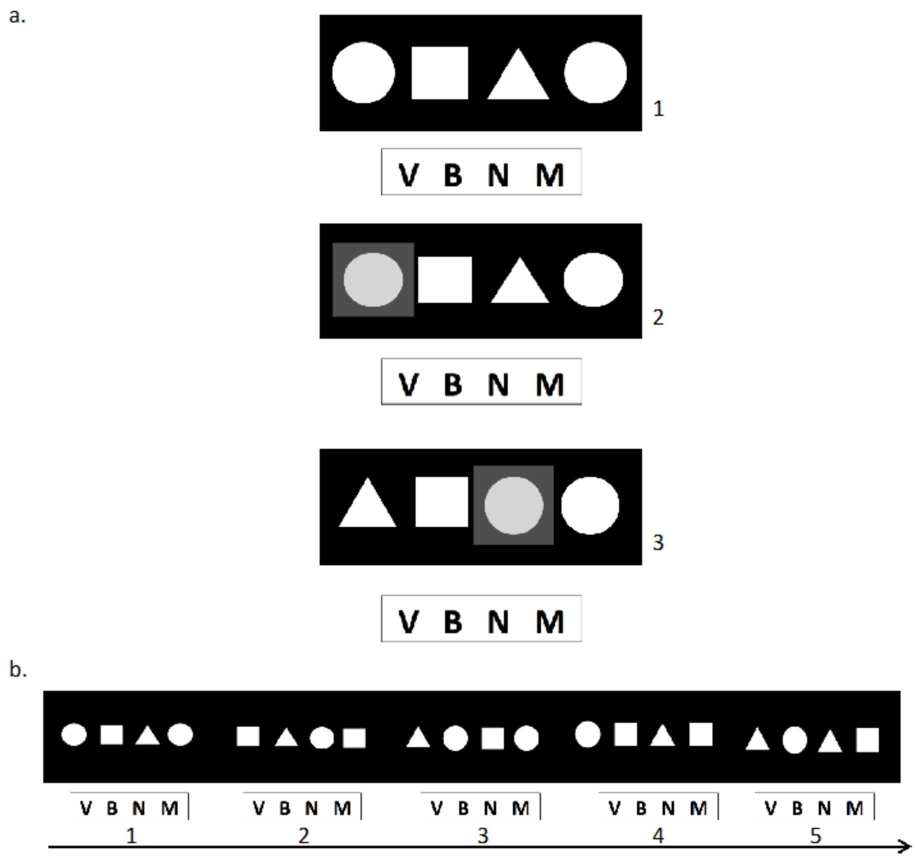


Figure 2

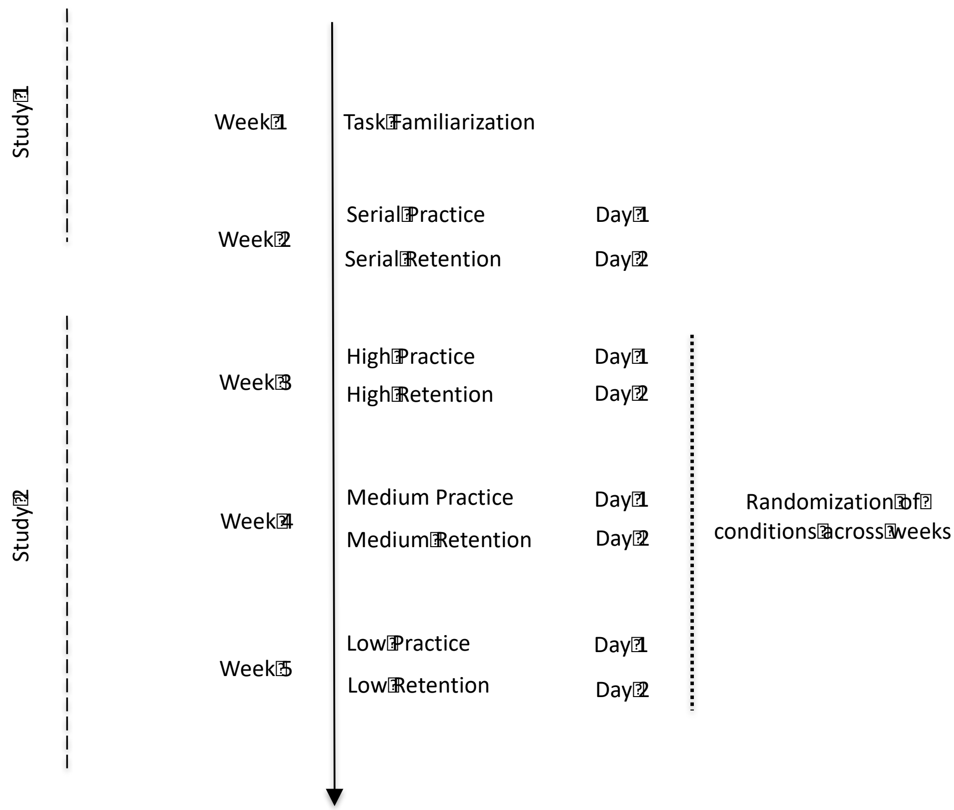
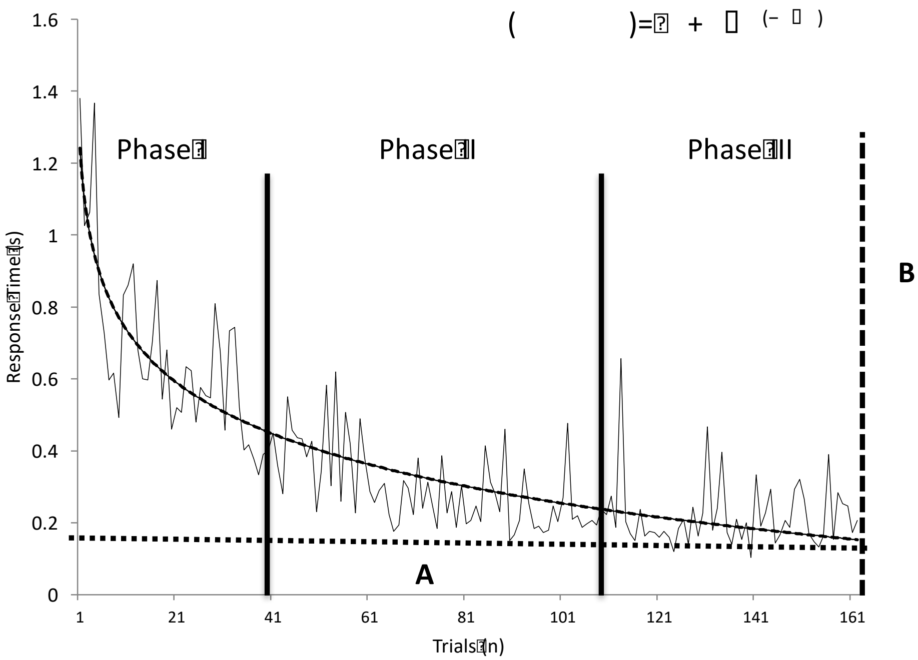

Study 1
Study 2
Week 1
Task Familiarization
Week 2
Serial Practice
Day 1
Serial Retention
Day 2
Week 3
High Practice
Day 1
High Retention
Day 2
Week 4
Medium Practice
Day 1
Medium Retention
Day 2
Week 5
Low Practice
Day 1
Low Retention
Day 2
Randomization of
conditions across weeks

Figure 3



1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Phase I
Phase II
Phase III
B
A
Response Time (s)
1
21
41
61
81
101
121
141
161
Trials (n)

Figure 4

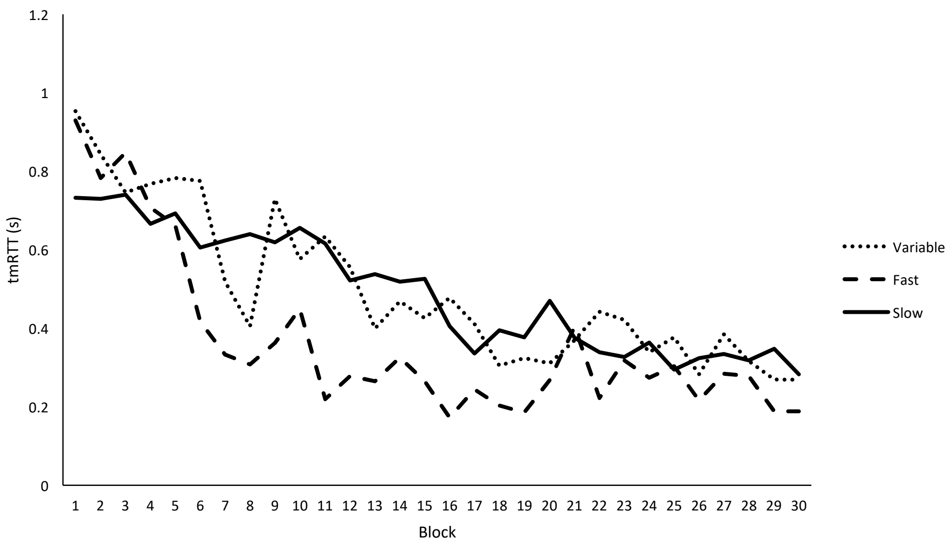

1.2
1
0.8
0.6
0.4
0.2
0
tmRTT (s)
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Block
Variable
Fast
Slow

Figure 5

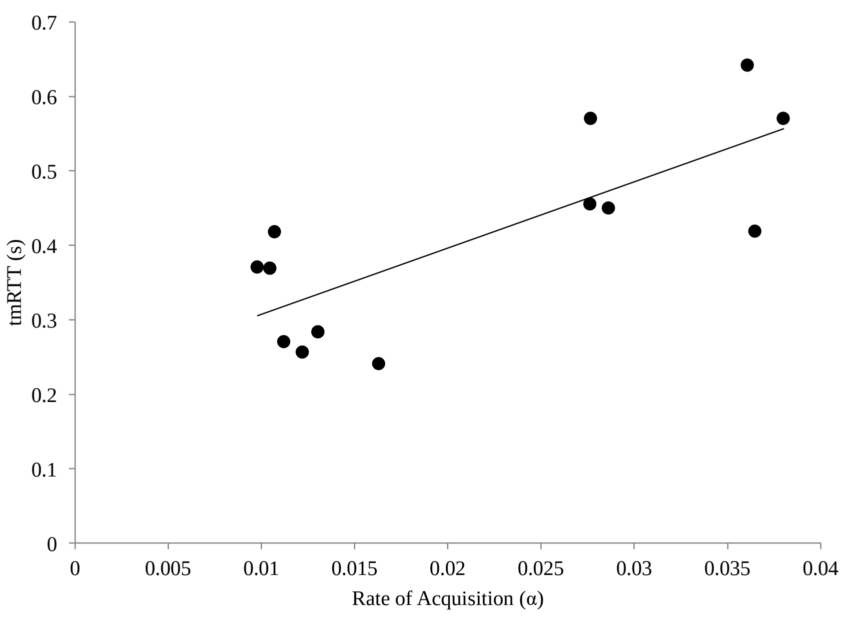

0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
tmRTT (s)
0 0.005 0.01 0.015 0.02 0.025 0.03 0.035 0.04
Rate of Acquisition (α)

Figure 6

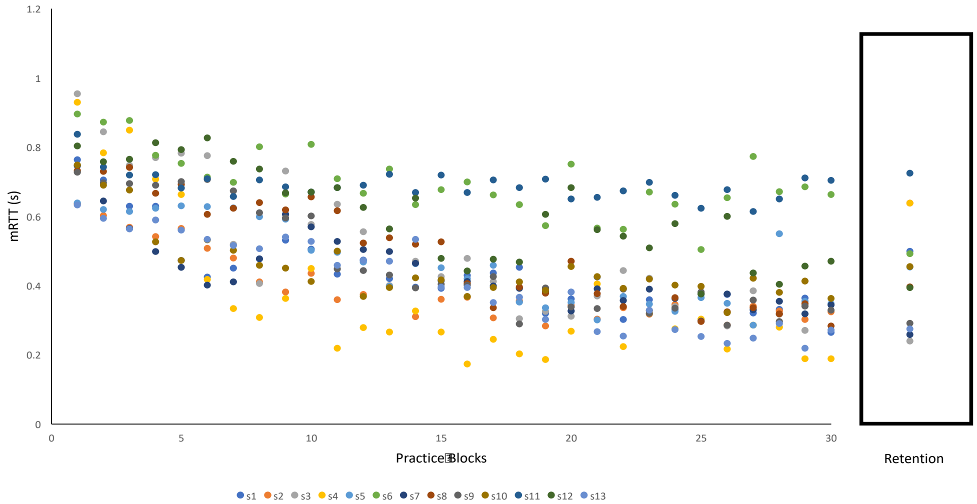


Figure 7

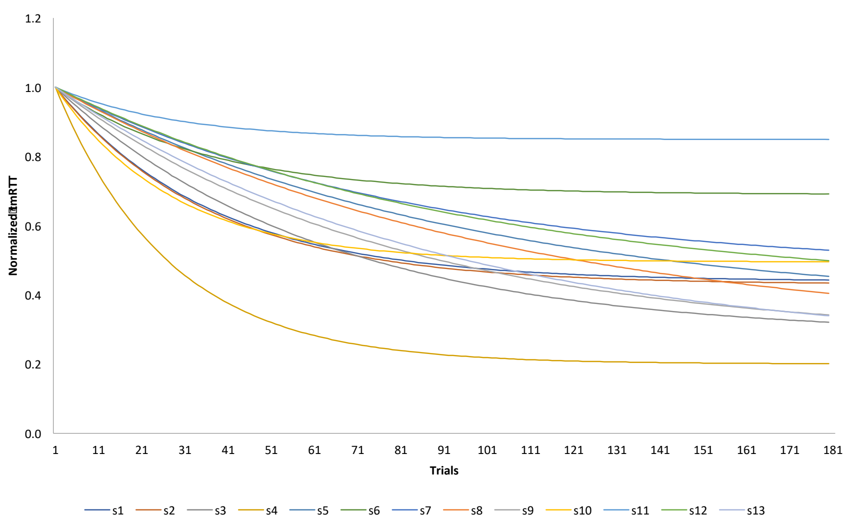


Figure 8

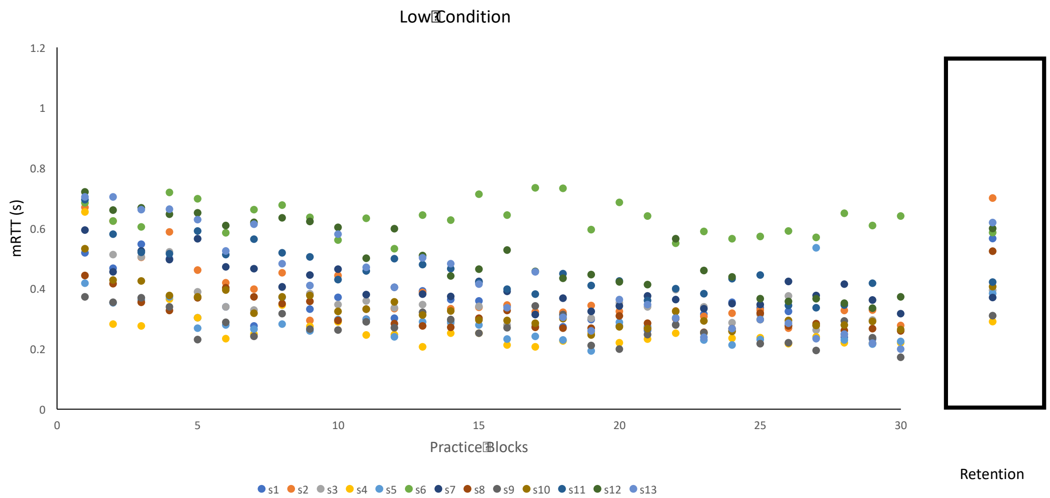


Figure 9

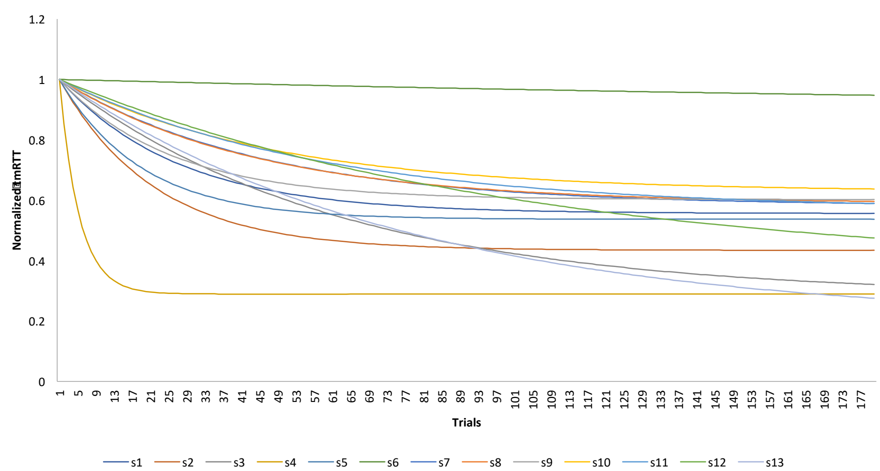


Figure 10

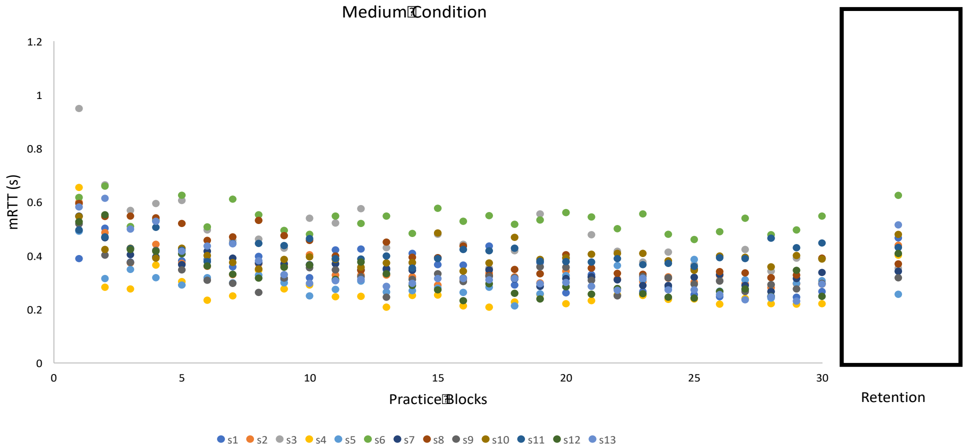


Figure 11

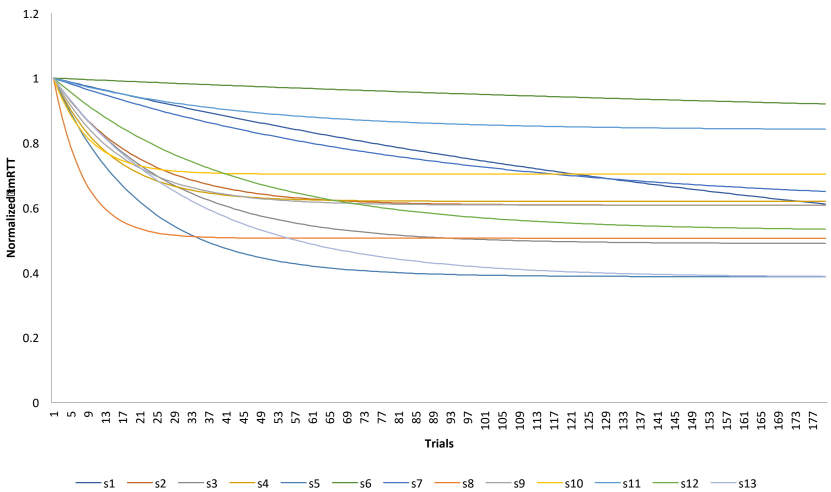


Figure 12

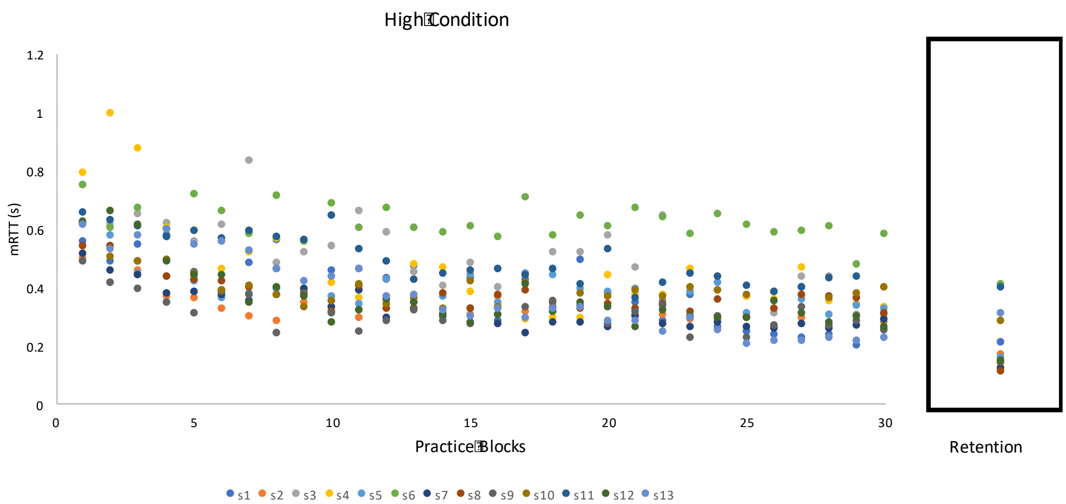


Figure 13

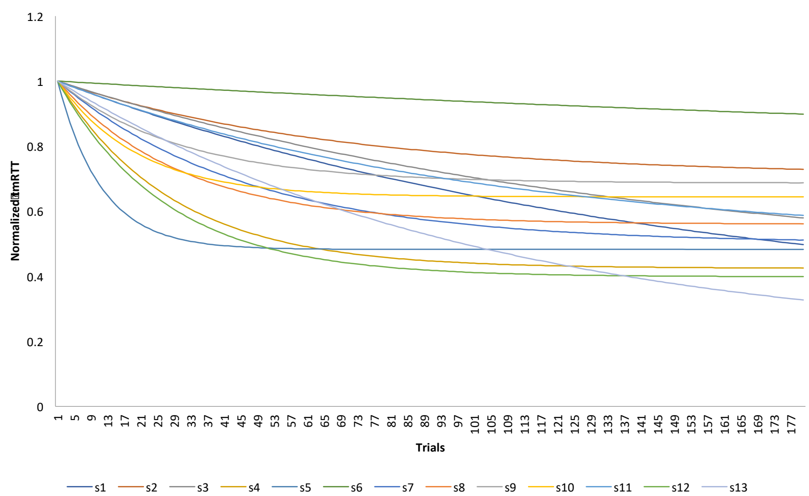
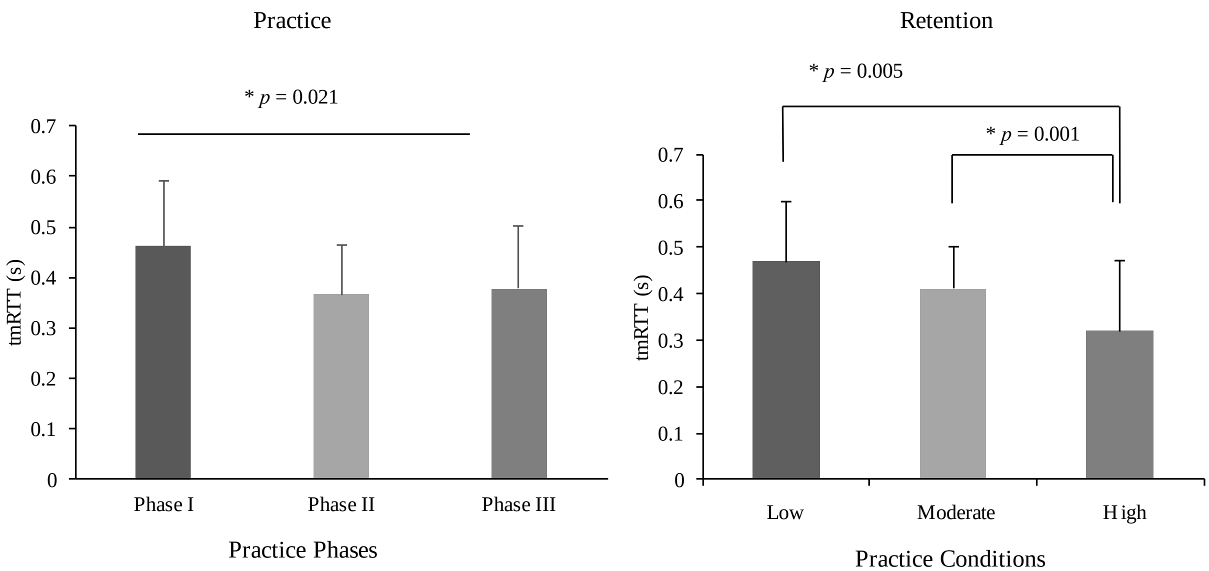


Figure 14


Practice
* p = 0.021
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
tmRTT (s)
Phase I
Phase II
Phase III
Practice Phases
Retention
* p = 0.005
* p = 0.001
Low
Moderate
High
Practice Conditions

a. b.