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Chunking, conscious processing, and EEG during sequence acquisition and performance pressure: A comprehensive test of reinvestment theory

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Abstract

This study was designed to test the theorized link between reinvestment, motor chunks, and conscious processing, to provide a thorough examination of reinvestment theory. We measured electroencephalographic power and connectivity alongside self-reported conscious processing and behavioral indices of chunking in a 2 (group) × 5 (block) mixed-model design. Fifty-five individuals acquired a motor sequence (blocks: A1, A2 A3, A4) via relatively explicit (errorful) or implicit (errorless) paradigms. Then they performed in a pressure condition (block: T). Results confirmed that chunking characterizes both modes of acquisition. However, explicit acquisition resulted in quicker chunking, reduced conscious processing, and increased cortical efficiency (left-temporal high-alpha power). In support of reinvestment theory, self-reported conscious processing tended to increase under pressure among explicit trainees only. In contrast to reinvestment theory, this had no adverse effect on performance. Our results endorse explicit acquisition as an effective mode of training and provide a new neurophysiological explanation why.

Keywords: chunking; cortical efficiency; explicit learning; high-alpha power; motor learning; verbal-analytic processing;

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Acquired motor skills, ranging from everyday life actions, such as keyboard typing, to skilled and specialized maneuvers typical of sport stars or expert surgeons, are essentially sequences of elementary movements which with practice are progressively organized in efficient memory units (Sakai, Kitaguchi, & Hikosaka, 2003). For instance, the elementary components of a golf swing include gripping the shaft, initiating the backswing, rotating the hips, transferring weight from one foot to the other. With practice, this sequence of separate elements is organized into a single efficient technique. Indeed, classical models of motor learning (Fitts & Posner, 1967) describe the progression from a verbal-analytic stage, supporting the performance of novices, to an autonomous stage, which supports the performance of experts. At the verbal-analytic stage, movements are performed with a high degree of conscious processing since the different components of the skill need to be held in working memory (Baddeley, 2012) while the performer tries to find a set of verbal-analytic rules to guide movement execution. The resulting performance is jerky and errors are numerous. At the automatic stage, the elementary movement components are integrated (i.e., chunked) in a single memory unit and stored in a procedural and non-verbalizable format in long-term memory (Willingham, 1998). At this stage, performance is effortless and consistent. In sum, practice allows a progressively quicker and more accurate execution at a reduced cognitive cost (e.g., Willingham, 1998).

However, even after automatization, skill execution is not flawless; from time to time, so-called *choking* (i.e., movement failures under pressure) can occur even in the most skilled professionals (Baumeister, 1984). A motor learning-based explanation for choking under pressure is offered by reinvestment theory (Masters & Maxwell, 2008). It contends that contingencies such as increased psychological pressure, social evaluation, and errors during execution may prompt, in some individuals, explicit action monitoring via reinvestment of the verbal-analytic rules that supported skill acquisition during the early stages of learning. This results in the de-automatization of well-learned skills, characterized by the performer reverting back to a more conscious, less efficient form of control, and the de-chunking of movement back to elementary components (MacMahon & Masters, 1999). In other words, some of the benefits that occur with practice (e.g., increased speed and reduced cognitive cost) can be occasionally undone under pressure, causing impaired motor performance.

Chunking and De-chunking

Evidence to support the notion that elementary movement components are "chunked" together during skill acquisition is compelling (for review see Abrahamse, Ruitenberg, de Kleine, & Verwey, 2013 or Shea & Wrights, 2012). For example, in a study by Sakai and colleagues (2003), participants learned to press a sequence of buttons during an explicit visuomotor learning paradigm called the 2×10 task. Acquisition was considered explicit because participants learned the correct sequence by trial-and-error (Abrahamse et al., 2013). This promotes hypothesis-testing behavior that leads performers to accumulate a bank of explicit and verbalizable rules to guide the correct solution (Raab et al., 2009). Participants were required to press a sequence of ten pairs (i.e., 2×10) of buttons, which illuminated in a predetermined order. Initially, while participants began memorizing the sequence, execution was jerky and characterized by many elongated time gaps between pairs. With practice, these gaps decreased and the execution became smoother as the sequence was organized into fewer and larger motor chunks, exactly as is said to happen during the acquisition of motor skills displayed in sport (Fitts & Posner, 1967). Such chunking is said to lessen the load on working memory since conscious processing is needed only for retrieving the first element of the chunk (Willingham, 1998).

Importantly, chunking is not restricted to explicit learning paradigms. Implicit learning, where skills are acquired with little awareness and limited accumulation of verbal-analytic rules, can also support chunking (Song & Cohen, 2014; Willingham, 1998). For example, MacMahon and Masters (1999) had participants acquire a sequence of button presses during a serial reaction time task, which is deemed to induce a relatively implicit mode of learning (Robertson, 2007). Like

Sakai and colleagues (2003), MacMahon and Masters found that with practice, the time gaps between consecutive button presses decreased and execution became smoother, implying the progressive organization of the sequence into fewer and larger motor chunks. Interestingly, the progressive chunking observed during acquisition was followed by de-chunking (i.e., the re-emergence of elongated time gaps) in a transfer phase where participants performed the same serial reaction time sequence under elevated levels of social-evaluative pressure. This finding is supportive of reinvestment theory's idea that pressure-induced de-chunking is a mechanism to explain choking under pressure. However, it is surprising that such de-chunking was observed following acquisition conditions (i.e., serial reaction time task) that are thought to promote relatively implicit learning. Indeed, a core prediction of reinvestment theory is that learning in an implicit fashion should reduce the possibility of de-chunking under pressure, since implicit learners, compared to their explicit counterparts, have few conscious rules to reinvest. Put simply, reinvestment and therefore de-chunking under pressure should be less likely after implicit than explicit learning. To date, there are no experiments that directly examine this specific de-chunking prediction. Addressing this void in the literature is one aim of the present experiment.

Cortical Indices of Conscious Motor Processing

In addition to behavioral manifestations such as chunking and, possibly, de-chunking, the variations in verbal-analytic conscious processing that characterize motor learning and reinvestment under pressure are said to be accompanied by changes in the EEG high-alpha (around 10-12 Hz) frequency band. In brief, increased high-alpha power is viewed as an index of active inhibition of non-essential neural processes (Klimesch, 2012). Accordingly, increased high-alpha power recorded over the left temporal regions (T7), which are traditionally associated with verbal-analytic and language processes (e.g., Springer & Deutsch, 1998), has been argued to reflect lower levels of verbal-analytic activity (e.g., less conscious processing) during preparation for complex motor skills (e.g., Hillman, Apparies, Janelle, & Hatfield, 2000). Researchers have also shown interest in measures of connectivity between different electrode sites (e.g., magnitude squared coherence or inter-site phase clustering). Connectivity reflects the degree of similarity of activity at different electrode sites, and has been interpreted to reflect the amount of functional communication between different brain regions, where more connectivity reflects greater communication (Von Stein & Sarnthein, 2000). Consequently, researchers have interpreted reduced high-alpha power connectivity between left-temporal sites, and frontal midline sites overlaying areas deputed to motor sequence planning (Ashe, Lungu, Basford, & Lu, 2006) as less verbal-analytic involvement (e.g., less conscious processing) during motor planning (e.g., Deeny, Haufler, Saffer, & Hatfield, 2009).

In support of these assertions, research has reported greater T7 high-alpha power and reduced T7-Fz high-alpha connectivity in expert sport performers compared to less experienced performers (e.g., Deeny, Hillman, Janelle, & Hatfield, 2003; Janelle et al., 2000). Research has also demonstrated a progressive increase in left-temporal high-alpha power, and a reduction in T7-Fz high-alpha connectivity, during motor skill training (Gallicchio, Cooke, & Ring, 2017; Kerick, Douglas, & Hatfield, 2004; Landers, Han, Salazar, & Petruzzello, 1994). Moreover, Zhu, Poolton, Wilson, Maxwell, and Masters (2011) found that high-alpha T7-Fz connectivity was higher in individuals prone to consciously control movements, as determined by the Movement Specific Reinvestment Scale (Masters, Eves, & Maxwell, 2005), than in their less prone counterparts, during a golf putting task. High-alpha T7-Fz connectivity was also higher in novices after undergoing an explicit learning protocol (i.e., trial-and-error condition), which fostered the accumulation of verbal-analytic rules, compared to those who underwent an implicit (i.e., errorless) protocol (Zhu et al., 2011). Taken together these studies endorse T7 power and T7-Fz connectivity in the high-alpha band as indices that are sensitive to the reduction in conscious processing that characterizes the progression from the verbal-analytic stage to the automatic stage of learning.

These cortical measures could also be sensitive to reinvestment under pressure. For example, Zhu and colleagues (2011) found that T7-Fz high-alpha connectivity increased during transfer to a high-pressure condition in their explicit learning group, but not in the implicit group. This provides some tentative support for reinvestment theory’s prediction that reinvestment under pressure is more likely to happen in explicit learners than implicit learners. However, these differences in EEG connectivity were not accompanied by differences in putting performance, thereby questioning the presumed link between connectivity, conscious processing and performance. In a similar vein, Hatfield and colleagues (2013) found that pistol shooters displayed decreased T7 high-alpha power and increased T7-Fz connectivity (in the 8-13 Hz alpha broadband) upon transfer from low-pressure to high-pressure conditions, but again performance outcome was maintained. Of note, kinematic measures obtained in this study provided some evidence that these pressure-induced EEG changes were accompanied by reductions in movement efficiency (i.e., reduced fluency of aiming trajectory). This could imply increased segmentation of the action as if the movement components had been de-chunked. However, since the elementary movements constituting complex sport skills such as shooting are difficult to isolate, this conclusion is somewhat speculative. A strength of sequence button pressing tasks such as those adopted by MacMahon and Masters (1999) and Sakai and colleagues (2003) is that they permit the investigation of the same basic mechanisms that underlie the acquisition of complex sport skills (Abrahamse et al., 2013; Shea & Wrights, 2012), while allowing precise and objective measures of chunking and de-chunking to be obtained. Button sequence practice tasks could thus be used to provide a more precise examination of pressure-induced reinvestment effects (e.g., dechunking).

The Present Experiment

To address the limitations of previous research and to offer a comprehensive examination of reinvestment theory, the present experiment was designed to be the first to examine chunking and de-chunking, together with cortical measures of conscious processing, during acquisition and performance under pressure, following explicit and implicit skill acquisition. Chunking was expected for both explicit and implicit modes of practice. However, based on reinvestment theory, we expected initially higher conscious processing (self-report, T7 high-alpha power and T7-Fz high-alpha connectivity) followed by a more pronounced reduction during explicit acquisition, compared to implicit acquisition. This is due to the greater hypothesis-testing and verbal-analytic processing associated with explicit compared to implicit practice (e.g., Zhu et al., 2011). Moreover, we expected choking under pressure to be more likely in participants who underwent explicit rather than implicit training, since this latter mode of practice should theoretically be protective against reinvestment of verbal-analytic conscious processing under pressure (Masters & Maxwell, 2008).

Methods

Participants

Fifty-six students (male = 34, female = 21, M_{age} = 21.87 years, SD_{age} = 2.56) gave informed consent and volunteered to participate in the study. They were recruited via email and posters displayed across a University campus. All participants were right-handed as indicated by Edinburgh Handedness Inventory (EHI; Oldfield, 1971) scores ≥ +70 (M = 93.27, SD = 11.06). Participants were assigned either to an explicit group (N = 28) or an implicit group (N = 28).

Previous EEG studies of reinvestment theory (Hatfield et al., 2013; Zhu et al., 2011) reported medium-to-large effect sizes for group by condition interactions ($\eta_p^2 > .15$). Sensitivity calculations indicated that our sample size was more than adequate to detect similar effects; our 2×5 mixed-model ANOVAs were powered at .80 to detect even small interaction effects ($\eta_p^2 = .02$) at the 5% level of significance). Approval was granted by the Institutional Research Ethics Committee.

Task

Two variations of a sequence learning task were employed to examine explicit and implicit visuomotor sequence acquisition. The two tasks were employed to manipulate the degree of conscious processing needed to perform the sequence by inducing relatively errorful (*2×10 task*) and errorless (*1×20 task*) practice conditions (e.g., Zhu et al., 2011). Participants assigned to the explicit group completed the *2×10* sequential button-press task (Sakai et al., 2003). This requires participants to acquire, with a trial-and-error strategy, the correct order in which to press a sequence of 20 buttons on a bespoke 4×4 keypad matrix (see Figure 2B). Participants were informed of the existence of a sequence and asked to execute the presses as quickly and accurately as possible using the index finger of the right hand. The task started when participants pressed the "start-button", which lit-up in blue at the bottom left of the matrix. Subsequently, a pair of buttons ("a set") lit-up in green. Participants were required to press one button at a time in an attempt to learn the correct order of pre-programmed button presses. If they chose the correct button to press first, the associated green light was turned off and participants were able to press the remaining button. Once the pair of buttons were pressed in the correct order, there was a 100 ms interval before a new pair of buttons (the next set) lit-up. The above cycle then repeated. The complete sequence required participants to correctly press ten pairs of buttons without error. Whenever an error occurred the whole 4×4 matrix lit-up in red, and participants had to start a new trial from the beginning (Figure 2C). The sequence was the same in all acquisition blocks across all participants (Figure 2A). This task was chosen for members of the explicit group because the extensive hypothesis-testing that characterizes the task is known to prompt explicit awareness of the movement/sequence rules (Sakai et al., 2003).

Participants assigned to the implicit group completed the *1×20* button-press task. In essence, this task is the same as that performed by the explicit group insofar as the requirement to press a sequence of 20 buttons with the index finger of the right hand. However, for members of the implicit group, the buttons lit-up one at a time, rather than lighting up in pairs (Figure 2D). This removed the hypothesis-testing that characterizes the *2×10 task* and made the task akin to the discrete sequence production task (DPS). Typically, in DPS tasks participants struggle to develop any explicit, in-depth, verbalizable knowledge about the sequence (i.e., structural knowledge, see Abrahamse, 2013; Verwey & Abrahamse, 2012), despite being informed of the presence of a repeating sequence. Since in the *1×20 task* participants were not told about the existence of a sequence, the chances of developing of verbalizable knowledge were deemed even lower compared to a typical DPS task. In short we believe that the *1×20 task* limits motor awareness during training and reduces the number of errors thereby creating the conditions for relatively more implicit acquisition (i.e., errorless learning; Maxwell, Masters, Kerr, & Weedon, 2001).

Design

We employed a mixed-model design with Group (explicit, implicit) as a between-subjects factor, and Block (A1, A2, A3, A3, T) as a within-subjects factor. The Block factor represents a four-block acquisition phase (A1, A2, A3, A4), followed by a transfer to a comparatively high-evaluative pressure condition (T). Each block during acquisition and transfer consisted of 20 complete (i.e., correct) repetitions of the sequence.

Measures

Manipulation Check. In order to assess the effectiveness of the pressure manipulation used in the transfer condition (see Procedure section below), we monitored self-report cognitive anxiety and movement self-consciousness.

Cognitive Anxiety. Cognitive anxiety was assessed using the cognitive anxiety subscale of Mental Readiness Form-3 (MRF-3; Krane, 1994). This measure consists of one statement (i.e., "my mind feels…") rated on an 11-point Likert scale (range 1-11) anchored *calm-worried*.

Movement Self-Consciousness. To assess movement self-consciousness during sequence performance, we used the movement self-consciousness subscale of the Movement Specific Reinvestment Scale (Masters et al., 2005). Although originally conceived as a trait measure, this questionnaire is frequently used as a state measure where it shows high internal consistency (e.g., Gallicchio et al., 2017). Participants were asked to indicate how they felt while performing the previous block in relation to four items (e.g., "I felt that I was watching myself") rated on a 6-point Likert scale (1 = strongly disagree, 6 = strongly agree). The mean Cronbach's α coefficient was .73.

Conscious processing

To monitor conscious processing during both acquisition and transfer, we used the conscious motor processing subscale from a the Movement Specific Reinvestment Scale (Gallicchio, Cooke, & Ring, 2016; Masters et al., 2005). Participants were asked to indicate how they felt while performing the previous block in relation to five items (e.g., "I was aware of the way my body was working") that were rated on a 6-point Likert scale (1 = strongly disagree, 6 = strongly agree). The mean Cronbach's α coefficient was .77.

Task Performance

Percentage of sequence chunked. The percentage of sequence chunked (*chunked%*) was considered in order to explore chunking and de-chunking in the two groups. To obtain this measure we first extracted all of the choice times (ChTs; time from a pair of buttons illuminating to the first button being pressed) for members of the explicit group, and response times (RTs; time from a single button illuminating to the button press) for members of the implicit group. These data were logarithmically (Log_{10}) transformed in order to ensure a normal distribution (Sakai et al., 2003). Next, the upper bound of the 95% confidence interval for Log_{10}ChTs/RTs across all blocks for each participant was calculated and taken as an individualized critical value to determine any disproportionately long time-gaps in the execution of the sequence, which are thought to distinguish temporally adjacent chunks (Sakai et al., 2003). Finally, these individual cut-offs were applied to yield the number of chunks per block for each participant.

The maximum number of chunks (Max_{chunks}) was 10 for members of the explicit group, and 20 for members of the implicit group. Such scores would represent disproportionately long time-gaps between every choice (explicit group) and every response (implicit group). To permit between-group comparisons we express the mean number of chunks ($Mean_{chunks}$) as a percentage using the following formula:

$$chunked\% = \ (Mean_{chunks} * 100)/Max_{chunks}$$

This ensures a consistent scale for each group (i.e., 0-100%) with a higher percentage representing fewer chunks (i.e., less disproportionately long time-gaps) and signifying a more holistic representation of the sequence.

Movement Errors. The mean number of errors was recorded as an additional index of performance effectiveness. This measure is related to chunking, since a reduction in number of chunks typically coincides with fewer errors (Sakai et al., 2003).

Cortical activity

EEG activity was recorded from four scalp locations (T7, T8, Fz, Pz) using active recording electrodes and a DC amplifier (PET-4, Braininquiry EU, NL) connected to a computer running BioExplorer (CyberEvolution, Inc.) software. Reference electrodes were positioned at the mastoids (linked), and a ground electrode was located at Fpz (Jasper, 1958). Recording sites were cleaned, abraded and conductive gel (Electro-gel, ECI) was applied to ensure electrode impedances were below 10 kΩ. The signals were sampled at 1000 cycles per second. Offline signal processing was performed using EEGLAB (Delorme & Makeig, 2004) and custom scripts in MATLAB (Mathworks Inc., USA). Signals were resampled (256 Hz) and band-pass filtered (1-30 Hz). Gross muscular and ocular artefacts were then removed using the following two step process. First, data segments containing drifts exceeding ±50 μV in a 250ms sliding window were identified by the Darbeliai EEGLAB extension (Baranauskas, 2008). Second, all identified data segments were reviewed by an experienced EEG analyst, and those containing artefacts were rejected.

Data for each block were then decomposed into their frequency representation by multiplying the power spectrum of the EEG, obtained from the fast Fourier transform, by the power spectrum of complex Morlet wavelets:

$$e^{i2\pi tf} e^{-t^2/2\sigma^2}$$

where t is time, f is frequency bin, which increased from 4 to 28 Hz in 49 linearly spaced steps (thus 0.5 Hz resolution), and σ defines the width of each frequency band, set according to $4/2\pi f$ (thus, 4 cycles), and then taking the inverse fast Fourier transform. This procedure was done separately for each channel to obtain a complex signal from each convolution.

Power. From the complex signals, power at each frequency bin (f) was defined as the squared magnitude of the result of the convolution Z {real $[z(t)]^2$ + imag $[z(t)]^2$} and averaged across high-alpha (10-12 Hz) frequency band. In order to ensure normal distribution all power estimates were subjected to a logarithmic (Log_{10}) transformation (Delorme & Makeig, 2004) prior to analysis.

Connectivity. Functional connectivity between sites was computed in terms of inter-site phase clustering (ISPC). While most previous studies estimated functional connectivity by calculating magnitude squared coherence (e.g., Hatfield et al., 2013; Zhu et al., 2011), we report ISPC because magnitude squared coherence (a measure derived from power) could be confounded by the expected between-block differences in high-alpha power (Cohen, 2014). Moreover, Gallicchio and colleagues (2016) reported that high-alpha frontotemporal connectivity was more sensitive to experience-related differences in conscious processing when computed by ISPC compared to magnitude squared. ISPC was calculated as follows:

$$ISPC_{xy}(f) = \left| n^{-1} \sum_{t=1}^{n} e^{i(\theta_x(tf) - \theta_y(tf))} \right|$$

Where n is the number of data points, i is the imaginary operator, θ_x and θ_y are the phase angles of the recorded signal at two different scalp locations, t is the time point, and f is the frequency bin, $e^{i(\theta_x(tf) - \theta_y(tf))}$ is the complex vector with magnitude 1, $n^{-1} \sum_{t=1}^{n}(.)$ denotes averaging over time points, and $|.|$ is the magnitude of the averaged vector (Cohen, 2014). The resulting ISPC is a real number between 0 (no functional connection) and 1 (perfect functional connection), which represents the consistency of the phase angle differences across time between two electrodes. ISPC estimates were calculated and averaged for the high-alpha (10-12 Hz) frequency band. Based on our hypotheses, the main analysis focused on the electrodes pairs T7-Fz and T8-Fz, which have been argued to represent, respectively, verbal-analytic and visuospatial involvement in motor planning (e.g., Zhu et al., 2011). In accord with previous research (e.g., Zhu et al., 2011), we subjected all ISPC estimates to a Fisher's Z transformation (also known as inverse hyperbolic tangent) before conducting statistical analyses in order to reduce inter-subject variability and approximate normal distribution (Halliday et al., 1995).

Procedure

Participants individually attended a 2-hour testing session. On arrival, they were welcomed, briefed and invited to ask any questions, before providing written consent to take part. Next, the experimenter attached the EEG electrodes. Participants then underwent a familiarization block, which involved pressing a simple sequence of buttons that illuminated one at a time from top left to bottom right. This ensured familiarity with the force required for each button press to register and allowed participants to become accustomed to pressing the buttons while instrumented for EEG recordings. This was followed by the acquisition phase, which consisted of four blocks of practice (A1, A2, A3, A4) on the assigned task (i.e., *2×10 task* for members of the explicit group, *1×20 task* for members of the implicit group). Each block ended when participants successfully completed 20 correct repetitions of the sequence. Adjacent blocks were separated by five-minute breaks. Finally, participants underwent the transfer phase (T), in which they performed a final block (20 sequence repetitions) on their assigned task, while evaluative pressure was manipulated (see pressure manipulation section below). Cortical activity was recorded continuously throughout each block. Our self-report measure of conscious motor processing was administered at the end of each block, while our manipulation check questionnaires were administered immediately before (anxiety measure) and after (movement self-consciousness measure) blocks A4 (end of acquisition) and T (transfer). At the end of the experiment, participants were thanked and asked not to disclose specific detail about the pressure manipulation to others.

Pressure Manipulation. Social evaluation was manipulated based on previous research deeming evaluative pressure as more likely to induce conscious processing and reinvestment than outcome-based (e.g., rewards for success) pressures (DeCaro, Thomas, Albert, & Beilock, 2011). In order to maximize evaluation apprehension, prior to the beginning of the transfer phase, the experimenter played a scripted video where a senior academic informed participants that their performance during the transfer phase would be filmed from three different locations in order for students and motor control lecturers at the university to view how people perform this skill. In addition, participants were told that the footage might also be used in a YouTube film on visuomotor skill acquisition, which would be available worldwide for researchers and psychology classes. The three cameras were placed approximately 1 m above, in front, and adjacent to the participant, and the footage was presented in real time, on a screen visible to the participant. Moreover, the experimenter, who sat out of sight during the acquisition phase, repositioned to now stand in very close proximity to the participant, and very obviously watch their performance.

Statistical Analyses

Data were un-scorable for one participant, accordingly, the sample-size retained for statistical analyses was fifty-five (27 for explicit group, 28 for implicit group).

Cognitive anxiety and movement self-consciousness scores during the last block of acquisition and transfer in the two groups were subjected to 2 Group (explicit, implicit) × 2 Block (A4, T) ANOVAs. Conscious motor processing, percentage of sequence chunked, errors, power estimates at T7, T8, Fz, and Pz; and connectivity values between T7-Fz, and T8-Fz (as a control analysis), were subjected to mixed-model ANOVAs with Group (explicit, implicit) as the between-subject factor and Block (A1, A2, A3, A4, T) as the within-subject factor. Significant effects were probed by separate ANOVAs for each Group, and by polynomial trend analyses[1].

The multivariate method of reporting results was adopted as it minimizes the risk of violating sphericity and compound symmetry assumptions in repeated measures ANOVA (Vasey & Thayer, 1987). The multivariate statistic Wilks' lambda (not reported), equals $1-\eta_p^2$. Effect size is reported with partial eta squared (η_p^2) values of .10, .25, and .40 (for repeated measures ANOVA), and .02, .15, and .35 (for multivariate ANOVA) indicating relatively small, medium, and large effect sizes, respectively (Cohen, 1988).

Results

Manipulation Check

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[1] Although Reinvestment theory does not make specific predictions about gender, gender could be considered as an additional between-subject factor in our experiment. We analysed all our data with and without gender as a factor. There were no consistent effects relating to gender, so this factor is not included in the reported analyses. In brief, the only gender effects that emerged were a Gender × Condition interaction for cognitive anxiety ($F(1,51) = 7.31$, $p < .01$, $\eta_p^2 = .12$; greater increase from A4 to T among females than males), and a Gender main effect for connectivity (T7-Fz: $F(1,51) = 1.67$, $p < .05$, $\eta_p^2 = .10$; T8-Fz: $F(1,51) = .58$, $p = .048$, $\eta p^2 = .07$; marginally higher connectivity for females than males).

The 2×2 mixed-model ANOVAs revealed main effects of Block for cognitive anxiety, $F(1, 53) = 17.07$, $p < .001$, $\eta_p^2 = .24$, and movement self-consciousness, $F(1, 53) = 21.62$, $p < .001$, $\eta_p^2 = .29$, but no effect of Group, nor Block × Group interaction. These results confirm that the pressure manipulation was successful in inducing a relative increase in cognitive anxiety and movement self-consciousness from the final block of acquisition (A4; $M_{\text{anxiety}} = 2.72$; $M_{\text{self-consciousness}} = 2.27$) to the transfer phase (T; $M_{\text{anxiety}} = 3.71$; $M_{\text{self-consciousness}} = 2.73$) in both the explicit and the implicit group.

Conscious Processing

The 2×5 mixed-model ANOVA employed to examine how conscious processing changed across acquisition and transfer in the two groups revealed a significant effect of Block, $F(4, 50) = 3.50$, $p = .013$, $\eta_p^2 = .22$, no effect of Group, and a significant Group × Block interaction, $F(4, 50) = 7.01$, $p < .001$, $\eta_p^2 = .36$. The results of the separate repeated-measures ANOVAs conducted to probe the interaction are summarized in Table 1. The main effect of Block was apparent for the explicit group only and was best characterized by a quadratic trend ($p < .001$, $\eta_p^2 = .51$), with initially high scores decreasing during acquisition and increasing under pressure.

Task performance

Chunks. The 2×5 mixed-model ANOVA employed to examine how participants in the explicit and implicit group chunked the sequence across acquisition and transfer revealed a significant effect for Group, $F(1, 53) = 21.91$, $p < .001$, $\eta_p^2 = .29$, Block, $F(4, 50) = 143.76$, $p < .001$, $\eta_p^2 = .92$, and a significant Group × Block interaction, $F(4, 50) = 7.68$, $p < .001$, $\eta_p^2 = .38$. The effect of Block was significant in both groups with the percentage of sequence chunked increasing in a linear fashion (linear trend, explicit: $p < .001$, $\eta_p^2 = .93$; implicit: $p < .001$, $\eta_p^2 = .85$) during acquisition and under pressure (Table 1). The interaction reflected a significant quadratic trend that emerged for members of the explicit group only ($p < .001$, $\eta_p^2 = .47$), indicative of performance asymptote during explicit but not implicit acquisition (see Table 1).

Movement Errors. The 2×5 mixed-model ANOVA employed to examine the number of errors committed revealed a significant effect for Group, $F(1, 53) = 37.38$, $p < .001$, $\eta_p^2 = .41$, Block, $F(4, 50) = 10.18$, $p < .001$, $\eta_p^2 = .45$, and a significant Group × Block interaction, $F(4, 50) = 11.48$, $p < .001$, $\eta_p^2 = .48$. As shown in Table 1, the error-rate remained stable and very low throughout acquisition and transfer for members of the implicit group, while an initially high number of errors at the start of acquisition decreased sharply (quadratic trend, $p < .001$, $\eta_p^2 = .62$) for members of the explicit group.

Cortical activity

Power. Separate 2×5 mixed-model ANOVAs conducted for each electrode revealed main effects of Block (Fz: $F(4, 50) = 3.25$, $p < .05$, $\eta_p^2 = .21$; Pz: $F(4, 50) = 3.40$, $p < .05$, $\eta_p^2 = .21$; T8: $F(4, 49) = 3.02$, $p < .05$, $\eta_p^2 = .20$, T7: $F(4, 50) = 3.53$, $p < .05$, $\eta_p^2 = .22$). This was characterized by an increasing linear trend at all sites (Fz: $p = .001$, $\eta_p^2 = .18$; Pz: $p < .001$, $\eta_p^2 = .20$; T8: $p = .002$, $\eta_p^2 = .16$; T7: $p = .001$, $\eta_p^2 = .18$). There were no effects of Group. Importantly, a Group × Block interaction emerged at the T7 electrode only, $F(4, 50) = 2.65$, $p < .05$, $\eta_p^2 = .17$. Separate repeated-measures ANOVAs conducted for each group revealed that the linear increase in high-alpha power at T7 was significant for the explicit group only ($p = .004$, $\eta_p^2 = .28$, Figure 1A).

Connectivity. The 2 × 5 ANOVA on T7-Fz high-alpha (10-12 Hz) connectivity estimates revealed a main effect for Block, $F(4, 50) = 5.26$, $p = .001$, $\eta_p^2 = .30$, but no effect for Group, nor Block × Group interaction. As shown in Figure 1B, T7-Fz connectivity changes were best described by a linear trend ($p = .006$, $\eta_p^2 = .14$), reflecting an increase in connectivity from acquisition to transfer. This effect was confined to the left-hemisphere since the 2 × 5 ANOVA on T8-Fz connectivity revealed no main or interaction effects.

Discussion

Utilizing a novel multi-method approach, the present study tested whether conscious processing during motor learning and performance under pressure changed as predicted by classic models of skill acquisition (Fitts & Posner, 1967; Willingham, 1998) and reinvestment theory (Masters & Maxwell, 2008). To do so we designed the first experiment to simultaneously examine behavioral measures of chunking, alongside proposed cortical indices of conscious processing, during acquisition and pressure. Our experiment, to our knowledge, contains the largest sample and the highest statistical power of any published EEG study of reinvestment theory. Our results are discussed in relation to our hypotheses in the following sections.

Chunking and conscious processing during acquisition

The sequence learning literature suggests that chunking is a common mechanism underpinning both explicit (e.g., Sakai et al., 2003) and implicit (e.g., MacMahon & Masters, 1999) acquisition. Our results endorse this hypothesis. Specifically, our results showed that movements were progressively chunked during both explicit and implicit practice schedules, implying that verbal-analytic conscious processing is not strictly necessary for the chunking process to occur during motor skill acquisition (Masters & Maxwell, 2008; Song & Cohen, 2014, Willingham, 1998).

We expected that conscious processing would progressively decrease during explicit skill acquisition, reflecting a reduction in hypothesis testing as the rules that govern successful performance become automatized with practice (e.g., Fitts & Posner, 1967). On the contrary, when acquisition was comparatively implicit, we expected stable levels of conscious processing, due to low error rates and the removal of the decision-making component from our sequence learning task (e.g., Maxwell et al., 2001). Our measures of conscious processing provided mixed support for this hypothesis. On the one hand, self-reported data supported our hypothesis, with stable conscious processing scores throughout implicit acquisition and initially higher scores that progressively reduced during explicit acquisition. On the other hand, of our cortical measures of conscious processing, only T7 high-alpha power appeared sensitive to the different levels of verbal-analytic conscious processing required by explicit versus implicit acquisition. Specifically, high-alpha power measured at the left-temporal site, overlying verbal-analytic areas (Springer & Deutsch, 1998), increased during acquisition in the explicit group only, implying that left-temporal cortical activity progressively decreased with explicit but not implicit training. However, since T7 high-alpha power was initially similar in the two groups, our results do not offer neurophysiological support for the idea that conscious processing should be higher during the early stages of explicit compared to implicit training.

Interestingly, our T7 high-alpha power findings more closely mirror performance than our self-report measure of conscious processing. Specifically, both T7 high-alpha power and chunking performance were initially similar in the two groups, then participants practicing the explicit schedule showed steeper increases than their implicit counterparts. Similar performance effects have been reported before (e.g., Masters & Maxwell, 2008). Our accompanying T7 high-alpha power data provide new evidence that the superior performance associated with explicit acquisition could be explained by explicit acquisition fostering more rapid increases in cortical efficiency (i.e., progressively lower left-temporal activation) than implicit acquisition.

In contrast to our findings for T7 high-alpha power, T7-Fz high-alpha connectivity was similar for both groups, and increased rather than decreased during acquisition. This contradicts previous research and could reflect an increase in communication between verbal-analytic areas and motor planning areas as participants transitioned from a novice stage to a more advanced stage of learning (Gallicchio et al., 2017; Kerick et al., 2004). For example, our participants may have evolved from pure novices, possessing no verbalizable knowledge, to moderately skilled performers, who had developed some verbal strategies to guide execution (e.g., Deeny et al. 2009). However, if we accepted this explanation it would not be clear why, in the present study, left-temporal connectivity increased following both explicit and implicit practice schedules, and in spite of decreases in self-reported conscious processing and left-temporal activity among members of the explicit group.

An alternative interpretation of this cortical measure can be offered when one considers the following two features. First, it is important to recognize that connectivity simply measures the similarity between signals recorded at two different sites, with any relations drawn to neural communication pathways being inferred rather than directly assessed (Cohen, 2014). Second, it is important to remember that activity in the high-alpha frequency band is said to have an inverse relationship with cortical activity (Klimesch, 2012). Based on these two points, one would expect that the functional interpretation of any changes in high-alpha connectivity over time should consider whether absolute high-alpha power increased or decreased during the same time period. In previous studies simultaneously measuring power and connectivity, high-alpha power decreased (Gallicchio et al., 2017; Hatfield et al., 2013; Kerick et al., 2004), and, hence, the simultaneous increase in high-alpha connectivity that those studies reported could indeed represent more similar *co-activation* of the two sites. However, if high-alpha power increased, as in the present study, increased high-alpha connectivity could represent more similar *co-inhibition* of two sites. Consequently, our finding of increased left-frontotemporal connectivity with practice could reflect a progressively stronger inhibitory communication between left-temporal and frontal electrode sites that characterized both types of training. It would be interesting for future studies to scrutinize this interpretation by comparing connectivity between tasks or regions known to be associated with practice-induced increases versus decreases in power, or to examine connectivity when power has been experimentally manipulated (e.g., via neurofeedback training).

Conscious processing and performance during pressure

Our second set of predictions concerned psychological pressure. Specifically, based on reinvestment theory (Masters & Maxwell, 2008), we expected that an increase in pressure would elicit increases in conscious processing and possibly de-chunking of the movements in explicit trainees. In contrast, we expected this to be less likely for implicit trainees since implicit training should limit the accrual of verbal-analytic rules that would be needed for reinvestment to occur. Although manipulation check data suggested that cognitive anxiety and movement self-consciousness increased significantly from the last block of acquisition to transfer (A4 to T), our results indicate that choking did not occur. Rather, performance improved in both groups, alongside further changes in self-report and EEG measures characteristic of those already observed during the acquisition phase. As a consequence, it was not possible to conclusively support or refute reinvestment theory's prediction that de-chunking and increased conscious processing cause choking under pressure among explicit learners and not among implicit learners.

The absence of choking might be attributed to the high number of trials during the transfer block diluting the effect of our pressure manipulation, and resulting in moderate levels of conscious processing which did not impair performance (e.g., Cooke et al., 2014). With fewer trials the pressure manipulation would likely have been stronger (cf., Woodman & Davis, 2008), providing a greater chance for choking and, possibly, de-chunking to occur. However, simply reducing the number of trials is problematic as it compromises the EEG signal-to-noise ratio (Cohen, 2014). An alternative solution to this issue would be to employ multiple, potentially more impactful stressors (e.g., a live audience), and/or recruit participants with dispositionally high-levels of anxiety and/or self-consciousness (e.g., Zhu et al., 2011). Future investigations on choking under pressure should consider these methodological practicalities.

Limitations and future directions

Our results should be interpreted in light of certain methodological limitations. First, we concede that our task lacked ecological validity, with participants using only their index finger to make movements. While this task was chosen, based on previous research (e.g., Sakai et al., 2003), due to its suitability for evaluating chunking/de-chunking, we recommend that future investigations employ more complex motor tasks involving the coordination of multiple joints such as occurs in sport. Indeed, it is possible that movements involving more degrees of freedom than we investigated here would encourage the accrual of even more verbal-analytic rules during explicit acquisition, and provide an increased likelihood of choking under pressure (Zhu et al., 2010).

Second, although in our study participants reached a high-degree of proficiency, there was still scope for further improvement since the movements were not fully chunked at the end of acquisition. Thus, we cannot rule out the possibility that had we trained participants for longer, the sequence would have likely become even more automatized, and a reinvestment related de-chunking under pressure more probable. Future endeavours aiming to further examine reinvestment theory's prediction that de-chunking causes choking under pressure among explicit learners would do well to ensure that participants are trained to an extremely high-level of proficiency before the undertaking the pressure test. This is because, according to reinvestment theory de-chunking occurs in movements that are highly automated (Masters & Maxwell, 2008). In contrast, contingencies that increase conscious processing (e.g., pressure) among performers at cognitive and associative stages of acquisition may enhance performance (e.g., Beilock, Carr, MacMahon, & Starkes, 2002; Gray, 2004; Malhotra et al., 2015). In addition to extending the acquisition phase, future studies could also introduce a period of sleep consolidation, which has been argued to further automatize skills (e.g., Mazza et al., 2016; Walker & Stickgold, 2006), prior to delayed retention and pressure tests. Delayed retention tests in particular would allow assessment of the extent to which participants truly learned the sequence, rather than their proficiency at acquiring and memorising it in a single day, as we tested here.

Third, although the two tasks employed here induced relatively errorful and errorless forms of training, it is possible that participants in our so-called implicit group still used some degree of conscious processing to perform the task. We are confident that our tasks provided appropriate conditions to foster relatively high (explicit) and low (implicit) levels of hypothesis testing (see Abrahamse et al., 2013, Sakai et al., 2003), but future investigations could design different tasks that further dichotomize explicit and implicit training to their extremes.

Fourth, it is important to recognize that EEG is limited by poor spatial resolution. Thus, despite being frequently advocated in the literature, the assumption that electrical activity recorded by T7 and Fz electrodes reflects verbal-analytic and motor planning processes, respectively, is overly simplistic (Cooke, 2013). Although resolving the *inverse problem* with certainty is mathematically impossible, applying spatial filters such as surface Laplacian, independent component analyses (ICA), or generalized Eigen decomposition (GED) could all improve the spatial resolution of EEG and allow more confident assertions about the underlying generators of the signals recorded on the scalp to be made (Cohen, 2014; Delorme & Makeig, 2004; Perrin, Pernier, Bertrand, & Echallier, 1989). However, all these solutions would require a higher number of electrodes than were employed here. It is important for future research to adopt denser electrode arrays and apply spatial analyses such as these to gain much greater insight into the underlying cortical dynamics of explicit versus implicit learning and performance under pressure.

Fifth, in light of the inconsistencies between our self-report and cortical measures of conscious processing, it is possible that both high-alpha T7 power and T7-Fz connectivity are influenced by a broader range of processes than simply verbal-analytic conscious processing. For example, motivational self-talk may involve some activation of the language regions, without involving conscious motor processing (cf., Hardy, 2006). Accordingly, within and between-person variability in the use of motivational self-talk could confound our interpretation of left temporal high-alpha power and connectivity. Assessing how power and connectivity change based on the direct manipulation of instructional versus motivational self-talk during motor skill acquisition and performance under pressure would facilitate further understanding of our cortical markers. This would be a fruitful avenue for future research.

Finally, we would also encourage future research to more closely examine individual differences variables in addition to the practice schedule (i.e., explicit versus implicit) factor employed here. For instance, personality traits such as reinvestment or neuroticism are likely to moderate the relationship between chunking, conscious processing, and performance under pressure (e.g, Barlow, Woodman, Gorgulu, & Voyzey, 2016). Such designs might be better equipped to test reinvestment theory's specific de-chunking prediction, because anecdotal evidence indicates that de-chunking (choking) under pressure does not occur uniformly for all individuals during all pressure situations.

In conclusion, by simultaneously examining chunking and a combination of self-report and psychophysiological measures of conscious processing during both explicit and implicit acquisition, and transfer (pressure), this large-scale EEG experiment is the first to specifically investigate reinvestment theory's pivotal dechunking hypothesis and provides the most comprehensive test of the theory to date. Our results confirmed that chunking is a general mechanism underpinning both explicit and implicit motor sequence acquisition (e.g., Hikosaka et al., 1999; Song & Cohen, 2014; Willingham, 1998). They also provide new neurophysiological evidence that explicit training can support quicker chunking than implicit training by promoting the active inhibition of the left-hemisphere, and a more pronounced increase in cortical efficiency. While the specific de-chunking hypothesis of reinvestment theory warrants further scrutiny, our results add support to the literature endorsing explicit learning as a means of accelerating movement acquisition, and provide a new neurophysiological explanation why.

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