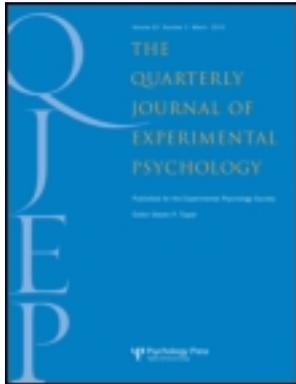


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The implicit learning of metrical and nonmetrical temporal patterns

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Implicit learning (IL) occurs unintentionally. IL of temporal patterns has received minimal attention, and results are mixed regarding whether IL of temporal patterns occurs in the absence of a concurrent ordinal pattern. Two experiments examined the IL of temporal patterns and the conditions under which IL is exhibited. Experiment 1 examined whether uncertainty of the upcoming stimulus identity obscures learning. Based on probabilistic uncertainty, it was hypothesized that stimulus-detection tasks are more sensitive to temporal learning than multiple-alternative forced-choice tasks because of response uncertainty in the latter. Results demonstrated IL of metrical patterns in the stimulus-detection but not the multiple-alternative task. Experiment 2 investigated whether properties of rhythm (i.e., meter) benefit IL using the stimulus-detection task. The metric binding hypothesis states that metrical frameworks guide attention to periodic points in time. Based on the metric binding hypothesis, it was hypothesized that metrical patterns are learned faster than nonmetrical patterns. Results demonstrated learning of metrical and nonmetrical patterns but metrical patterns were not learned more readily than nonmetrical patterns. However, abstraction of a metrical framework was still evident in the metrical condition. The present study shows IL of auditory temporal patterns in the absence of an ordinal pattern.

Keywords: Meter; Rhythm; Temporal cognition; Process dissociation procedure.

Rhythm surrounds us constantly, whether it is the hum of an oscillating fan or the drum and bass from an mp3-player. Exposure to rhythms allows

humans to develop temporal expectancies—that is, knowledge of when something should occur. Temporal expectancies are useful in a range of

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human activities and interactions such as music, dance, and language. Temporal expectancies can be acquired with an intention to learn (Chapin et al., 2010) or unintentionally (e.g., Brandon, Terry, Stevens, & Tillmann, 2012; Karabanov & Ullén, 2008; Salidis, 2001; Ullén & Bengtsson, 2003). However, how humans unintentionally learn nonverbal rhythms has received little consideration. Furthermore, of the studies that have examined the unintentional learning of rhythm, only a few have demonstrated learning (e.g., Brandon et al., 2012; Karabanov & Ullén, 2008; Salidis, 2001; Ullén & Bengtsson, 2003). The present study has two aims: first, to investigate the conditions under which the implicit learning of temporal patterns can be observed; second, to examine how rhythmic properties of temporal patterns—namely, meter—might aid implicit learning.

Implicit learning of temporal patterns

Implicit learning (IL) is learning that occurs unconsciously, unintentionally, and without the ability to show declarative knowledge of what has been learned (Shanks, 2005). IL allows humans to learn complex structures with less effort and attention than does deliberate learning (Perruchet & Pacton, 2006; Reber & Lewis, 1977). Temporal patterns are constructed from a series of temporal intervals between subsequent event onsets (Povel & Essens, 1985). A complex temporal pattern is formed through the sequencing of temporal intervals of varying length. For example, the Morse code signal for “SOS” ($\cdot\cdot\cdot\text{---}\text{---}\text{---}\cdot\cdot\cdot$), where intervals between the onsets of short (\cdot) events are half as long as intervals between the onsets of long (---) events, is a temporal pattern that consists of the relative intervals 1–1–1–2–2–2–1–1–1. Ordinal patterns are constructed from an ordered series of movements or stimuli that vary along one or more categorical dimensions (e.g., different spatial locations or different pitches). For example, an ordinal pattern of letters A, B, and C could be A–C–B–C–A–B–C–B.

Few studies have investigated the IL of temporal patterns, and, of those that have, most have only shown IL of temporal patterns in the presence of a predictable ordinal pattern (e.g., Buchner &

Steffens, 2001; Miyawaki, 2006; O’Reilly, McCarthy, Capizzi, & Nobre, 2008; Shin, 2008; Shin & Ivry, 2002). Those studies have generally used visual stimuli (except Buchner & Steffens, 2001) and have been unable to observe temporal learning when the ordinal pattern is not predictable. In contrast, the studies that have demonstrated IL of temporal patterns in the absence of an ordinal pattern have used auditory–visual stimuli in an immediate recall task (Karabanov & Ullén, 2008; Ullén & Bengtsson, 2003), or auditory stimuli in a stimulus-detection task (Salidis, 2001) or three-alternative forced-choice task with a random ordinal sequence (Brandon et al., 2012). The present study uses auditory stimuli to explore two possible explanations for the mixed results of temporal pattern learning in previous studies: probabilistic uncertainty regarding the identity of upcoming stimuli, and temporal uncertainty regarding inter-onset intervals.

Probabilistic uncertainty of stimulus identities

Previous experiments have used the serial reaction-time task (SRT) to investigate the learning of temporal patterns in the presence of ordinal patterns of tones (Buchner & Steffens, 2001) or visual spatial locations (O’Reilly et al., 2008; Shin, 2008; Shin & Ivry, 2002). In the SRT, participants are presented with sequential stimuli and are asked to identify each item as it occurs (Nissen & Bullemer, 1987). Participants are not informed that stimuli follow a repeating pattern. Learning is characterized by decreases in reaction time (RT) over blocks containing the repeating pattern, increases in RT upon introduction of a block containing a random or novel sequence (i.e., a test block), and recovery of RT to pretest levels when the repeating pattern is reintroduced.

In some SRT studies (O’Reilly et al., 2008; Shin & Ivry, 2002), both the timing and the identities of the stimuli followed a repeating pattern. Independent learning of the temporal pattern was measured by comparing RT increases when the temporal sequence was random but the ordinal pattern was maintained, with RT increases when

the ordinal sequence was random but the temporal pattern was maintained. When examining RT increases in test blocks, these studies have found greater RT increases when the ordinal sequence is random than when the temporal sequence is random and concluded that temporal patterns cannot be learned in the absence of an ordinal pattern. However, in the SRT (which requires identification of the ordinal events), when the ordinal sequence is random, participants are unable to prepare for the next response because the identity of the stimulus is unpredictable, even if they have knowledge of the temporal pattern. Thus, it is possible that the multiple-alternative forced-choice SRT paradigm was insensitive to temporal knowledge due to probabilistic uncertainty of the identity of the next stimulus.

Based on probabilistic uncertainty, whenever the ordinal sequence is random, the exhibition of temporal knowledge could be underestimated or masked by uncertainty of the identity of the upcoming stimulus (as suggested by Ullén & Bengtsson, 2003). A task that does not require stimulus identification, such as a stimulus-detection task, might be a more sensitive test of temporal pattern learning. In fact, Salidis (2001) demonstrated IL of temporal patterns using a stimulus-detection task. Salidis, however, used nonmusical temporal patterns whereas our present study uses complex musical rhythms.

To examine whether temporal pattern learning occurs when responses are not dependent on the identity of the stimulus, the present study compares a multiple-alternative forced-choice task with a stimulus-detection task. It is hypothesized that IL of temporal patterns occurs more strongly in the absence of probabilistic uncertainty of responding to the identity of the stimulus—that is, in the stimulus-detection task.

Temporal uncertainty of inter-onset intervals

Another possible reason for why temporal pattern learning was not observed in previous studies is that the majority of these studies (e.g., Buchner & Steffens, 2001; Miyawaki, 2006; Shin & Ivry, 2002, Experiment 1) have used patterned response-

stimulus intervals. With response-stimulus intervals, the inter-onset interval (IOI) consists of both the response-stimulus interval itself (controlled by the experimental design) and the RT of the participant (uncontrolled). As IOIs produced by response-stimulus intervals (inclusive of RT) can be variable, participants may have difficulty acquiring temporal expectancies for the onset of events. Musical rhythms, however, consist of fixed IOIs that could facilitate the acquisition of temporal expectancies.

Research into music cognition (e.g., Järvinen & Toiviainen, 2000; Palmer & Krumhansl, 1990) suggests that musical rhythm has properties, such as meter, that aid in the acquisition of temporal expectancies. Rhythm is the “systematic patterning of sound in terms of timing, accent, and grouping” (Patel, 2008, p. 96). Meter is a cognitive framework that can be abstracted from rhythm. A metrical framework consists of an underlying isochronous (evenly spaced) pulse that periodically aligns with event onsets at the level of the pulse and equal groupings of pulses (London, 2004). An arrangement of the pulse and pulse groupings is shown in Figure 1. The grouping of pulses depends on the meter that is abstracted and how often events correspond with pulses (Lerdahl & Jackendoff, 1981).

Three types of rhythms are described here: strongly metrical (SM), weakly metrical (WM), and nonmetrical (NM) rhythms (Essens & Povel, 1985; Povel & Essens, 1985). Rhythms are SM if events always occur on the first pulse (i.e., the strong beat) of a group of pulses (also called a measure). Rhythms are WM when events do not always occur on the strong beat, but still often align with the pulse. Lastly, a rhythm is considered nonmetrical if events rarely align with the pulse or the strong beat. Examples of SM, WM, and nonmetrical rhythms are presented in Figure 1. In the SM example, events occur periodically every four pulses. This periodicity is not realized in the WM example. In the case of nonmetrical patterns, events rarely fall on pulses and do not occur periodically.

The *dynamic attending theory* (Jones & Boltz, 1989) relates to how temporal expectancies are formed. The dynamic attending theory supposes that attention oscillates over time and that attending oscillations adaptively synchronize to

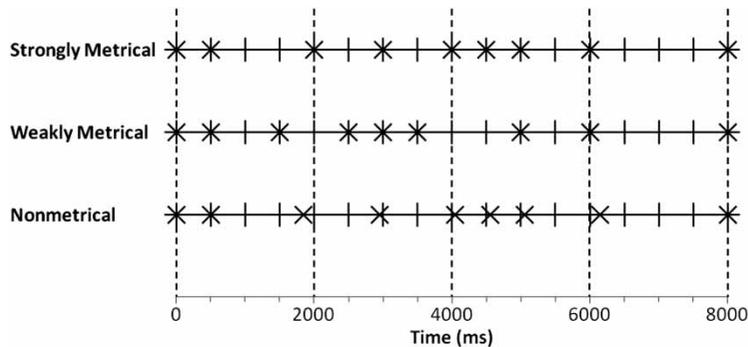


Figure 1. Pulses (short vertical lines), strong beats (long vertical lines), and events (crosses) of the strongly metrical, weakly metrical, and nonmetrical temporal patterns.

regularities in the timing of external events. This process is called entrainment. The periodic occurrence of events within a metrical framework can induce entrainment, thus strengthening expectancies (and quicken responses) for event onsets that conform to the metrical framework. The *metric binding hypothesis* (Jones, 2009) is an extension of the dynamic attending theory that relates to how meter is learned through exposure to rhythm. While the dynamic attending theory relates to “in-the-moment” expectancies” (Jones, 2009, p. 83), the metric binding hypothesis posits that when two or more oscillations are concurrently established, the levels of entrainment will eventually bind and form a “metric cluster” (Jones, 2009, p. 84). Metric clusters consist of multiple concurrent oscillations with continuing associations at various time levels based on bindings. Metric clusters strengthen expectancies to various metrical levels; in other words, expectancies are strengthened in pulse locations, the first pulse of groups, and coincidences of the two.

With repeated exposure to an external rhythm, internal entrainment to the rhythm and the formation of a metrical framework may occur (Large & Jones, 1999). In this way, temporal regularities activate oscillators that guide attention to metrical points in time when a metrical framework is available and can be momentarily perturbed if an event does not align with the metrical framework. In line with the dynamic attending theory, evidence from

sensorimotor synchronization (e.g., Essens & Povel, 1985; Patel, Iversen, Chen, & Repp, 2005; Povel & Essens, 1985), psychophysical (e.g., Grube & Griffiths, 2009), and neuroscience (e.g., Vuust, Ostergaard, Pallesen, Bailey, & Roepstorff, 2009) research suggests that people have greater difficulty developing temporal expectancies in response to WM and nonmetrical patterns than in response to SM patterns.

Based on the dynamic attending theory and the metric binding hypothesis, we hypothesized that metrical patterns can be learned more readily than nonmetrical patterns. We also hypothesized that, when trained on SM patterns, greater performance decrements occur when a new rhythm with a weaker metrical framework is introduced (i.e., WM patterns) than when the new rhythm maintains the original metrical framework (i.e., a novel SM pattern; in Experiments 1 and 2). Such differences were not expected for nonmetrical patterns as metric binding cannot occur during training (in Experiment 2).

Using the modified process dissociation procedure to determine implicit learning

The SRT assesses whether learning has occurred and how much learning has occurred, but it does not assess whether the newly acquired knowledge is implicit. To ensure that learning in the SRT is implicit, modified versions of the *process dissociation*

procedure (Jacoby, 1991) were used. The process dissociation procedure is a measure of implicit learning where the method avoids the assumption of process purity—that is, the assumption that performance in a particular task represents one process (Shanks & St. John, 1994). In the process dissociation procedure, each participant is required to perform a task under two different types of instruction: inclusion and exclusion. The inclusion instruction requires participants to demonstrate knowledge of what has been learned. The exclusion instruction requires participants to suppress knowledge about what has been learned (e.g., completing word stems with different words from those learned in a study phase; Jacoby, Toth, & Yonelinas, 1993). While performance under the inclusion instruction is facilitated by both explicit and implicit processes, performance under the exclusion instruction is facilitated by explicit processes and interfered with by implicit processes. Thus, differences between the two instructions can provide insights into the contribution of implicit and explicit influences.

Initially, the process dissociation procedure involved only a recollection task but several modifications of the process dissociation procedure have since been established (e.g., Destrebecqz & Cleeremans, 2001, 2003). An adaptation of the process dissociation procedure that has been successfully used to ascertain implicit and explicit temporal pattern learning is the free-generation task (Karabanov & Ullén, 2008). In the free-generation task, participants generate patterns under two types of instruction: (a) an inclusion instruction, where participants are asked to reproduce the training pattern, and (b) an exclusion instruction where participants are asked to create new rhythmic sequences. The sequences produced in both tasks are then compared to the pattern learned in the SRT and are given similarity scores that reflect how much they resemble the training pattern. If similarity in the inclusion instruction is less than or equal to similarity in the exclusion instruction, then declarative knowledge of the training pattern has not been shown, and learning is implicit. By contrast, higher similarity scores in the inclusion instruction than the

exclusion instruction indicate that learning is explicit.

Karabanov and Ullén (2008) demonstrated that similarity was greater in the inclusion instruction than in the exclusion instruction for an explicit learning condition, but not an implicit learning condition. Thus, the generation task can be used to assess whether learning is implicit. The present study used a generation task and analysis (see Appendix) based on the process dissociation procedure, using the methods of Karabanov and Ullén (2008), to test whether learning was implicit.

EXPERIMENT 1

The aim of Experiment 1 was to determine whether metrical rhythms can be learned implicitly in an SRT. We investigated whether the IL of (strongly) metrical rhythms is evident in the single response SRT (i.e., stimulus-detection task) compared with the traditional multiple response SRT (i.e., a three-alternative forced-choice task).

Design and hypotheses

In the SRT, participants completed nine blocks where Blocks 1–5, 7, and 9 contained the repeating temporal pattern, and Blocks 6 and 8 contained the SM and WM test patterns (the presentation order of test patterns was counterbalanced across participants). Independent variables were block (1–9; within-subjects), test block type (SM, WM; within-subjects), and task (single response, multiple response; between-subjects). Responses were retained if the spatial location was correctly identified (in the multiple response SRT) and if the response occurred close to the stimulus onset—that is, between 100 ms and 850 ms for the multiple response SRT, and between –100 ms and 650 ms for the single response SRT. Dependent variables were proportion of retained responses, RT, improvement of RT over training blocks (i.e., RT difference between first and last training block), and RT increase in test blocks defined as the difference between RT in test blocks and mean RT in adjacent training blocks (Shin & Ivry, 2002).

It is hypothesized that metrical rhythms can be learned implicitly. Learning would be indicated by a decline in RT over training blocks in the SRT. RT increases in test blocks were used to examine whether the rhythmic structure and metrical framework were learned. If the metrical framework is learned, then greater RT increases should occur when the strength of the metrical structure is changed in the WM test block than when it remains the same in the SM test block. IL is indicated in the generation task if similarity in the inclusion instruction is not greater than similarity in the exclusion instruction. It is also hypothesized that temporal pattern learning should be demonstrated when the task is not affected by probabilistic uncertainty of stimulus identities, indicated by greater RT improvement in the single response SRT than in the multiple response SRT.

Method

Participants

Participants ($N=60$) were first-year psychology students from the University of Western Sydney. Of these students, 12 were male. Ages ranged from 17 to 45 years, with a mean age of 22.5 years ($SD=6.70$). No participants reported a hearing impairment, and 59 of the participants were right-handed.

Materials

Sequences consisted of tones constructed from a triangle waveform of 394 Hz (200 ms duration, 94 dB SPL, 10 ms rise/decay times) created with MAX-MSP software. The tone was presented through the left channel, the right channel, or both channels, henceforth referred to as "tone location". Tone location is the stimulus identity in the present study. To prevent effects of binaural summation (Marks, 1978), the presentation through both channels was 4 dB less (i.e., 90 dB) than monaural presentation.¹

Each block consisted of 24 repetitions of the eight-event pattern (plus one event to complete

the final interval) without breaks between patterns, with a total of 193 events per block. Within each block, the order of tone location was pseudorandom so that the frequency of occurrence of each location was equal, no location was repeated twice in a row, and the location frequency was equally distributed over the eight events of a pattern. Different location orders were used for each of the nine blocks. Three different distributions of the nine location orders across blocks were used (counterbalanced across participants). The eight-item patterns (duration 8 s) were repeated 24 times to create an auditory file for each block (using MatLab).

Temporal patterns were constructed based on the SM and WM patterns of Povel and Essens (1985). Povel and Essens presented a clock model where metrical strength was defined by how often rhythmic accents corresponded with metrical accents. Rhythmic accents are perceptual accents that occur (a) on isolated events, (b) on the second event of a group of two events, and (c) on the first and last event of a group of three or more (Povel & Essens, 1985). The clock model measured metrical strength with a counterevidence score (c score) where lower scores represented greater metrical strengths. Patterns in the present study were categorically SM and WM as per the clock model with SM patterns (training and test patterns) fitting in the more strongly metrical categories (c score = 1), and the WM pattern fitting in the more weakly metrical categories (c score = 4).

The timing of tones occurred according to metrical rhythms based on patterns of IOIs, as shown in Figure 2. For example, the SM training pattern in Figure 2 refers to an IOI pattern of 500–1,500–1,000–1,000–500–500–1,000–2,000. Patterns in Experiment 1 consisted of three 500-ms IOIs, three 1,000-ms IOIs, one 1,500-ms IOI, and one 2,000-ms IOI. Patterns maintained simple frequency information as outlined by Reed and Johnson (1994). Simple frequency information refers to statistical features of patterns that follow second-order conditional probabilities. Namely,

¹ An experiment ($N=12$) was conducted to determine the point of subjective equality between the loudness of the binaural and monaural stimuli. A 4 dB reduction in the intensity of the binaural stimulus resulted in subjective equality for 11 of the 12 participants.

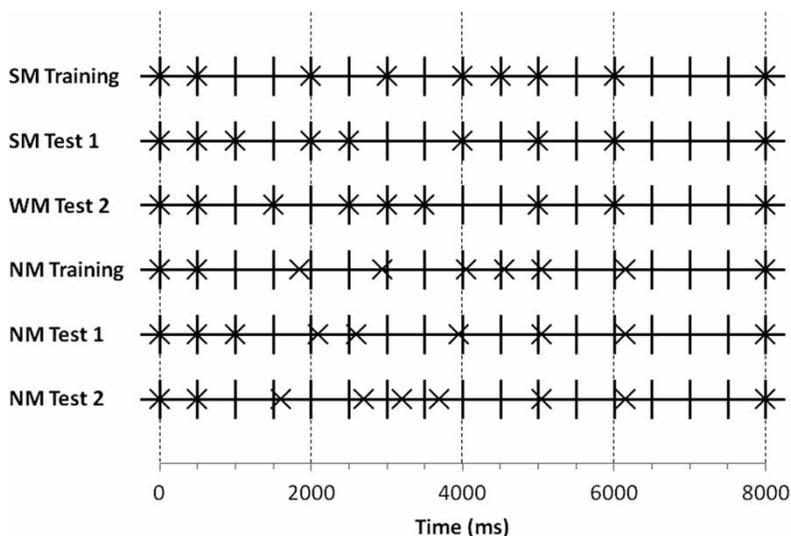


Figure 2. Pulses (short vertical lines), strong beats (long vertical lines), and events (crosses) of the metrical (SM training, SM Test 1, WM Test 2) and nonmetrical (NM training, NM Test 1, NM Test 2) temporal patterns used in the present study (SM = strongly metrical; WM = weakly metrical; NM = nonmetrical). Metrical patterns were used in Experiments 1 and 2, and nonmetrical patterns were only used in Experiment 2.

these features are the item frequency (the number of times an IOI occurs in a pattern), transition frequency (the number of times a pair of items occur in the same order), the rate of full coverage (the average number of items necessary to view each unique IOI in the pattern at least once), and the rate of full transition usage (the average number of items necessary to view each transition at least once).

Simple frequency information was maintained for the SM training, SM test (except for rate of full coverage), and WM test patterns. Furthermore, the number of changes to higher order conditional probabilities (i.e., third-, fourth-, fifth-order conditional probabilities and higher) was kept constant between the training block and SM and WM test blocks. Control of these features is important so that RT increases in test blocks cannot be attributed to changes in simple frequency information (i.e., not to changes in surface statistical features) but, instead, to changes in metrical and rhythmic features.

It should also be noted that the size of rhythmic groupings (i.e., groups of two or three proximal events) were kept constant between patterns in the training block and test blocks, while the order

in which groups occurred changed. This means that RT increases in test blocks cannot be attributed to differences in motor demands or grouping differences related to changes in the sizes of groups of temporally proximal events.

The SRT consisted of five blocks containing the SM training pattern followed by the SM or WM test pattern in the sixth and eighth blocks (the test block). The order in which the test blocks were introduced (i.e., first SM then WM, or first WM then SM) was counterbalanced over participants. The training pattern was reintroduced in the seventh and ninth blocks. Each block had a duration of 3.12 min. A 15 s break occurred between blocks.

Auditory stimuli were presented through Sennheiser HD650 headphones using Edirol UA-25EX sound drivers. PsyScope (Cohen, MacWhinney, Flatt, & Provost, 1993) software (installed on Macbook Pros) was used to present the auditory file and collect responses.

Procedure

Participants were given an information sheet that provided the cover story of a computer game for

the blind where they would hear a sound from the left, right, or both headphones. The cover story was used to promote IL and reduce awareness of temporal patterns. After reading the information sheet and signing the consent form, participants were seated in front of the computer and received instructions that related to the specific condition. Participants in the multiple response SRT were asked to use keys "1", "2", and "3" on the number pad to respond to the left channel, both channels, or right channel, respectively. Keys were labelled according to stimulus identity, and participants were able to view these labels at all times. Participants in the single response SRT were asked to press the "0" key every time they heard a beep regardless of which channel(s) the sound came from. Prior to the blocks, there was a practice block that contained approximately four repetitions of a different WM pattern (with duration of 30 s). Following the practice, the SRT commenced.

After the SRT, participants were asked whether they: (a) noticed anything peculiar in the SRT, or (b) noticed any regularity in the SRT, and to write down the peculiarities or regularities they noticed (Karabanov & Ullén, 2008; Shin & Ivry, 2002; Ullén & Bengtsson, 2003). These responses were coded according to whether participants reported a timing regularity/rhythm or not. Any terminology that reflected a timing regularity (e.g., rhythm, timing pattern, regular timing) was accepted as an indication of awareness of the temporal pattern. Then participants completed the generation task. The order of instruction (inclusion and exclusion) within the generation task was counterbalanced across participants.

In the generation task, participants were to generate sequences by tapping the "0" key. The binaural tone used in the SRT was presented for each key-press. In the inclusion instruction, participants were asked to reproduce the temporal patterns from the SRT. The exclusion instruction required participants to create new temporal

patterns that are different from those in the SRT, but use the same number of beeps and the same groups of beeps (e.g., groups of one, two, three, etc.). This instruction was given to prevent participants from producing isochronous temporal sequences in the exclusion instruction. Participants were instructed to produce the pattern at least twice and were given 20 s for each attempt and five attempts overall. Experiment sessions did not exceed 60 minutes.

Data analysis

Only RTs to correct responses were analysed. In each block, the response to the first item was removed. Responses that were inaccurate, early (multiple response task < 100 ms; single response task < -100 ms), or late (multiple response task > 850 ms; single response task > 650 ms) were removed.² As only one response was possible for the single response condition, proportion of retained responses for the single response condition only reflects the percentage of responses that fell within the window -100 ms to 650 ms. Anticipatory responses were allowed for the single response condition because participants were able to predict when a stimulus should occur (as in O'Reilly et al., 2008; Shin & Ivry, 2002). To examine rate of learning in the SRT, we compared RT improvement over training blocks (i.e., the difference between the first and fifth blocks) between the single response and multiple response SRT. To assess differences between SM and WM test blocks, the dependent variable RT increase (calculated as the RT difference between the mean of adjacent training blocks and the test block) was used with test block meter (SM, WM) as a within-subjects independent variable and task (single response, multiple response) as a between-subjects independent variable. For the generation task, similarity was compared between instruction (inclusion, exclusion; within-subjects)

² A number of different thresholds for early and late responses were implemented for the multiple response and single response conditions. These thresholds were chosen in order to maximize the number of responses retained. Using other thresholds did not greatly affect the pattern of RT, but it did result in decreases in the proportion of retained responses in the single response condition when anticipatory responses occurred. No such anticipatory responses were evident in the multiple response condition.

and between task (single response, multiple response; between-subjects).

Results

Two participants in the multiple response group were excluded due to more than 33% of responses being inaccurate, early, or late. To ensure the sample only contained implicit learners, participants who reported a timing regularity or rhythm in the free verbal reports were excluded from the analysis. However, it should be mentioned that previous studies have suggested that verbal reports are an insensitive measure of IL (Karabanov & Ullén, 2008; Shanks & St John, 1994). The remaining sample consisted of 19 participants in the single response condition (of 25 participants) and 30 participants in the multiple response condition (of 35 participants).

The serial reaction-time task

Proportion of retained responses

A repeated measures analysis of variance (ANOVA) was conducted on the proportion of retained responses with block (1–9) as a within-subjects variable and task (single response, multiple response) as a between-subjects variable. There was a significant main effect of task, $F(1, 47) = 42.97$, $p < .001$, $\eta_p^2 = .48$, indicating that fewer responses were retained in the multiple response condition ($M = .71$, $SD = .17$) than in the single response condition ($M = .94$, $SD = .06$). No significant main effect of block, $F(8, 376) = 0.69$, $p = .70$, $\eta_p^2 = .01$, or interaction between block and task, $F(8, 376) = 0.88$, $p = .53$, $\eta_p^2 = .02$, was evident.

Reaction time

A repeated measures ANOVA was conducted on RT with block (1–9) as a within-subjects variable and task (single response, multiple response) as a between-subjects variable. Only RTs for correct responses were considered in the analysis. The main effect of block, $F(8, 376) = 8.37$, $p < .001$, $\eta_p^2 = .15$, and task, $F(1, 47) = 338.08$, $p < .001$, $\eta_p^2 = .88$, was significant, as was the interaction between block and task, $F(8, 376) = 4.61$, $p = .003$,

$\eta_p^2 = .09$. The main effect of task reflects that RTs were slower for the multiple response SRT than for the single response SRT. The interaction between block and task reflects that there were differences in the pattern of RT over blocks between single response and multiple response tasks.

To test the hypothesis that learning is more evident in the single response SRT than in the multiple response SRT, RT improvement over training blocks (i.e., the difference between Blocks 1 and 5) was calculated for each participant. A significant main effect of task was evident, $F(1, 47) = 19.27$, $p < .001$, $\eta_p^2 = .29$, with RT improvement for the single response condition ($M = 67.10$, $SD = 62.28$) being significantly greater than that for the multiple response condition ($M = 8.01$, $SD = 31.79$). RT improvement for the single response condition differed significantly from zero, $t(18) = 4.70$, $p < .001$, and RT improvement for the multiple response condition was not significantly different from zero, $t(29) = 1.38$, $p = .18$. This suggests that the single response SRT demonstrated stronger learning than the multiple response SRT (see Figure 3a).

To test the hypothesis that metrical patterns are learned, RT differences between test blocks (SM, WM) and the mean RT of adjacent blocks (preceding and following blocks) were examined in a repeated measures ANOVA with test block type as a within-subjects factor and task as a between-subjects factor. Main effects were significant for test block type, $F(1, 46) = 34.80$, $p < .001$, $\eta_p^2 = .43$, and task, $F(1, 46) = 19.86$, $p < .001$, $\eta_p^2 = .30$, and a significant interaction was evident between test block type and task, $F(1, 46) = 12.02$, $p = .001$, $\eta_p^2 = .21$. One-sample t tests revealed that RT increases were significantly greater than zero in the single response SRT for both SM ($p = .03$) and WM ($p < .001$) test blocks. The multiple response SRT did not show a significant RT increase for the SM test block ($p = .98$), but demonstrated a significant RT increase for the WM test block ($p = .004$). Planned comparisons for test block type (SM, WM) were conducted for the single response and multiple response tasks. As shown in Figure 3b, in the single response SRT,

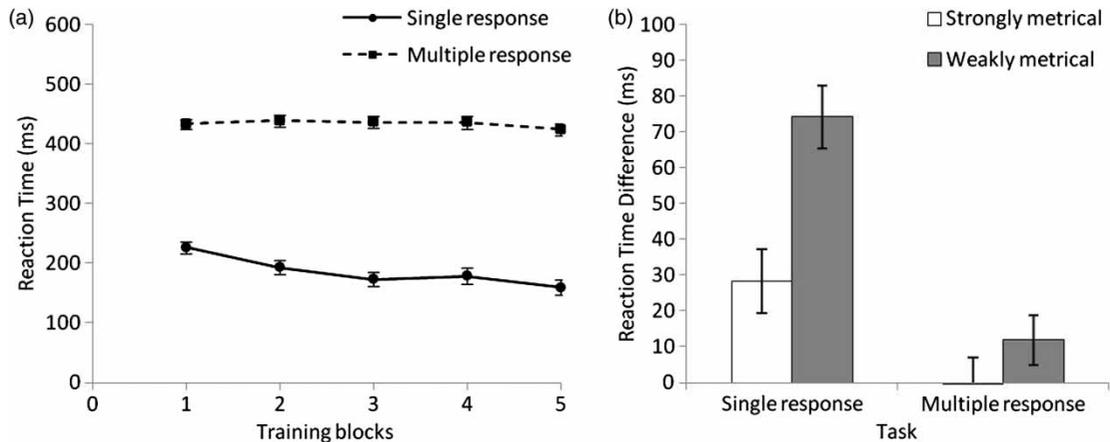


Figure 3. Results from the serial reaction-time task (SRT) in Experiment 1. (a) Mean reaction time (RT; correct responses only) for the single response and multiple response conditions over blocks. Blocks 1–5 contain the training pattern. Error bars represent standard error of the mean. (b) Mean RT increases between the test block and the mean of the adjacent blocks for strongly metrical and weakly metrical test blocks in the single response and multiple response conditions. Error bars represent standard error of the mean.

RT increases were significantly greater for the WM test block than for the SM test block, $F(1, 24) = 10.23, p = .004, \eta_p^2 = .30$. Similarly, in the multiple response SRT, RT increases were significantly greater for the WM test block than for the SM test block, $F(1, 30) = 5.76, p = .02, \eta_p^2 = .16$.

Generation task

Similarity scores between the IOI sequence generated by participants and the IOI sequence of the training pattern were calculated by comparing the sequences generated under inclusion and exclusion instructions with the pattern from the training blocks. To adjust for differences in tempo, the generated IOIs were normalized so that the shortest IOI was equal to 500 ms (i.e., the shortest IOI of the training pattern). A generated interval was considered correct if it was within $\pm 30\%$ of the training pattern interval and occurred in the correct position of the pattern—that is, in the correct order. To account for the use of different starting positions, a similarity score was calculated using each possible starting point of the generated sequence, and the maximum score was used in analyses (see Appendix).

Similarity scores in the generation task were analysed using a 2×2 repeated measures ANOVA with instruction (inclusion, exclusion) as a within-subjects factor and task as a between-subjects factor. There was no significant main effect of instruction, $F(1, 47) = 0.06, p = .80, \eta_p^2 = .001$, no significant main effect of task, $F(1, 47) = 0.30, p = .59, \eta_p^2 = .006$, and no significant interaction between instruction and task, $F(1, 47) = 0.20, p = .68, \eta_p^2 = .004$ (see Figure 4). This suggests that learning in the SRT was implicit. Performance under both instructions and for both tasks was significantly greater than chance (estimated at .27; see Appendix; $ps < .001$) indicating that participants were not responding randomly and were able to reproduce some part of the pattern under the inclusion instruction and were unable to suppress learned knowledge in the exclusion instruction.

Reports of awareness

In the single response condition, six participants reported awareness of a timing regularity or rhythm, and 19 participants did not report awareness of a temporal pattern. In the multiple response condition, three participants reported

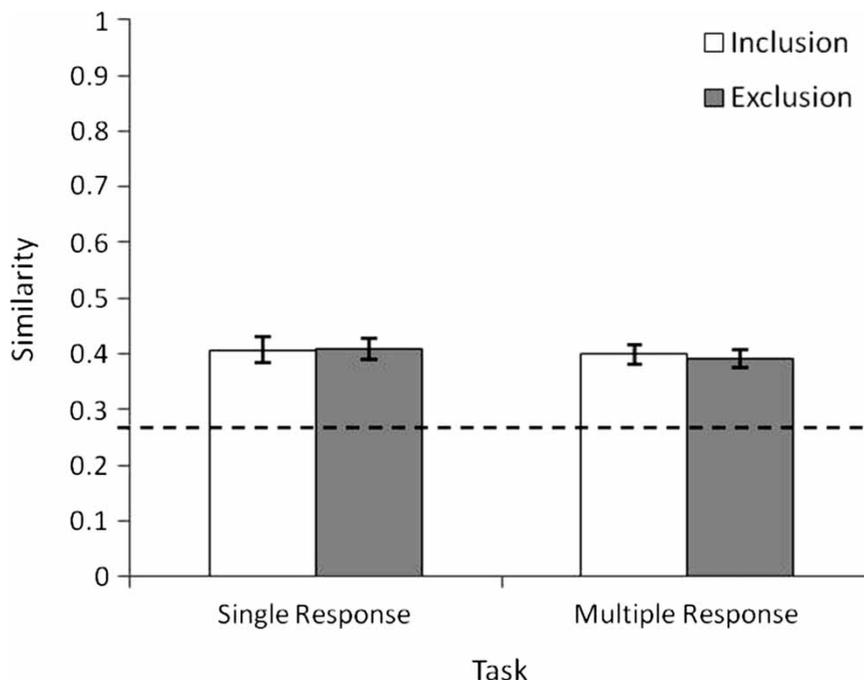


Figure 4. Similarity scores (between the training and produced patterns) in the inclusion and exclusion instructions of the generation task for the single response and multiple response conditions. Error bars represent standard error of the mean. The dashed line represents chance levels (.27) as determined by a pseudorandom number generator (see Appendix).

awareness of a timing regularity or rhythm, and 30 participants did not report awareness of a temporal pattern. When the above analyses were conducted including participants who reported awareness of the temporal pattern, similar results to those reported above were obtained.

Discussion

Experiment 1 demonstrated IL of metrical patterns in the single response SRT but evidence for learning was not as strong in the multiple response SRT. Only the single response SRT demonstrated a significant RT decrease over training blocks and significant RT increases in both test blocks. The multiple response SRT did not demonstrate a significant RT decrease over test blocks and only showed a significant RT increase for the WM test block (but not for the SM test block). In the generation task, no differences in similarity scores were demonstrated between

inclusion and exclusion instructions. This indicated that learning that occurred in the single response and multiple response SRT (if any) was implicit.

Overall, weaker evidence of learning was indicated in the multiple response SRT than in the single response SRT, probably due to probabilistic uncertainty of the identity of upcoming stimuli in the multiple response SRT. The results of Experiment 1 support the hypothesis that responding to the identity of an uncertain stimulus prevents temporal learning or may underestimate learning. As participants could not anticipate the identity of the next stimulus in the multiple response SRT, RTs were less sensitive to the learning of the temporal pattern. Thus, the IL of temporal patterns may not have been demonstrated in previous studies (e.g., Miyawaki, 2006; O'Reilly et al., 2008; Shin, 2008; Shin & Ivry, 2002) due to the use of a multiple response SRT (or multiple-alternative forced-choice task). In

these studies, blocks containing random ordinal sequences may have prevented RTs from reflecting learned knowledge of the temporal pattern. In other words, decision times in a multiple-alternative forced-choice task with uncertain identities may obscure or prevent the learning of temporal patterns.

In light of probabilistic uncertainty, it is likely that the acquisition of temporal expectancies is evident in tasks where stimulus identification is not the primary focus. The process of identifying stimuli may mediate response speed as a result of responding to an unpredictable identity, even if the timing is predictable. This resulted in a lack of robust RT decreases over blocks in the multiple response SRT that did not show learning over blocks (beyond, perhaps, task learning). This suggests that the learning of temporal patterns occurs in pure speed tests more than multiple-alternative forced-choice paradigms where the identity cannot be anticipated, at least insofar as the SRT is concerned. The results of Experiment 1 suggest that the SRT is sensitive to temporal learning when the task is not reliant on stimulus identification.

Experiment 1 provides evidence for why the previous study using a stimulus-detection task (Salidis, 2001) was somewhat successful in ascertaining temporal learning; the stimulus-detection task used was not dependent on stimulus identities. Thus, RT more adequately reflected temporal pattern learning. The study by Salidis showed IL of temporal patterns consisting of a symmetrical pattern of response-stimulus intervals (e.g., short-medium-short-long-medium-long). In the present study, Experiment 1 demonstrates IL of complex rhythmic patterns consisting of IOIs using a stimulus-detection task.

In the single response SRT (and multiple response SRT), RT increases were greater for WM test blocks than for SM test blocks. This can be viewed as evidence for the metric binding hypothesis: Expectancies to metrical temporal locations were strengthened over training blocks allowing speeded responses to upcoming events. When expectancies were violated in the WM test block, expectancies were forced to be revised in

accordance with the weaker metrical framework, resulting in slowed responses to upcoming events. In contrast, metrical expectancies were not violated in the SM test block, and this facilitated the processing and detection of upcoming events even though the temporal pattern was new. This is in line with the notion of attentional oscillators attuning to the temporal pattern and guiding attention to expected points in time. In this way, perceivers could anticipate and efficiently process upcoming events. Furthermore, metric binding increased expectancy at periodic or metrical points in time as indicated by larger performance decrements when the metrical framework was changed than when the metrical framework was maintained.

Results of Experiment 1 support the hypothesis that metrical patterns can be implicitly learned. The acquisition of temporal expectancies was demonstrated, and learning was possibly facilitated by the metrical framework as implied by the dynamic attending theory (Jones & Boltz, 1989). The hypothesis that greater performance decrements occur when a new temporal pattern with a weaker metrical framework is introduced (i.e., the WM test pattern) than when the new temporal pattern maintains the original strength of the metrical framework (i.e., the SM test pattern) was supported. This provides partial support to the metric binding hypothesis (Jones, 2009). However, to ensure that these differences are attributable to metric binding and not to baseline differences between SM and WM test patterns, a comparison of metrical and nonmetrical patterns is required, as done in Experiment 2.

EXPERIMENT 2

The first aim of Experiment 2 was to compare the IL of strongly metrical and nonmetrical rhythms. According to the dynamic attending theory, events that conform to a periodic or metrical framework should correspond to moments of high expectancy. Thus, once a metrical framework has been abstracted, faster responses should occur

for metrical patterns than for nonmetrical patterns.

A secondary aim was to test the metric binding hypothesis by examining whether differences between SM and WM test blocks are attributable to metric binding. Nonmetrical versions of the SM training pattern and SM and WM test block patterns were constructed (i.e., NM training, NM Test 1, and NM Test 2, respectively). Nonmetrical patterns matched the metrical patterns in regards to figural groupings and statistical structure, but used IOIs with complex integer ratios to prevent periodic alignment with metrical frameworks. According to the metric binding hypothesis, this should prevent metric binding in the nonmetrical condition. By comparing the effects of test blocks in metrical and nonmetrical conditions, one can examine whether differences between SM and WM test blocks occur as a result of metric binding. If differences between Test 1 and Test 2 exist for both metrical and nonmetrical patterns, then disruptions cannot be attributable to metric binding and may, instead, be attributable to baseline differences between Test Patterns 1 and 2. If, however, the RT increases do not differ between nonmetrical test blocks that were matched with the SM and WM test blocks in all aspects except for the presence of meter, then differences between SM and WM test blocks in the metrical condition must be due to metric binding.

The design was identical to that of Experiment 1 except that metricality (i.e., metrical, nonmetrical) was examined as a between-subjects factor. As results of Experiment 1 indicated that learning is better demonstrated in the single response SRT than in the multiple response SRT, the single response task was used. The metrical condition in Experiment 2 is a replication of the single response condition of Experiment 1. As in Experiment 1, the dependent variables were proportion of retained responses, RT, RT improvement over training blocks, and RT increase in test blocks (Shin & Ivry, 2002).

Based on previous experiments on the IL of temporal patterns, it was hypothesized that metrical (Brandon et al., 2012) and nonmetrical

(Salidis, 2001) temporal patterns can be implicitly learned. Based on the dynamic attending theory (Jones & Boltz, 1989), it was hypothesized that temporal expectancies are acquired more readily for metrical rhythms than for nonmetrical temporal patterns. As per the metric binding hypothesis, it was hypothesized that larger RT increases occur in the WM test block than in the SM test block in the metrical condition. Differences between the nonmetrical versions of SM and WM test blocks are not anticipated in the nonmetrical condition as metric binding should not be possible.

Method

Participants

Participants ($N = 51$) were first-year psychology students from the University of Western Sydney who had not participated in Experiment 1. Of these, 11 were male. Ages ranged from 17 to 54 years, with a mean age of 22 years ($SD = 6.60$). No participant reported a hearing impairment, and 46 of the participants were right-handed.

Materials

Metrical patterns were identical to those of Experiment 1. Nonmetrical patterns were constructed based on the metrical patterns, but used IOIs with complex integer ratios. The use of complex integer ratios results in temporal patterns that are not conceivable in terms of a metrical framework (Essens & Povel, 1985). Furthermore, as in Essens and Povel (1985), only the between-group IOIs (i.e., IOIs greater than 500 ms) were manipulated, but the within-group IOI (i.e., 500-ms IOI) was maintained. As shown in Figure 2, the rhythmic groupings for all patterns in the nonmetrical condition were identical to those in the metrical condition. However, the nonmetrical patterns consisted of three 500-ms IOIs, three 1,100-ms IOIs, one 1,350-ms IOI, and one 1,850-ms IOI. These intervals were chosen so that events in nonmetrical patterns rarely aligned with any metrical framework and that timing deviations were larger than the just-noticeable difference (2.5% of

the pulse, for the tempi of our patterns; Friberg & Sundberg, 1995).³

Procedure

The procedure was identical to that of the single response SRT and generation task in Experiment 1 except for the addition of nonmetrical patterns in the nonmetrical condition.

Results

The serial reaction-time task

Data were analysed in the same way as in the single response condition in Experiment 1. Participants who reported awareness of a temporal pattern or rhythm in free verbal report were excluded from analysis. The final sample consisted of 18 participants (of 25) in the metrical condition and 20 participants (of 26) in the nonmetrical condition.

Proportion of retained responses

A repeated measures ANOVA was conducted on the proportion of retained responses with block (1–9) as a within-subjects variable and metricality (metrical, nonmetrical) as a between-subjects variable. There was a near-significant effect of block, $F(8, 288) = 1.72, p = .09, \eta_p^2 = .05$, no significant main effect of metricality, $F(1, 36) = 0.35, p = .56, \eta_p^2 = .01$, and no interaction between block and metricality, $F(8, 288) = 0.54, p = .83, \eta_p^2 = .02$. The near-significant main effect of block reflects that the proportion of retained responses decreased in the test blocks compared to other blocks. Overall, there were no differences in the proportion of retained responses between metrical ($M = .94,$

$SD = .07$) and nonmetrical ($M = .93, SD = .09$) conditions.

Reaction time

A repeated measures ANOVA was conducted on RT with block (1–9) as a within-subjects variable and metricality (metrical, nonmetrical) as a between-subjects variable. The main effect of block was significant, $F(8, 288) = 12.00, p < .001, \eta_p^2 = .25$, but there was no main effect of metricality, $F(1, 36) = 1.23, p = .27, \eta_p^2 = .03$, or significant interaction between block and metricality, $F(8, 288) = 0.78, p = .62, \eta_p^2 = .02$. This suggests that RT decreased over training blocks and increased in test blocks regardless of metricality (see Figures 5a and 5b).

To test the hypothesis that metrical and nonmetrical temporal patterns were learned, RT improvement was calculated for RT over training blocks (i.e., the difference between Blocks 1 and 5) for each participant. RT improvement was then compared in a two-way ANOVA with metricality as the between-subjects factor. No significant main effect of metricality was evident, $F(1, 36) = 0.30, p = .59, \eta_p^2 = .01$, with RT improvement for the metrical condition ($M = 67.33, SD = 75.82$) not differing significantly from that in the nonmetrical condition ($M = 54.47, SD = 69.21$).⁴ RT improvement was significantly different to zero for the metrical, $t(17) = 3.77, p = .002$, and nonmetrical conditions, $t(19) = 3.52, p = .002$. This confirms that learning was evident for both the metrical and nonmetrical conditions, but that metrical patterns were not learned more readily than nonmetrical patterns (see Figure 5a).

³ A finger-tapping experiment ($N = 11$) was conducted to examine whether participants were sensitive to differences between metrical and nonmetrical patterns. Seven participants were considered musically trained, with more than five years of musical training ($M = 12.00, SD = 5.97$); three others had received no training, and one other had received two years of informal training. Participants were presented with the metrical (SM training, SM Test 1, and WM Test 2) and nonmetrical (NM training, NM Test 1, NM Test 2) patterns and were instructed to tap the perceived beat. Patterns were presented eight times each (each starting from a different interval in the pattern), and the order of patterns was randomized. In trials, the pattern was cycled continuously until the participant produced 54 taps. There was a significant difference between metrical and nonmetrical patterns in regards to standard deviations of intertap intervals, $F(1, 9) = 22.14, p = .002, \eta_p^2 = .74$, with larger standard deviations for nonmetrical patterns ($M = 32.76, SEM = 2.54$) than for metrical patterns ($M = 24.04, SEM = 1.29$). However, there were no differences between the training pattern and Test Patterns 1 and 2 for metrical or nonmetrical conditions. These results suggest that metrical patterns were interpreted as metrical regardless of whether they were strongly or weakly metrical.

⁴ A measure of slope that included the gradient across all five data points was also calculated and was subjected to these analyses. Results replicated the same data pattern as those reported here.

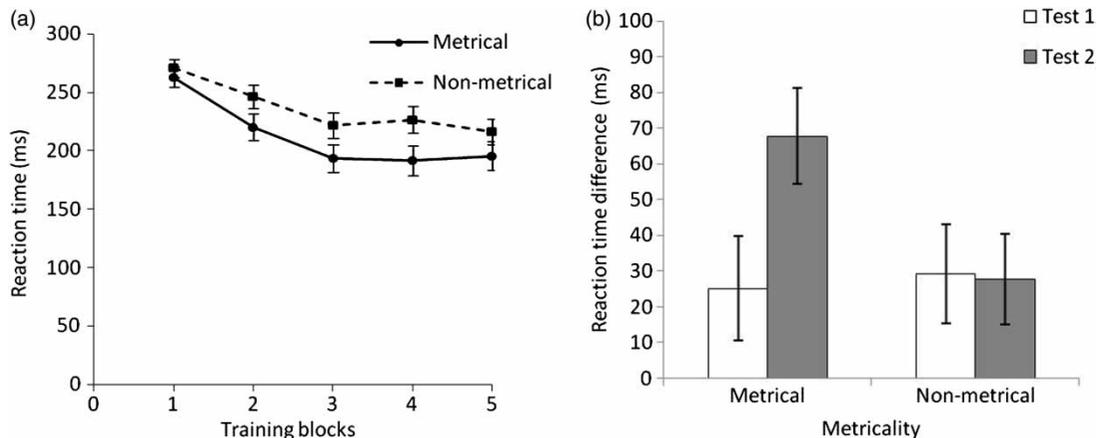


Figure 5. Results of the serial reaction-time task (SRT) in Experiment 2. (a) Mean reaction time (RT; correct responses only) for the metrical and nonmetrical conditions over blocks. Error bars represent standard error of the mean. (b) Mean RT increases for Tests 1 and 2 in the metrical and nonmetrical conditions. In the metrical condition, Test 1 was strongly metrical (SM), and Test 2 was weakly metrical (WM). In the nonmetrical condition, Tests 1 and 2 were nonmetrical versions of the patterns in the metrical condition. Error bars represent standard error of the mean.

To test for structure learning of the temporal patterns, RT increases between the test block and the mean of adjacent blocks were examined in a repeated measures ANOVA with test block type (Test 1, Test 2) as a within-subjects factor and metricity as a between-subjects factor. There was a main effect of test block type, $F(1, 36) = 4.75$, $p = .04$, $\eta_p^2 = .12$, no main effect of metricity, $F(1, 36) = 1.14$, $p = .29$, $\eta_p^2 = .03$, and a significant interaction between test block and metricity, $F(1, 36) = 5.46$, $p = .03$, $\eta_p^2 = .13$.

Planned comparisons revealed that, for the metrical condition, RT increases were significantly smaller in Test 1 (SM; $M = 25.08$, $SD = 79.88$) than in Test 2 (WM; $M = 67.81$, $SD = 74.53$), $F(1, 17) = 7.18$, $p = .02$, $\eta_p^2 = .30$. In the metrical condition, Test 1 (SM) did not show a significant RT increase, $t(17) = 1.33$, $p = .20$, but Test 2 (WM) demonstrated a significant RT increase, $t(17) = 3.86$, $p = .001$. For the nonmetrical condition, there was no significant difference in RT increase between Test 1 ($M = 29.23$, $SD = 39.55$) and Test 2 ($M = 27.76$, $SD = 33.23$), $F(1, 19) =$

0.19 , $p = .89$, $\eta_p^2 = .001$. The nonmetrical condition demonstrated significant RT increases for Test 1, $t(19) = 3.31$, $p = .004$, and Test 2, $t(19) = 3.74$, $p = .001$.⁵ These results indicate that metric binding occurred for the metrical group, as disruptions to the metrical framework in Test 2 (WM) resulted in greater RT increases than when the metrical framework was maintained in Test 1 (SM). It is in line with our predictions that no significant differences between Test 1 and Test 2 were evident for the nonmetrical condition as there was no metrical framework to disrupt (see Figure 5b).

Generation task

Similarity scores in the generation task were analysed using a 2×2 repeated measures ANOVA with instruction (inclusion, exclusion) as a within-subjects factor and metricity as a between-subjects factor. The generation task demonstrated no significant effects for instruction, $F(1, 36) = 0.13$, $p = .72$, $\eta_p^2 = .004$, metricity, $F(1, 36) = 1.04$, $p = .31$, $\eta_p^2 = .03$, or the interaction between

⁵ Raw RTs reflect that performance in Test 2 was similar for metrical ($M = 255$ ms, $SD = 35.38$) and nonmetrical ($M = 244$ ms, $SD = 53.04$) conditions. The metrical condition had faster RTs in the adjacent blocks, resulting in a larger RT increase in Test 2 (WM).

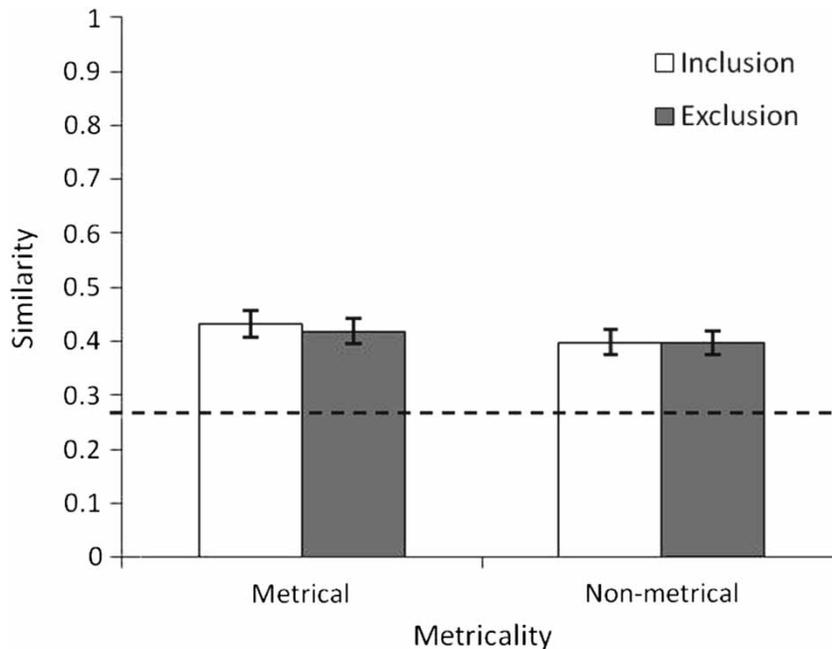


Figure 6. Similarity scores in the inclusion and exclusion instructions of the generation task for the metrical and nonmetrical conditions. Error bars represent standard error of the mean. The dashed line represents chance levels as determined by a pseudorandom number generator (see Appendix).

instruction and metricity, $F(1, 36) = 0.10$, $p = .72$, $\eta_p^2 = .003$. As in Experiment 1, results of the generation task indicate that learning in the SRT was implicit (see Figure 6). Performance was significantly above chance for both tasks in both conditions (p s < .001), demonstrating that participants could reproduce parts of the temporal pattern in both metrical and nonmetrical conditions under inclusion and exclusion instructions.

Reports of awareness

In the metrical condition, seven participants reported awareness of a timing regularity, and 18 did not report awareness of the temporal pattern. In the nonmetrical condition, six participants reported awareness of a timing regularity, and 20 did not report awareness of the temporal pattern. Analyses that included participants who reported awareness of the temporal pattern did not produce results that differed substantially from

those reported above. However, it should be noted that a main effect of block for the proportion of retained responses became significant, $F(8, 392) = 2.78$, $p = .005$, $\eta_p^2 = .05$. This main effect reflected decreases in the number of retained responses in Tests 1 and 2.

Discussion

The results of Experiment 2 show that temporal expectancies are acquired for metrical and nonmetrical temporal patterns—that is, both are learned. Exposure to the temporal patterns in training blocks allowed participants to form more precise expectancies for upcoming events, thus speeding responses. The generation task indicated that this learning was implicit. The results support the hypothesis that metrical and nonmetrical temporal patterns can be implicitly learned in the absence of an ordinal pattern (i.e., the sequence of tone locations here were random). Results for the

metrical condition replicated those found in the single response condition in Experiment 1: RT decreased over training blocks, RT increases were greater in the WM test block than in the SM test block, and the generation task indicated that learning was implicit.

The hypothesis that temporal expectancies are acquired more readily for metrical patterns than for nonmetrical patterns was not supported. In light of the dynamic attending theory (Jones & Boltz, 1989), it is possible that with repeated exposure to the nonmetrical pattern, attending oscillations were able to adapt and synchronize to local periodic timings such as in rhythmic groups and when an inter-onset interval occurs more than once, consecutively. In this way, expectancies may have been guided to points in time without the occurrence of metric binding or the utilization of a periodic pulse on a more global level.

A difference between SM and WM test blocks was evident for the metrical condition, but not between nonmetrical versions of the SM and WM test blocks for the nonmetrical condition. This suggests that in the metrical condition metric binding occurred (Jones, 2009), and thus expectancies were strengthened for events occurring in metrical (i.e., periodic) locations. Furthermore, when a metrical framework persists for a novel metrical pattern, the extrapolated expectancies are utilized, and RT increases are not as large. This is in line with the metric binding hypothesis: Entrainment to the metrical structure of the metrical pattern can occur and strengthen temporal expectancies for upcoming events. However, when temporal expectancies to metrical locations were violated (i.e., the WM test block), participants could not use the same metrical structure to facilitate responses to the new metrical pattern.

The nonmetrical pattern did not contain events on metrically salient points, so metric binding was not possible. The lack of a difference between RT increases in Test 1 and Test 2 for the nonmetrical pattern suggests that expectancies were not based on a periodic or metrical framework. Thus, the metrical condition indicated that temporal expectancies were based on metric binding whereas the

nonmetrical condition demonstrated that a metrical structure could not be abstracted. However, learning of the nonmetrical patterns still occurred.

Overall, results suggest that while metric binding only occurs when a metrical framework can be abstracted, temporal expectancies to temporal patterns may be implicitly acquired with similar effectiveness regardless of the presence or absence of meter. However, the manner in which temporal expectancies are acquired appears to be different depending on the presence or absence of meter—that is, metric binding occurred in the metrical condition but not in the nonmetrical condition.

GENERAL DISCUSSION

Two experiments demonstrated the learning of complex metrical and nonmetrical patterns in an SRT and provided evidence that this learning was implicit. Experiment 1 demonstrated that IL of metrical patterns is evident in a single response SRT, but less so in the multiple response SRT where probabilistic uncertainty might obscure learning. Thus, the single response SRT is a useful method for revealing IL of temporal patterns, as this paradigm more directly measures the development of temporal expectancies and the impedimentary effects of violating these expectancies.

Experiment 2 demonstrated that metrical and nonmetrical patterns can be implicitly learned but that metrical patterns are not learned more readily or more effectively than nonmetrical patterns. However, differences between SM and WM test blocks still occurred for metrical patterns. The rhythmic groupings and rhythmic complexity were equivalent for metrical and nonmetrical patterns for training and test blocks. Thus, this result suggests that metric binding only occurred when a metrical framework was available (i.e., in the metrical condition). As hypothesized, metric binding was not indicated when no metrical framework was available (i.e., in the nonmetrical condition) even though other rhythmic aspects were

maintained, such as interval sizes and the size of groups of temporally proximal events.

It might be argued that differences between the metrical and nonmetrical patterns in the present study were too subtle to evoke significantly different responses. In other words, although the nonmetrical patterns were mathematically nonmetrical, they may have been perceived as categorically metrical (Clarke, 1987) or as metrical patterns performed with expressive timing (Repp, 1990). This is congruent with Handel (1998, p. 1546) who states that “each rhythm is metric to some degree, depending on the strength of the meter interpretation it evokes”. However, in the present study there was no evidence of metric binding in the nonmetrical condition (i.e., no difference between nonmetrical versions of the SM and WM test blocks). Thus, it is unlikely that the nonmetrical pattern was interpreted as metrical.

In line with the present findings, there is evidence that timings that deviate from metrical frameworks can be imitated (albeit, explicitly) with some precision (Clarke, 1993). Such timing deviations could be interpreted as the speeding or slowing of a pattern in order to fit the pattern to a metrical framework. Large, Fink, and Kelso (2002) found evidence that participants are able to synchronize with and adapt to metrical patterns that contain phase and tempo perturbations. Similarly, the present study found evidence that the learning of nonmetrical patterns may involve a flexible and adaptive mechanism when timing deviations are predictable.

In contrast with the dynamic attending hypothesis, no differences in the rate of learning were evident between metrical and nonmetrical patterns even though average RTs in the metrical condition were (nonsignificantly) faster than those in the nonmetrical condition. The lack of a difference between metrical and nonmetrical pattern learning may reflect that, for the nonmetrical group, attentional oscillators were able to adapt and synchronize to the timing pattern even though the timings were not metrical (Large, 2008; Large et al., 2002). Although the learning of nonmetrical patterns may seem surprising, it is in line with previous evidence of temporal pattern learning using response-

stimulus intervals (Salidis, 2001). However, the patterns used by Salidis were simple symmetrical temporal patterns composed of response-stimulus intervals whereas the present study used complex temporal patterns that are more closely aligned with musical rhythms.

In the present study, it is evident that metrical frameworks aided responses to novel metrical patterns, as demonstrated by the larger increases for WM test blocks than for SM test blocks for the metrical condition. These results suggest that attentional oscillators in the metrical condition allowed expectancies to be based on the metrical framework, subsequently leading to metric binding (as per the metric binding hypothesis; Jones, 2009). However, despite the fact that meter was abstracted in the metrical condition, RT improvement over training blocks was similar for metrical and nonmetrical conditions. It is possible that learning in the nonmetrical condition may have been compensated via a flexible and adaptive oscillator to account for the learning of regular timing deviations (Large et al., 2002). The activation of a flexible and adaptive oscillator may have prevented metric binding from occurring in the nonmetrical condition, as suggested by the present results.

Taking into consideration previous evidence for a benefit of meter in tasks where participants were made explicitly aware of the temporal pattern (e.g., Essens & Povel, 1985; Keller & Burnham, 2005; Large & Jones, 1999), it is possible that temporal expectancies are acquired differently when temporal patterns are learned implicitly. In particular, the abstraction of musical meter may not improve the rate at which temporal expectancies are developed implicitly. There might be more general mechanisms for implicitly learning temporal patterns that do not necessarily rely on the presence of meter such as learning the serial order of IOIs. Previous rhythm perception studies have used temporal patterns that do not necessarily have probability-based structures (e.g., Povel, 1981, 1984; Sternberg & Knoll, 1984) and instead use complex temporal patterns consisting of distributions of IOIs that may occur in any order. Based on these studies, it has been concluded that a series of intervals cannot be stored in memory in the absence of a facilitating structure (e.g.,

meter). In the present study, however, it is possible that temporal patterns were learned via expectancies of the IOI length based on the second-order conditional probability from preceding IOIs. Thus, learning of the temporal patterns in the present study might be based on statistical structures (as well as metrical structures for metrical patterns).

The results have implications for temporal cognition relating to both rhythm and meter perception and implicit learning. Regarding music cognition, numerous studies use methods where participants are under explicit instruction to perceive, produce, or synchronize with temporal patterns and have found that participants synchronize to and reproduce metrical patterns better than nonmetrical patterns (Essens & Povel, 1985; Povel, 1984). It is possible that metric hierarchies may assist explicit learning more than implicit learning. Also, previous studies examining differences between metrical and nonmetrical patterns have used recognition, discrimination, or reproduction tasks that focus on memory of a rhythm or meter (e.g., Essens & Povel, 1985; Keller & Burnham, 2005; Large & Jones, 1999). To be successful in these tasks, the temporal pattern must be successfully encoded and retrieved from memory. Thus, a possible explanation for discrepancies between previous results and those in the present study could be that the benefit of metrical frameworks may be more pronounced in the encoding and retrieval of memory than for online attending (in tasks such as the SRT).

Now that the IL of metrical and nonmetrical patterns has been ascertained using the single response SRT, a next step is to find a way to apply this method to examine the independent learning of temporal patterns from concurrently presented ordinal patterns. As previous studies have claimed that temporal patterns cannot be learned independently from concurrent patterns (Buchner & Steffens, 2001; O'Reilly et al., 2008; Shin & Ivry, 2002), it is important to establish whether prior results could be attributed to probabilistic uncertainty of stimulus identities. It is a challenge for future investigations of the independent and integrated learning of temporal and

ordinal patterns to develop a method that allows response to both the timing of the stimuli (as in the single response SRT) and the identities of the stimuli (as in the multiple response SRT). Furthermore, future studies could examine how people implicitly learn other metrical frameworks, such as triple meters or temporal patterns with ambiguous metrical interpretations. Future research could also investigate the IL of complex rhythms and meters that occur less commonly in Western music (see Tillmann, Stevens, & Keller, 2011) to examine the extent to which previous exposure to rhythms (and meters) affects the acquisition of temporal (and metrical) expectancies.

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REFERENCES

- Brandon, M., Terry, J., Stevens, C. J., & Tillmann, B. (2012). Incidental learning of temporal structures conforming to a metrical framework. Manuscript submitted for publication.
- Buchner, A., & Steffens, M. C. (2001). Simultaneous learning of different regularities in sequence learning tasks: Limits and characteristics. *Psychological Research, 65*, 71–80.
- Chapin, H. L., Zanto, T., Jantzen, K. J., Kelso, S. J., Steinberg, F., & Large, E. W. (2010). Neural responses to complex auditory rhythms: The role of attending. *Frontiers in Psychology, 224*, 1–18.
- Clarke, E. F. (1987). Categorical rhythm perception: An ecological perspective. In A. Gabrielsson (Ed.), *Action and perception in rhythm and music* (pp. 19–33). Stockholm, Sweden: Royal Swedish Academy of Music.
- Clarke, E. F. (1993). Imitating and evaluating real and transformed musical performances. *Music Perception, 10*, 317–341.
- Cohen, J., MacWhinney, B., Flatt, M., & Provost, J. (1993). PsyScope: An interactive graphic system for designing and controlling experiments in the psychology laboratory using Macintosh computers. *Behavior Research Methods, Instruments, and Computers, 25*, 257–271.

- Destrebecqz, A., & Cleeremans, A. (2001). Can sequence learning be implicit? New evidence with the process dissociation procedure. *Psychonomic Bulletin & Review*, 8, 343–350.
- Destrebecqz, A., & Cleeremans, A. (2003). Temporal factors in sequence learning. In L. Jiménez (Ed.), *Attention and implicit learning* (pp. 181–213). Philadelphia, PA: John Benjamins.
- Essens, P., & Povel, D.-J. (1985). Metrical and nonmetrical representations of temporal patterns. *Perception & Psychophysics*, 37, 1–7.
- Friberg, A., & Sundberg, J. (1995). Time discrimination in a monotonic, isochronous sequence. *Journal of the Acoustical Society of America*, 98, 2524–2531.
- Grube, M., & Griffiths, T. D. (2009). Metricality-enhanced temporal encoding and the subjective perception of rhythmic sequences. *Cortex*, 45, 72–79.
- Handel, S. (1998). The interplay between metric and figural rhythmic organization. *Journal of Experimental Psychology: Human Perception & Performance*, 24, 1546–1561.
- Jacoby, L. L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory & Language*, 30, 513–541.
- Jacoby, L. L., Toth, J. P., & Yonelinas, A. P. (1993). Separating conscious and unconscious influences on memory: Measuring recollection. *Journal of Experimental Psychology: General*, 122, 139–154.
- Järvinen, T., & Toiviainen, P. (2000). The effects of metre on the use of tones in jazz improvisation. *Musicae Scientiae*, 4, 55–74.
- Jones, M. R. (2009). Musical time. In S. Hallam, I. Cross, & M. Thaut (Eds.), *The handbook of music psychology* (pp. 81–92). New York, NY: Oxford University Press.
- Jones, M. R., & Boltz, M. (1989). Dynamic attending and responses to time. *Psychological Review*, 96, 459–491.
- Karabanov, A., & Ullén, F. (2008). Implicit and explicit learning of temporal sequences studied with the process dissociation procedure. *Journal of Neurophysiology*, 100, 733–739.
- Keller, P. E., & Burnham, D. K. (2005). Musical meter in attention to multipart rhythm. *Music Perception*, 22, 629–661.
- Large, E. W. (2008). Resonating to musical rhythm: Theory and experiment. In S. Grondin (Ed.), *The psychology of time* (pp. 189–231). United Kingdom: Emerald.
- Large, E. W., Fink, P., & Kelso, J. A. S. (2002). Tracking simple and complex sequences. *Psychological Research*, 66, 3–17.
- Large, E. W., & Jones, M. R. (1999). The dynamics of attending: How people track time-varying events. *Psychological Review*, 106, 119–159.
- Lerdahl, F., & Jackendoff, R. (1981). On the theory of grouping and meter. *The Musical Quarterly*, 67, 479–506.
- London, J. (2004). *Hearing in time: Psychological aspects of musical meter*. New York, NY: Oxford University Press.
- Marks, L. E. (1978). Binaural summation of the loudness of pure tones. *Journal of the Acoustical Society of America*, 64, 107–113.
- Miyawaki, K. (2006). The influence of the response–stimulus interval on implicit and explicit learning of stimulus sequence. *Psychological Research*, 70, 262–272.
- Nissen, M. J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cognitive Psychology*, 19, 1–32.
- O'Reilly, J. X., McCarthy, K. J., Capizzi, M., & Nobre, A. C. (2008). Acquisition of the temporal and ordinal structure of movement sequences in incidental learning. *Journal of Neurophysiology*, 99, 2731–2735.
- Palmer, C., & Krumhansl, C. L. (1990). Mental representations of musical meter. *Journal of Experimental Psychology: Human Perception & Performance*, 16, 728–741.
- Patel, A. D. (2008). *Music, language, and the brain*. New York, NY: Oxford University Press.
- Patel, A. D., Iversen, J. R., Chen, Y., & Repp, B. H. (2005). The influence of metricality and modality on synchronization with a beat. *Experimental Brain Research*, 163, 226–238.
- Perruchet, P., & Pacton, S. (2006). Implicit learning and statistical learning: One phenomenon, two approaches. *Trends in Cognitive Science*, 10, 233–238.
- Povel, D.-J. (1981). Internal representations of simple temporal patterns. *Journal of Experimental Psychology: Human Perception & Performance*, 7, 3–18.
- Povel, D.-J. (1984). A theoretical framework for rhythm perception. *Psychological Research*, 45, 315–337.
- Povel, D.-J., & Essens, P. (1985). Perception of temporal patterns. *Music Perception*, 2, 411–440.
- Reber, A. S., & Lewis, S. (1977). Toward a theory of implicit learning: The analysis of the form and structure of a body of tacit knowledge. *Cognition*, 5, 333–361.

- Reed, J., & Johnson, P. (1994). Assessing implicit learning with indirect tests: Determining what is learned about sequence structure. *Journal of Experimental Psychology: Learning, Memory & Cognition*, 20, 585–594.
- Repp, B. H. (1990). Patterns of expressive timing in performances of a Beethoven minuet by nineteen famous pianists. *Journal of the Acoustical Society of America*, 88, 622–641.
- Salidis, J. (2001). Nonconscious temporal cognition: Learning rhythms implicitly. *Memory & Cognition*, 29, 1111–1119.
- Shanks, D. R. (2005). Implicit learning. In K. Lamberts & R. Goldstone (Eds.), *Handbook of cognition* (pp. 202–220). London, UK: Sage.
- Shanks, D. R., & St. John, M. E. (1994). Characteristics of dissociable human learning systems. *Behavioral & Brain Sciences*, 17, 367–447.
- Shin, J. C. (2008). The procedural learning of action order is independent of temporal learning. *Psychological Research*, 72, 376–386.
- Shin, J. C., & Ivry, R. B. (2002). Concurrent learning of temporal and spatial sequences. *Journal of Experimental Psychology: Learning, Memory & Cognition*, 28, 445–457.
- Sternberg, S., & Knoll, R. L. (1984). Timing by skilled musicians: Perception, production and imitation of time ratios. *Annals of the New York Academy of Sciences*, 423, 429–441.
- Tillmann, B., Stevens, C., & Keller, P. E. (2011). Learning of timing patterns and the development of temporal expectations. *Psychological Research*, 75, 243–258.
- Ullén, F., & Bengtsson, S. (2003). Independent processing of the temporal and ordinal structure of movement sequences. *Journal of Neurophysiology*, 90, 3725–3735.
- Vuust, P., Ostergaard, L., Pallesen, K. J., Bailey, C., & Roepstorff, A. (2009). Predictive coding of music—Brain responses to rhythmic incongruity. *Cortex*, 45, 80–92.

APPENDIX

The generation task analysis

Data for the generation task were analysed in MatLab using a method based on the serial-recall task used by Ullén and Bengtsson (2003) and adapted for examining the production of repeating patterns. First, for each trial (five inclusion and five exclusion trials) the time series of responses were extracted for each trial. Next, inter-onset intervals (IOIs) were calculated by treating the first button press as the starting point and calculating the time between the onsets of each tap. Then all intervals were divided by the smallest interval and multiplied by the 500, the smallest interval of the training pattern. In this way, the smallest interval was used as the referent for the smallest IOI (i.e., the smallest IOI became 500, and all other IOIs were standardized to this value). The metrical training pattern was analysed as [500–1,500–1,000–1,000–500–500–1,000–2,000] and the nonmetrical training pattern was [500–1,350–1,100–1,100–500–500–1,100–1,850].

The response IOI sequences were then compared to the actual patterns. No indication of a starting or ending points of the pattern was given in blocks because the pattern cycled 24 times each block, and different starting points were used for each block. As participants might reproduce the training pattern using any starting point of the pattern, the training pattern was compared to the produced sequence starting from every possible point of the produced sequence. For example, if the participant produced a sequence of 16 intervals, the training pattern would be compared to the produced sequence 16 times, and the 16-item sequence would be

concatenated with itself. For each starting position, the training pattern was compared to the produced sequence for each of the eight intervals of the training pattern. If the produced interval was equal to the training interval (with a tolerance of $\pm 30\%$ of the base pulse), the response was counted as correct. If the 8-item training pattern was compared with the reproduced sequence from positions 10 or greater, later items of the training pattern would be compared to the first intervals of the produced sequence (e.g., the 17th item of a 16-item produced sequence would be the first item, the 18th is the second, and so on). Each sequence comparison produced a similarity score (from 0 to 1). Then, the maximum similarity values were extracted from all sequence comparisons. The maximum values were used to ensure that a correct pattern reproduction was reflected regardless of the starting point selected by the participant.

To estimate chance levels, a pseudorandom number generator was used to create sequences. The constraints of the sequences were that: (a) they could be no longer than 20 s—that is, the amount of time allowed for sequence production, (b) intervals were only able to be between 200 ms and 2,800 ms in length—that is, within the approximate range of intervals produced by participants, and (c) they could contain a maximum of 16 intervals. Simulations calculated the mean similarity scores for 25 “participants” (with five “attempts” each) for both the metrical and the nonmetrical patterns. The results of the simulations produced a mean similarity score .27 ($SD = .01$) for both the metrical and the nonmetrical patterns. Thus, this value was used as an indication of chance performance in the generation task.