

Auditory perceptual learning depends on temporal regularity and certainty

Tysen Dauer¹, Molly J. Henry^{2,3}, & Björn Herrmann^{1,4,*}

¹Rotman Research Institute,
Baycrest Health Sciences, M6A 2E1, North York, ON, Canada

²Research Group Neural and Environmental Rhythms,
Max Planck Institute for Empirical Aesthetics, 60322 Frankfurt am Main, Germany

³Department of Psychology,
Ryerson University, M5B 2K3, Toronto, ON, Canada

⁴Department of Psychology,
University of Toronto, M5S 1A1, Toronto, ON, Canada

* Correspondence concerning this article should be addressed to Björn Herrmann, Rotman Research Institute, Baycrest, 3560 Bathurst St, North York, ON, M6A 2E1, Canada. E-mail: bherrmann@research.baycrest.org

Word count: 9175

Author note:

Data, analysis code, and research materials are available upon reasonable request. Institutional data protection policies currently prohibit public sharing of data.

Abstract

Detecting and learning structure in sounds is fundamental to human auditory perception. Evidence for auditory perceptual learning comes from previous studies where listeners were better at detecting repetitions of a short noise snippet embedded in longer, ongoing noise when the same snippet recurred across trials compared to when the snippet was novel in each trial. However, previous work has mainly used (a) temporally regular presentations of the repeating noise snippet and (b) highly predictable inter-trial onset timings for the snippet sequences. As a result, it is unclear how these temporal features affect perceptual learning. In five online experiments, participants judged whether or not a repeating noise snippet was present, unaware that the snippet could be unique to that trial or used in multiple trials. In two experiments, temporal regularity was manipulated by jittering the timing of noise-snippet repetitions within a trial. In two subsequent experiments, temporal onset certainty was manipulated by varying the onset time of the entire snippet sequence across trials. We found that both temporal jittering and onset uncertainty reduced auditory perceptual learning. In addition, we observed that these reductions in perceptual learning were ameliorated when the same snippet occurred in both temporally manipulated and unmanipulated trials. Our study demonstrates the importance of temporal regularity and onset certainty for auditory perceptual learning.

Significance Statement

The current study demonstrates that humans can learn noise structure in sounds. However, this perceptual learning is reduced when the noise structure occurs temporally unpredictably in time, for example, when repetitions of noise structure in sounds are temporally jittered or when the onset time of the noise structure is uncertain across different sounds. This study further indicates that this negative impact of temporal unpredictability can be mitigated when perceptual representations of the noise structure are established through accompanying sounds with temporally predictable features. Our study demonstrates the importance of temporal predictability for auditory perceptual learning.

Introduction

Our perceptions of a stimulus change because of experience or practice with the stimulus (Gibson, 1953; Gibson, 1963; Goldstone, 1998). This phenomenon is referred to as perceptual learning, the “improvement in perceptual discrimination with practice” (Irvine, Martin, Klimkeit, & Smith, 2000, p. 2964). In the auditory domain, perceptual learning includes processes like associating a complex sound with its source, such as linking a bird call with a particular species (example from Agus, Thorpe, & Pressnitzer, 2010). More abstractly, auditory perceptual learning is thought to underlie important abilities like speech perception (Norris, McQueen, & Cutler, 2003), speaker identification (Kraljic & Samuel, 2005), and musical skills (Gibson, 1953; Irvine et al., 2000; Kraus & Banai, 2007; Meyer, 1899), by transforming initially indiscriminate auditory signals into meaningful and recognizable auditory objects (Shinn-Cunningham, 2008). Researchers have further speculated that successful auditory perceptual learning may have had evolutionary survival benefits such as “signaling the presence of potential mates, prey, or predators” (Rajendran, Harper, Abdel-Latif, & Schnupp, 2016, p. 3). In the current suite of experiments, we investigated how temporal features of the auditory signal impact auditory perceptual learning.

Observing auditory perceptual learning in experimental settings can be challenging. Authors of previous work have discussed key concerns related to the study of perceptual learning (Agus et al., 2010): (1) Ideally, participants will have no prior exposure to the specific sound stimuli used in the experiment, otherwise they may already have learned the experimental stimuli to varying degrees. (2) Stimuli should not have obvious semantic labels since these could interfere with the acoustic memorization process (Cohen, Horowitz, & Wolfe, 2009). Lastly, (3) stimuli that are more difficult to memorize (i.e., contain more information) should be better tests of a learning mechanism because they make more processing demands (Overath et al., 2007). Various stimuli have been used to demonstrate auditory perceptual learning, including clicks (Kang, Agus, & Pressnitzer, 2017), tone bursts (Goossens,

van de Par, & Kohlrausch, 2008; Hawkey, Amitay, & Moore, 2004), tones sequences (Bianco et al., 2020; Herrmann, Araz, & Johnsrude, 2021; Kumar et al., 2014), and noise bursts (Viswanathan, Rémy, Bacon-Macé, & Thorpe, 2016). One branch of auditory perceptual learning research has taken advantage of acoustic noise as stimuli to address the concerns raised by Agus and colleagues (Agus, Carrión-Castillo, Pressnitzer, & Ramus, 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon, Kouider, Agus, & Pressnitzer, 2015; Andrillon, Pressnitzer, Léger, & Kouider, 2017). Although participants have likely heard noise before, it is extraordinarily unlikely that they have encountered the specific instantiations used in any given experiment, because each noise consists of randomly generated numbers. Individual samples of random noise do not have meaningful category labels that would allow semantic processing to bypass the perceptual learning process. Finally, noise stimuli are difficult to explicitly memorize, testing the limits of auditory perceptual learning mechanisms.

Numerous auditory perceptual learning experiments have used noise as stimuli (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017; Kaernbach, 2004; Luo, Tian, Song, Zhou, & Poeppel, 2013). Although detailed of their stimuli varied, in a subset of these studies researchers embedded a repeated, short snippet of noise inside of a longer, ongoing noise stimulus (see Figure 1; Andrillon et al., 2015; Andrillon et al., 2017). Both the short noise snippet and the longer noise were generated using the same procedure and noise distribution (e.g., Gaussian white noise). The short noise snippet has also been called “frozen noise” because the exact array of random values that makes up the snippet are “frozen” in place and repeated (Goossens et al., 2008; Guttman & Julesz, 1963; Rajendran et al., 2016; Warren, Bashford, Cooley, & Brubaker, 2001). In contrast, the longer, ongoing noise stimulus consists of non-repeating random values drawn from the same distribution. The repetition of the noise snippet in the ongoing noise forms a regular auditory pattern.

Stimuli with embedded noise snippets are typically separated into two types of conditions (Andrillon et al., 2015; Andrillon et al., 2017). In one condition, the snippet content is used for each repetition within a trial, but a new snippet is generated for each individual trial (Figure 1: “Unique

Pattern”). In the other condition, the snippet content is used for each repetition within a trial (as in “Unique Pattern”) *and*, additionally, recurs across trials (Figure 1: “Recurring Pattern”). In other words, the repeated snippet is either unique in each trial or recurs across trials. Previous studies have found that participants detect patterns made from recurring noise snippets better than patterns made from noise snippets that are unique in each trial (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017). Detection performance associated with unique patterns indicates the degree to which individuals are sensitive to a repeating noise snippet within a sound. The detection benefit for recurring over unique patterns (“recurrence benefit”) has been attributed to auditory perceptual learning; the effect is hypothesized to result from the formation of a memory trace lasting at least a few seconds (Agus et al., 2010; memory traces have also been shown to persist for weeks, see Bianco et al., 2020).

Studies using frozen noise typically presented the snippet repetitions in a temporally regular (i.e., isochronous) manner within the ongoing noise stimulus such that the rate at which a snippet repeated was constant (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017; Kaernbach, 2004). Outside of the perceptual learning literature, numerous studies have demonstrated that temporally regular presentations of sounds can facilitate perception when compared with temporally irregular or jittered presentations (Barnes & Jones, 2000; Henry & Herrmann, 2014; Jones, Johnston, & Puente, 2006; Jones, Moynihan, MacKenzie, & Puente, 2002; Large & Jones, 1999; Lawrance, Harper, Cooke, & Schnupp, 2014; Morillon, Schroeder, Wyart, & Arnal, 2016; Quené & Port, 2005; Werner, Parrish, & Holmer, 2009). Recent evidence also suggests that the rhythmic quality of stimulus presentations can impact memory (Hanslmayr, Axmacher, & Inman, 2019; Hickey & Race, 2021). For example, association memory for rhythmically presented visual and auditory stimuli was better when the rhythmic fluctuations of the visual and auditory stimulation were in-sync compared to out-of-sync, demonstrating that synchronized sensory stimulation improves associative memory (Clouter, Shapiro, & Hanslmayr, 2017; see also Hickey, Merseal, Patel, & Race, 2020; Jones & Ward,

2019; Thavabalasingam, O'Neil, Zeng, & Lee, 2016). These perceptual and memory benefits have been attributed to facilitated processing stemming from the synchronization of neural oscillatory activity with temporally regular acoustic structure (Hanslmayr et al., 2019; Henry & Herrmann, 2014; Lakatos, Gross, & Thut, 2019; Schroeder & Lakatos, 2009). In the context of auditory perceptual learning, isochronous presentations of a noise snippet may thus support a listener's ability to detect snippet repetitions and in turn enhance memory of that snippet.

Temporal regularity within stimuli is only one timing dimension that could impact auditory perceptual learning. Previous research has also demonstrated that certainty about when a stimulus occurs can facilitate perception and memory (Niemi & Näätänen, 1981; Nobre, Correa, & Coull, 2007; Nobre & van Ede, 2018). Receiving explicit cues about the time of a target stimulus can improve an individual's reaction time compared to when a target occurs at an unexpected time (Coull, Frith, Büchel, & Nobre, 2000; Coull & Nobre, 1998; Griffin, 2002; Griffin, 2001; Miniussi, Wilding, Coull, & Nobre, 1999; Nobre, 2001). Although much work about the effects of onset certainty on perception has been performed in the visual domain (Coull & Nobre, 2008; Coull & Nobre, 1998), similar perceptual benefits have been observed with auditory stimuli in animals (Jaramillo & Zador, 2011) and humans (Wilsch, Henry, Herrmann, Herrmann, & Obleser, 2018; Wilsch, Henry, Herrmann, Maess, & Obleser, 2015). For example, certainty about when a pair of auditory stimuli occurs enables listeners to better categorize whether the two stimuli are the same or different (Wilsch et al., 2018; Wilsch et al., 2015). Whether temporal certainty about when a snippet sequence occurs affects perceptual learning is unknown.

The aim of the current study was to test the effects of temporal regularity and onset certainty on perceptual learning of embedded patterns in noise. We predicted that both temporal regularity and onset certainty would affect perceptual learning. In Experiment 1, we aimed to replicate the perceptual learning effects reported in previous studies that used the frozen-noise paradigm (Andrillon et al., 2015; Andrillon et al., 2017). This would establish whether our stimuli and procedures are sufficiently sensitive to investigate the effects of temporality on perceptual learning. We then conducted two additional sets

of experiments. In one set of experiments (2A and 2B), we examined whether temporal regularity of the presentation of a frozen-noise snippet within a sound affects perceptual learning. In the other set of experiments (3A and 3B), we investigated whether certainty about the onset timing of the entire sequence of the repeated noise snippet impacts perceptual learning. The experiments all together show that temporal regularity and onset certainty are important for auditory perceptual learning.

General methods

Participants

In each of the five experiments we discuss below, we recruited participants on Amazon Mechanical Turk (MTurk) using the Cloud Research interface (formerly TurkPrime; Litman, Robinson, & Abberbock, 2017). Demographic details about participants are provided below for each individual experiment. Participants self-reported that they did not have a history of neurological disease or use a hearing aid. They indicated that they lived in the United States or Canada at the time of participation. Each participant provided informed consent before completing the experiment and received \$6 USD for their participation. We recruited new participants for each experiment such that participants in any one of the experiments were barred from participating in any of the other experiments. The study was conducted in accordance with the Declaration of Helsinki and the Canadian Tri-Council Policy Statement on Ethical Conduct for Research Involving Humans, and approved by the Research Ethics Board at the Baycrest Centre for Geriatric Care.

Stimulus details

All sounds were generated using custom MATLAB scripts. Each sound was a Gaussian white noise with a duration of 3.6 s sampled at 44.1 kHz and saved as a m4a file (121 kbps). Stimulus generation followed

procedures described in previous work (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017). Three main sound conditions were generated for each experiment: No Pattern (NP), Unique Pattern (UP), and Recurring Pattern (RP). Sounds in the NP condition had no additional characteristics – they did not contain a pattern. For the UP and RP conditions, a 0.14-s frozen-noise snippet, generated from the same Gaussian white-noise distribution, was embedded in the 3.6-s noise and repeated seven times at a constant onset-to-onset interval of 0.35 s (Figure 1). The duration of 0.14 s was selected based on pilot testing among lab members and aimed to make the task difficult but manageable. The first embedded snippet occurred 0.7 s after sound onset and the offset of the last snippet was at 2.94 s. There were no silences or other acoustic cues separating embedded snippet repetitions from the ongoing noise, because they were all generated from the same Gaussian white-noise (i.e., random-number) distribution (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017). Perception of a pattern in these sounds thus required the detection of the noise-snippet repetition within the ongoing noise stimulus. Critically, in the UP condition, a unique, newly created noise snippet was generated for each trial. For sounds in the RP condition, one noise snippet was generated and used for all trials (Figure 1). The same noise snippet was used for RP stimuli in all presentation blocks and the number of blocks depended on the specific experiment (see below). A higher detection rate for the patterns in the RP compared to the UP conditions indicates that participants are able to form a memory of the noise snippet (Agus et al., 2010; Andrillon et al., 2015).

These three stimulus conditions were used to replicate the previously reported perceptual learning effect (Andrillon et al., 2015) and establish that the current procedures are sufficiently sensitive to study perceptual learning with noise stimuli in an online setting (Experiment 1). In subsequent experiments, we presented additional stimulus conditions to investigate how perceptual learning is affected by temporal regularity (Experiment 2A and 2B) and temporal onset certainty (Experiments 3A

and 3B). We provide details regarding these temporal manipulations in the sections describing each individual experiment below.

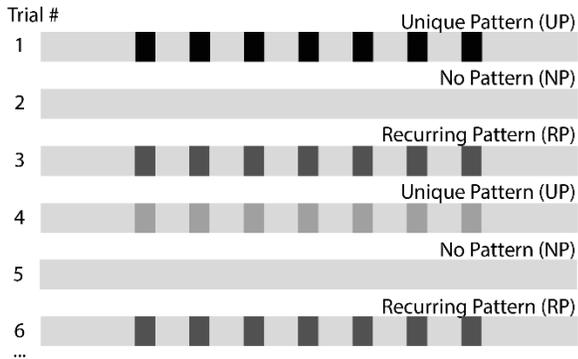


Figure 1: Stimulus design. Schematic of conditions: No Pattern (NP) consisted entirely of white noise with no repeated pattern, Unique Pattern (UP) contained seven repetitions of a noise snippet newly generated for each trial, and Recurring Pattern (RP) contained repetitions of a noise snippet used across trials. The light gray part of each trial represents the longer noise stimulus and darker gray boxes represent the repeated noise snippet (different colors indicate different spectro-temporal compositions of the noise snippet). Each row reflects one trial. Trial order was randomized in the experiments (and additional conditions were presented in Experiments 2A, 2B, 3A, and 3B).

In each experiment, 50% of the trials did not contain a pattern (i.e., the NP condition) and 50% contained a pattern. Half of the trials containing a pattern were UP sounds and the other half were RP sounds.

Experiments in the current study were conducted online. This required that stimuli were uploaded to an online server (Pavlovia: www.pavlovia.org). In order to ensure that any results observed in the current study are not related to a specific set of stimuli generated from a Gaussian white noise distribution, we generated multiple sets of stimulus files. Each list comprised stimuli from different random draws of 3.6-s Gaussian white noise and 0.14-s noise snippets. For each participant, one list was selected randomly at the beginning of the experimental session for presentation. Experiments 1, 2A, and 2B each had 20 sets, Experiments 3A and 3B each had 30 sets.

Procedure

At the beginning of each trial in the main task, participants were presented with a fixation cross for 0.3 s, followed by the 3.6-s noise stimulus (the fixation cross continued throughout). After the sound offset, a visual prompt replaced the fixation cross on the screen, asking participants to indicate whether or not they heard a pattern in the sound. Specifically, the instructions stated “Did the sound contain a

reoccurring structure?” and participants clicked either response button “Yes” or button “No” to indicate their judgement. After participants responded, they received visual feedback (“Correct” or “Incorrect”; see also Hodapp & Grimm, 2021). Our pilot testing indicated that feedback increased participants’ confidence about their responses. Finally, a 0.4-s blank screen was presented before the next trial started. The median interval between two successive sound onsets was 5.4 s (across experiments). All experimental procedures were implemented using jsPsych, a JavaScript library for running online experiments (de Leeuw, 2015). Scripts and stimuli were uploaded to Pavlovia (www.pavlovia.org) and Pavlovia was used to run the experiment and record data.

Participants underwent training before the main task blocks to introduce them to the stimuli and task procedures. To help participants hear a repetition embedded in ongoing noise, they first listened to stimuli where the repeated snippet was replaced with noises that were filtered to be slightly more narrow-band (0.2–21 kHz). Hence, for these initial training stimuli, the noise snippet was perceptually segregated from the ongoing white noise to help participants learn the temporal structure of the sound pattern. Subsequently, participants were introduced to the frozen-noise stimuli that were used in the experiment, and then completed a block with No Pattern and Unique Pattern stimuli to familiarize them with the detection task.

The whole experimental session lasted about 45-60 minutes.

Auditory setup and catch trials

At the beginning of the experiment, participants completed a volume check to set their computer volume to a comfortable level. Aggregated across experiments, approximately 97.5% ($N = 268$) of the participants self-reported using either in-ear or over-the-ear headphones. Approximately 2.2% ($N = 6$) reported using loudspeakers and one participant did not respond to the question about their sound-delivery system. We did not expect headphone versus speaker use to impact our results because the

experiments used a within-subject design and the choice of auditory presentation device did not uniquely impact any specific condition.

We included catch trials in an effort to identify individuals who did not engage with the experiment and so that we could exclude their data from analysis. One catch trial was included at the beginning and one at the end of each presentation block. Each catch trial consisted of an auditory, spoken stimulus asking participants to press a specific number key between 1 and 9 on their keyboard. While the audio signal of the catch trials was played, the visual screen was identical to the screen presented during main task trials. Hence, if participants were not listening to the auditory signal (for example if they were pressing buttons to proceed through the task but had sound muted), they had to guess (11.1% chance level) when the response screen was presented after the auditory stimulus ended. Two additional catch trials were placed in the questionnaires at the end of the experiment. These additional catch trials looked similar to the surrounding questions but instructed participants to select a specific response option from an 11-point scale. Hence, participants who did not read the questions and responded at random would likely fail these catch trials. We excluded participants who incorrectly answered three or more out of eight catch trials in Experiments 1, 2A, 2B, and three or more out of ten catch trials in Experiments 3A and 3B. Below, we provide the specific number of data sets that were excluded for each experiment.

Data analysis

For each trial, participants indicated whether or not they heard a “reoccurring structure” – a pattern – in the sound (i.e., whether they heard a repeating frozen-noise snippet). A hit was defined as a ‘pattern-present’ response when the sound that was presented contained a pattern (UP or RP trials). A false alarm was defined as a ‘pattern-present’ response to a sound that did not contain a pattern (NP trials). Some participants indicated that they detected a pattern for all trials where there was no pattern (NP), leading to a false alarm rate of one. We excluded data from these participants under the assumption

that they either did not understand the task or were intentionally selecting the same response on every trial.

False alarm and hit rates were used to calculate perceptual sensitivity (d-prime) for each participant in each condition (Macmillan & Creelman, 2005). D-prime values were calculated using custom MATLAB scripts. D-prime cannot be calculated when hit rates or false alarm rates are zero or one. To handle these cases, the following corrections were calculated. When the hit rate was zero, it was set to $\frac{1}{2 \times n}$ where n refers to number of stimuli containing a pattern. When the hit rate was one, it was set to $1 - \frac{1}{2 \times n}$. When the false alarm rate was zero, it was set to $\frac{1}{2 \times m}$ where m refers to the number of stimuli without a pattern. Data from participants with a false alarm rate of one were removed (see above; Macmillan & Creelman, 2005).

Repeated measures analyses of variance (rmANOVAs) were calculated in R (R Core Team, 2018) using the `anova_test` function from the `rstatix` package (Kassambara, 2020). For effect sizes we report generalized eta squared for ANOVA results (Bakeman, 2005; Lakens, 2013; Olejnik & Algina, 2003) and Cohen's d for paired t-tests (Cohen, 1988).

We observed that some of our online participants had low d-prime scores (around zero) and suspect that these participants were either unable (Agus et al., 2013; Agus et al., 2010) or unwilling to complete the task. In order to avoid (a) making inferences about condition effects based on low overall sensitivity to patterns or (b) excluding participants' datasets based on an arbitrary d-prime threshold, we opted to report our statistical findings with a median split as a between-subjects factor. For this median-split factor, the average d-prime value across all conditions of an experiment was calculated for each participant. Based on the median of this average d-prime value, participants were split into two groups: low performers and high performers (i.e., below or above median performance). Note that the results reported below are qualitatively similar to those from analyses excluding participants with d-prime values below 0.7 (a cutoff of 0.7 ensured sufficient statistical power).

Transparency and openness

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study, and we follow the Journal Article Reporting Standards (JARS; Kazak, 2018). Data, analysis code, and research materials are available upon reasonable request. Institutional data protection policies currently prohibit public sharing of data. Data were analyzed using MATLAB software (2020) and R (R Core Team, 2018). This study's design and its analysis were not pre-registered.

Experiment 1

Methods

Participants

Twenty-eight adults participated in Experiment 1 (mean age: 29.1 years, age range: 21-34 years). To observe a large effect ($f = 0.4$) assuming an alpha of 0.05 and power of 0.8 (1 minus beta) our sample size estimation suggested that 16 participants would be needed. Previous in-lab studies that investigated auditory perceptual learning with noise stimuli demonstrated a reliable perceptual learning effect with $N < 15$ participants (Agus et al., 2010; Andrillon et al., 2015). We opted here for a higher number of participants to ensure sufficient statistical power for our online experiment, because across-participant variability may be slightly higher during online than in-lab testing. Out of the 28 participants, 16 identified as male, 10 as female, 1 as genderqueer, and 1 as nonbinary. We excluded data from additional participants who reported using a hearing aid, having a neurological disease ($N = 1$), or both ($N = 3$), or because they failed three or more catch trials ($N = 2$).

Stimulus details

In the main experiment, participants performed the pattern-detection task in three blocks separated by short breaks. Each block contained 32 no pattern (NP), 16 unique pattern (UP), and 16 recurring pattern (RP) stimuli in randomized order (Figure 1), leading to a total of 96 NP, 48 UP, and 48 RP stimuli across the three blocks.

Data analysis

We submitted d-prime values for UP and RP for each participant to a rmANOVA with two factors: Pattern Type (Unique and Recurring; within-subjects factor) and Overall Performance (Above Median and Below Median; between-subjects factor).

Results and discussion

Figure 2A shows time courses for proportion of correct responses separately for the UP and the RP condition. Consistent with perceptual learning, performance increased with increasing number of trials for the RP, but not the UP condition. Statistical analyses focused on d-prime to account for false alarms. D-prime was higher for RP compared to UP (main effect of Pattern Type: $F_{1,26} = 15.204$, $p = 6.08 \times 10^{-4}$, $\eta_p^2 = 0.087$; Figure 2B). High-performing individuals showed a larger difference between RP and UP (i.e., “recurrence effect”) compared to low-performing individuals (Pattern Type \times Overall Performance interaction: $F_{1,28} = 10.879$, $p = 0.003$, $\eta_p^2 = 0.064$; Figure 2C and 2D). D-prime was statistically larger for RP compared to UP only for high-performing individuals (high performers: $t_{13} = 4.412$, $p = 7.018 \times 10^{-4}$, $d = 1.179$; low performers: $t_{13} = 0.519$, $p = 0.612$, $d = 0.139$).

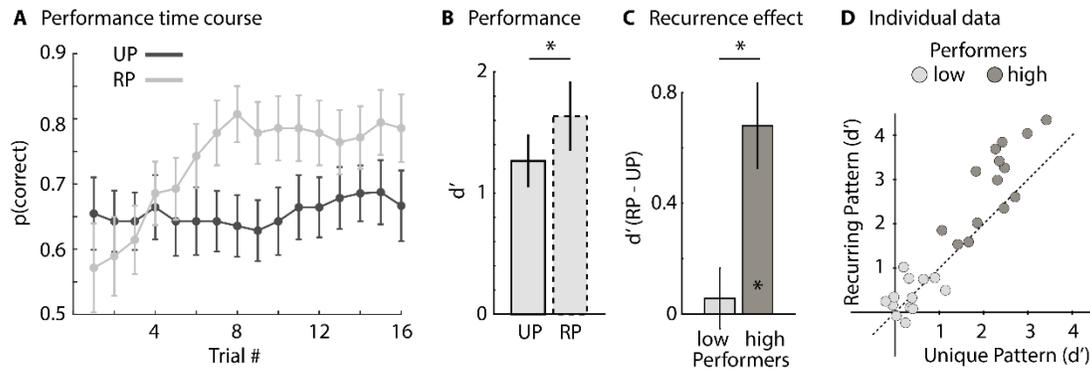


Figure 2: Results for Experiment 1. **A:** Proportion correct responses for the first 16 trials (first block), separately for the Unique Pattern (UP) and the Recurring Pattern (RP) condition. Because responses on single trials were binary, data were smoothed across trials using a sliding window (width: $N = 5$). **B:** Mean d' values for each pattern condition (UP and RP). **C:** The difference between Recurring Pattern (RP) and Unique Pattern (UP) for participants above and below median performance. **D:** d' data for each participant for Recurring Pattern (RP) and Unique Pattern (UP). The 45-degree line marks where data would fall if perceptual sensitivity for RP and UP were equal. Error bars reflect the standard error of the mean.

The results of Experiment 1 replicated – in an online setting – previous in-lab findings (Andrillon et al., 2015): Participants were sensitive to patterns embedded in ongoing white noise, and sensitivity was better for recurring patterns compared to unique patterns. The recurrence effect indicates that perceptual learning took place, that is, participants formed a memory trace for specific noise snippets (Agus et al., 2010; Andrillon et al., 2015). Experiment 1 established that our experimental approaches and procedures are sufficiently sensitive to detect perceptual learning in healthy participants, similar to previous work (Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017). This allowed us to turn to our main research questions about the effects of temporality on perceptual learning in subsequent experiments.

Experiment 2A

In Experiment 2A, we investigated the effects of manipulating the temporal regularity of the repeated noise snippet within the longer noise stimulus. If the temporal regularity of repetitions contributes to

perceptual learning, we would expect a larger recurrence effect for conditions with isochronous snippet timing when compared with jittered snippet timings.

Methods

Participants

Sixty-four adults participated in Experiment 2A (mean age: 27.8 years, age range: 20-34 years): 39 individuals identified as male, 24 as female, and 1 as nebularian. We excluded data from five additional participants because they failed to meet our catch-trial criterion. Note that we recruited approximately twice as many participants for Experiment 2A (and subsequent experiments) compared to Experiment 1 in order to increase statistical power, because we added a temporal regularity factor to the design, our hypothesis was related to interaction effects, and we found that approximately half of the participants in Experiment 1 were low performers.

Stimulus details

In addition to the isochronous noise snippets in UP and RP conditions and the No Pattern condition (NP) from Experiment 1, Experiment 2A also included conditions in which we jittered the timing of the five (of seven) middle snippet repetitions (Figure 3A). The timing of the first and last snippet of the sequence was kept constant for all conditions containing a pattern to avoid confounding the effects of temporal regularity with changes in temporal onset or offset. The manipulation of temporal regularity involved keeping one of the five middle snippet repetitions at its normal/non-jittered time, presenting two snippet repetitions 0.035 s after their non-jittered times (+10%), and presenting two snippet repetitions 0.035 s before their non-jittered times (-10%). Which of the five snippet repetitions was kept the same, presented late, or presented early was randomized for each stimulus. Manipulating temporal regularity in this way ensured that the timing statistics of the jittered and isochronous snippet sequences matched. We label UP and RP stimuli that contained jittered snippet repetitions jUP and jRP for “jittered Unique

Pattern” and “jittered Recurring Pattern”, respectively. UP and RP stimuli without jittered snippet repetitions are labelled iUP and iRP for “isochronous Unique Pattern” and “isochronous Recurring Pattern”, respectively. The frozen noise snippet – that is, the composition of random numbers making up the snippet – was the same for both the iRP and jRP conditions.

To accommodate the addition of two stimulus types, each of the three main task blocks in Experiment 2A contained 32 NP trials and 8 trials each for iUP, iRP, jUP, and jRP (for a total of 96 NP and 24 of each pattern type across the three blocks). The choice to present temporally regular (isochronous) and temporally irregular (jittered) conditions within the same block was based on previous work (Rajendran et al., 2016).

Training procedures used NP and jUP stimuli. We hypothesized that pattern detection would be more difficult for jittered than isochronous stimuli. To avoid introducing an advantage for isochronous stimuli in training, we chose to train participants on the jittered stimuli rather than the isochronous stimuli. Our training was thus designed to work against our hypothesis.

Data analysis

We submitted d-prime values for iUP, iRP, jUP, and jRP for each participant to a rmANOVA with three factors: Pattern Type (Unique Pattern and Recurring Pattern; within-subjects factor), Regularity (Isochronous and Jittered; within-subjects factor), and Overall Performance (Above Median and Below Median; between-subjects factor).

Results and discussion

D-prime was higher for recurring compared to unique patterns (main effect of Pattern Type: $F_{1,62} = 22.897$, $p = 0.001$, $\eta_G^2 = 0.058$). D-prime was also higher for isochronous compared to jittered patterns (main effect of Regularity: $F_{1,62} = 4.072$, $p = 0.048$, $\eta_G^2 = 0.003$; Figure 3B). High-performing individuals showed a larger difference between recurring and unique patterns (i.e., “recurrence effect”) compared

to low-performing individuals (Pattern Type \times Overall Performance interaction: $F_{1,62} = 33.784$, $p = 2.2 \times 10^{-7}$, $\eta_G^2 = 0.083$). High-performing individuals also showed a larger difference between isochronous and jittered patterns compared to low-performing individuals (Regularity \times Overall Performance interaction: $F_{1,62} = 9.213$, $p = 0.004$, $\eta_G^2 = 0.006$). For both of these interactions, the difference in Pattern Type or Regularity was only significant for high-performing individuals (Figure 3C and 3D; Above Median, effect of Pattern Type: $t_{31} = 5.837$, $p = 1.955 \times 10^{-6}$, $d = 1.032$; Above Median, effect of Regularity: $t_{31} = 3.343$, $p = 0.002$, $d = 0.591$; Below Median, effect of Pattern Type: $t_{31} = 1.205$, $p = 0.237$, $d = 0.213$; Below Median, effect of Regularity: $t_{31} = 0.727$, $p = 0.473$, $d = 0.128$). The interaction between Pattern Type and Regularity was not significant ($F_{1,62} = 0.003$, $p = 0.958$, $\eta_G^2 = 2.16 \times 10^{-6}$).

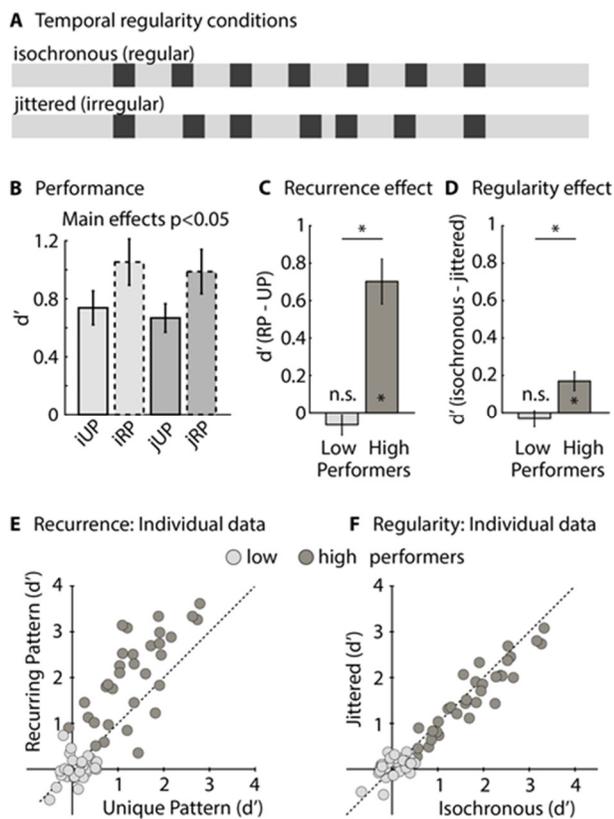


Figure 3: Stimulus conditions and results for Experiment 2A. **A:** Example stimulus schematics for isochronous and jittered conditions. Snippet repetitions in isochronous trials were equally spaced in time (onset every 0.35 s). In jittered trials, the middle five repetitions were shifted in time relative to their isochronous counterparts. **B:** Mean d' -prime values for each pattern condition: isochronous Unique Pattern (iUP), isochronous Recurring Pattern (iRP), jittered Unique Pattern (jUP), and jittered Recurring Pattern (jRP). **C:** The difference between recurring (iRP and jRP) and unique (iUP and jUP) patterns for both median-split groups. **D:** The difference between isochronous (iUP and iRP) and jittered (jUP and jRP) conditions for both median-split groups. **E:** Individual data points underlying panel C along with a 45-degree line, showing where data would fall if Unique Pattern and Recurring Pattern values were equal. **F:** Individual data points underlying panel D along with a 45-degree line, showing where data would fall if isochronous and jittered values were equal. Error bars reflect the standard error of the mean.

In sum, Experiment 2A replicated the finding that listeners are better able to detect stimuli with recurring than unique noise structure (Experiment 1; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017), indicating that participants perceptually learned a recurring, embedded noise snippet.

Introducing a temporal irregularity by jittering the timing of noise snippet repetitions reduced participants' sensitivity to the auditory patterns (i.e., d' was lower for jittered compared to isochronous conditions). However, we found no evidence that temporal irregularity diminished perceptual learning: jittering the timing of snippets did not statistically affect the difference in sensitivity between RP and UP sounds (i.e., the Pattern Type \times Regularity interaction was not statistically significant).

In Experiment 2A, we used the same noise snippet in both the isochronous and jittered recurring conditions (iRP and jRP). Because the noise snippet was shared among the two regularity conditions, the perceptual representation of the recurring snippet for sounds with temporally irregular patterns may have been strengthened by the perceptual representation of the recurring snippet for sounds with temporally regular patterns. In order to test whether perceptual learning is affected by temporal regularity when the noise snippets for recurring patterns are distinct from isochronous versus jittered conditions, we conducted Experiment 2B.

Experiment 2B

Methods

Participants

Sixty-one adults participated in Experiment 2B (mean age: 29.6 years, age range: 21-34 years): 39 of these participants identified as male, 21 as female, and 1 as nonbinary. Sample size estimation was similar to Experiment 2A. We excluded data from additional participants who reported a neurological disease ($N = 3$) or because they failed our catch-trial criterion ($N = 4$).

Stimulus details

Stimulus details mirrored those of Experiment 2A with one exception: iRP and jRP stimuli each had their own, unique noise snippet that recurred across trials. The number of trials for each condition was the same as in Experiment 2A: 96 trials for the NP condition, and 24 trials for each of the iUP, jUP, iRP, and jRP conditions, across three blocks of stimulation.

Data Analysis

The rmANOVA format and median split followed the same procedures as Experiment 2A.

Results and discussion

D-prime was higher for recurring compared to unique patterns (main effect of Pattern Type: $F_{1,59} = 24.051$, $p = 7.71 \times 10^{-6}$, $\eta_G^2 = 0.036$). D-prime was also higher for isochronous compared to jittered patterns (main effect of Regularity: $F_{1,59} = 6.712$, $p = 0.012$, $\eta_G^2 = 0.018$; Figure 4A and 4B). High-performing individuals showed a larger difference between recurring and unique patterns compared to low-performing individuals (Pattern Type \times Overall Performance interaction: $F_{1,59} = 11.544$, $p = 0.001$, $\eta_G^2 = 0.017$; Figure 4C). Specifically, d-prime was larger for recurring compared to unique patterns for high-performing individuals ($t_{29} = 5.505$, $p = 6.235 \times 10^{-6}$, $d = 1.005$), but not for low-performing individuals ($t_{30} = 1.193$, $p = 0.242$, $d = 0.214$).

Critically, we observed an interaction between Pattern Type and Regularity ($F_{1,59} = 4.946$, $p = 0.03$, $\eta_G^2 = 0.013$). D-prime was larger for iRP than iUP ($t_{60} = 5.03$, $p = 4.689 \times 10^{-6}$, $d = 0.644$), but did not statistically differ between jRP and jUP ($t_{60} = 1.088$, $p = 0.28$, $d = 0.139$). These results suggest that the perceptual learning of a repeated noise snippet is reduced when the snippet repetitions are temporally irregular. Note that despite reduced perceptual learning (as indicated by the absence of a difference between jRP and jUP), there was no statistical difference between sensitivity to iUP and jUP

($t_{60} = 0.531$, $p = 0.598$, $d = 0.068$), suggesting that participants were able to detect patterns comparably in both conditions (consistent with Rajendran et al., 2016).

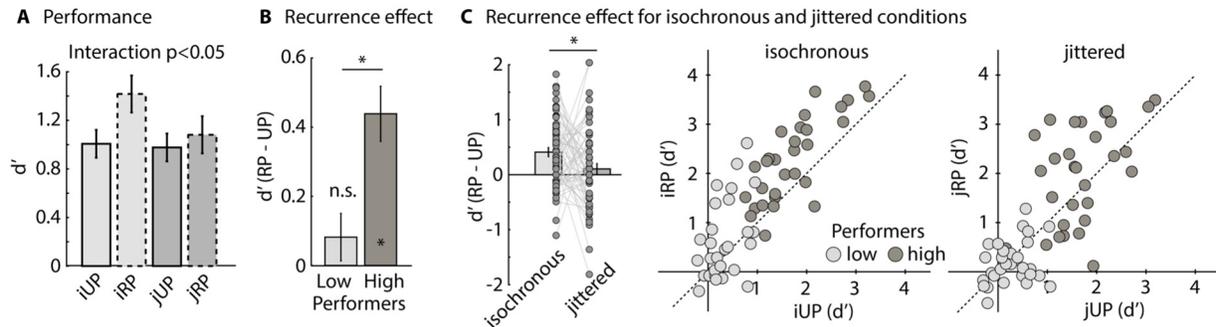


Figure 4: Results for Experiment 2B. **A:** Mean d' -prime values for each condition: isochronous Unique Pattern (iUP), isochronous Recurring Pattern (iRP), jittered Unique Pattern (jUP), and jittered Recurring Pattern (jRP). **B:** The difference in d' -prime values between RP and UP conditions for low (below median) and high (above median) performers. **C:** The mean difference between Recurring Pattern and Unique Pattern for isochronous and jittered conditions with individual data points and connecting lines (leftmost). Individual data for isochronous conditions (center), and jittered conditions (rightmost) with 45-degree lines showing where data would fall if values were equal between conditions. Error bars reflect the standard error of the mean.

Experiments 2A and 2B demonstrated the impact of temporal regularity on the detection and perceptual learning of patterns in noise. In Experiment 2A, we did not find an effect of temporal regularity on perceptual learning, only an overall reduction in pattern detectability for temporally irregular snippet repetitions. However, in Experiment 2A, iRP and jRP shared the same snippet composition – that is, the same sampling of random numbers. The shared noise snippet may have led to a heightened perceptual representation for that snippet in the jittered condition (jRP). When we used distinct snippets for iRP and jRP in Experiment 2B, we found an effect of temporal regularity on perceptual learning: the perceptual benefit of recurring over unique patterns was reduced when noise snippets within a sound were presented in a temporally irregular compared to regular manner. This is consistent with the idea that sharing snippets across isochronous and jittered conditions can benefit perceptual learning for jittered conditions (Experiment 2A) and that using distinct snippets in these two conditions removes this benefit (Experiment 2B).

Temporal regularity is only one temporal cue that may facilitate auditory perception. Previous research has also shown that certainty about the onset timing of sounds and sound sequences improves perceptual accuracy and discrimination (Jaramillo & Zador, 2011; Wilsch et al., 2018; Wilsch et al., 2015). In Experiments 2A and 2B, the onset of the entire snippet sequence (i.e., the seven snippet repetitions) was fixed across trials and participants could thus rely on temporal expectations about when the pattern would start and end within each stimulus. Experiments 3A and 3B were designed to investigate whether temporal certainty about pattern onset affects perceptual learning.

Experiment 3A

Methods

Participants

Sixty-four adults participated in Experiment 3A (mean age: 29.4 years, age range: 20-35 years): 38 of these participants identified as male and 26 as female. Sample size estimation was similar to Experiment 2A. We excluded data from participants who reported hearing aid use ($N = 1$) or because they failed our catch-trial criterion ($N = 5$).

Stimulus and procedural details

Experiment 3A contained NP and isochronous UP and RP stimuli as in Experiments 1, 2A, and 2B; none of the conditions with within-trial jittering were utilized here. In order to investigate whether sensitivity to patterns is affected by pattern-onset certainty, we created UP and RP stimuli with variable pattern-onset timings. For the UP and RP conditions with variable onsets, the timing of the onset of the snippet sequence took one of sixteen potential values across trials. Onset timings ranged in linear increments from 0.3 to 1.1 s after stimulus onset (Figure 5A). To distinguish the different UP and RP conditions, we

label UP and RP stimuli with “certain” onset timings as cUP and cRP, respectively. For cUP and cRP, the onset timing of the snippet sequences was fixed at 0.7 s across trials. We label UP and RP stimuli with “uncertain” onset timings as uUP and uRP, respectively. In Experiment 3A, the frozen noise snippet – i.e., the composition of random numbers making up the snippet – was the same in both the “certain” and “uncertain” recurring conditions (cRP and uRP), mirroring Experiment 2A in this respect.

In order to investigate sensitivity to patterns with certain and uncertain onset timings, we expanded the main task of the experiment to four blocks separated by short breaks. Two blocks contained NP, cUP, and cRP stimuli and the other two blocks contained NP, uUP, and uRP stimuli. We randomized across participants whether the experiment began with a block containing certain or uncertain stimuli and alternated block type thereafter. Each block in the main task contained 32 NP stimuli, 16 cUP or uUP stimuli, and 16 cRP or uRP stimuli. “Certain” and “uncertain” conditions were presented in separate blocks in Experiment 3A, because certainty about pattern onset times is established across trials (as opposed to the temporal jittering within trials used in Experiments 2A and 2B). Mixing “certain” and “uncertain” trials within a block would prohibit listeners from establishing temporal representations for “certain” trials.

Each of the four blocks included catch trials as described in Experiment 1, bringing the total number of catch trials for Experiment 3A to ten (eight from main task blocks and two from the questionnaires). Training procedures used NP and uUP stimuli.

Data analysis

Sets of either certain or uncertain blocks were used to separately calculate d-prime for each of the four pattern conditions (certain: 64 total NP, 32 cUP, 32 cRP; uncertain: 64 NP, 32 uUP, 32 uRP). D-prime values for cUP, cRP, uUP, and uRP were submitted to a rmANOVA with three factors: Pattern Type (Unique Pattern and Recurring Pattern, within-subject factor), Onset Timing (Certain and Uncertain,

within-subject factor), and Overall Performance (Above Median and Below Median, between-subject factor).

Results and discussion

D-prime was higher for recurring compared to unique patterns (main effect of Pattern Type: $F_{1,62} = 6.522$, $p = 0.013$, $\eta_G^2 = 0.033$). There was an interaction between Pattern Type and Overall Performance ($F_{1,62} = 7.141$, $p = 0.01$, $\eta_G^2 = 0.036$; Figure 5B and 5C) such that d-prime was larger for recurring compared to unique patterns for high-performing individuals ($t_{31} = 3.010$, $p = 0.005$, $d = 0.532$) but not for low-performing individuals ($t_{31} = 0.119$, $p = 0.906$, $d = 0.021$; Figure 5C and 5E). Uncertain onset conditions did not statistically impact d-prime (no main effect of Onset Timing: $F_{1,62} = 0.086$, $p = 0.77$, $\eta_G^2 = 1.2 \times 10^{-4}$; Figure 5D and 5F). The interaction between Pattern Type and Onset Timing was not statistically significant ($F_{1,62} = 0.015$, $p = 0.903$, $\eta_G^2 = 9.28 \times 10^{-6}$).

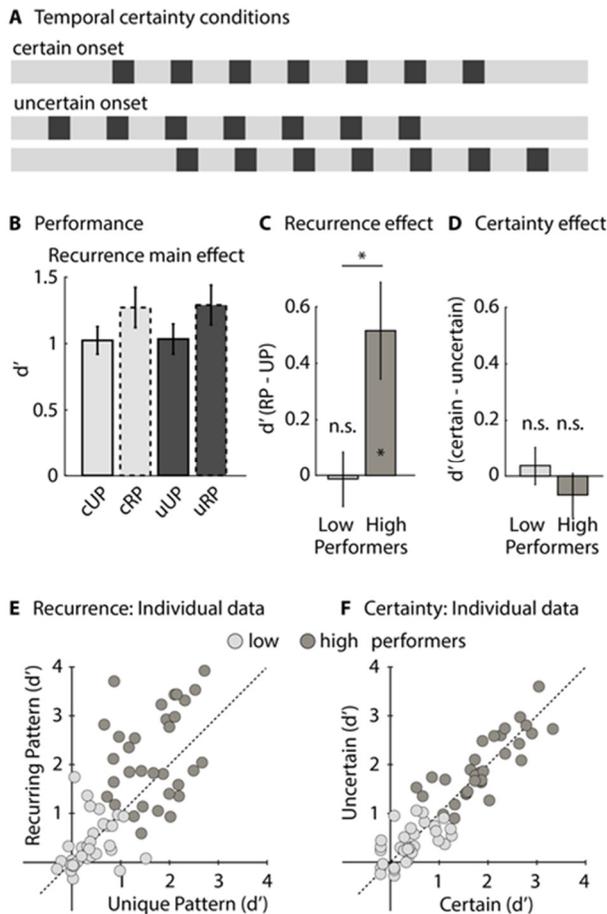


Figure 5: Stimulus conditions and results for Experiment 3A. **A:** Schematic of stimulus conditions with certain and uncertain onset timing. Snippet sequences in certain trials always began at the same time (0.7 s). Snippet sequences in uncertain trials began at one of various potential times (selected from a uniform distribution). **B:** Mean d' -prime values for each condition: certain Unique Pattern (cUP), certain Recurring Pattern (cRP), uncertain Unique Pattern (uUP), and uncertain Recurring Pattern (uRP). **C:** Difference between Recurring Pattern and Unique Pattern trials grouped by below- and above-median performance (low and high performers, respectively). **D:** Difference between certain and uncertain trials for low and high performers. **E:** Data points underlying panel C. The 45-degree line marks where the data would fall if perceptual sensitivity for RP and UP were equal. **F:** Data points underlying panel D. The 45-degree line marks where the data would fall if perceptual sensitivity for certain and uncertain conditions were equal. Error bars reflect the standard error of the mean.

As in Experiments 1, 2A, and 2B, we found that participants were more sensitive to RP than UP stimuli. The absence of an interaction between Pattern Type and Onset Timing suggests that perceptual learning was not impacted by onset uncertainty. However, as in Experiment 2A, in this experiment we used the same frozen-noise snippet for certain and uncertain conditions. As a result, the effects of onset uncertainty may have been ameliorated by forming a perceptual representation of the snippet in blocks with onset certainty. To test whether onset timing matters when snippets are distinct for certain and uncertain recurring patterns, we ran Experiment 3B.

Experiment 3B

Methods

Participants

Sixty-three adults participated in Experiment 3B (mean age: 28.4 years, age range: 21-35 years): 44 of these participants identified as male, 18 as female, and 1 as nonbinary. Sample size estimation was similar to Experiment 2A. We excluded data from additional participants who reported hearing aid use ($N = 10$), having a neurological disease ($N = 2$), or both ($N = 1$), or because they failed our catch-trial criterion ($N = 11$).

Stimulus details

Stimulus details mirrored those of Experiment 3A with one exception: cRP and uRP stimuli each had their own, unique noise snippet that recurred across trials. The number of trials for each condition was the same as in Experiment 3A. Across the two blocks with certain onset timing, 64 NP, 32 cUP, and 32 cRP stimuli were presented. Across the two blocks with uncertain onset timing, 64 NP, 32 uUP, and 32 uRP stimuli were presented.

Data analysis

The rmANOVA format and median split followed the same procedures as Experiment 3A.

Results and discussion

D-prime was higher for recurring compared to unique patterns (main effect of Pattern Type: $F_{1,61} = 68.95$, $p = 1.32 \times 10^{-11}$, $\eta_G^2 = 0.077$). D-prime was also higher for patterns with certain compared to uncertain onset timing across trials (main effect of Onset Timing: $F_{1,61} = 6.125$, $p = 0.016$, $\eta_G^2 = 0.02$; Figure 6A and 6B). There was an interaction between Pattern Type and Overall Performance ($F_{1,61} = 32.243$, $p = 4.03 \times$

10^{-7} , $\eta_G^2 = 0.038$) such that the difference between d -prime for recurring compared to unique patterns was greater for high-performing individuals ($t_{30} = 8.954$, $p = 5.614 \times 10^{-10}$, $d = 1.608$) than for low-performing individuals ($t_{31} = 2.175$, $p = 0.037$, $d = 0.384$; Figure 6C).

Critically, we observed an interaction between Pattern Type and Onset Timing ($F_{1,61} = 8.393$, $p = 0.005$, $\eta_G^2 = 0.022$) such that the difference between cRP and cUP was greater than the difference between uRP and uUP (Certain: $t_{62} = 5.794$, $p = 2.477 \times 10^{-7}$, $d = 0.730$; Uncertain: $t_{62} = 2.309$, $p = 0.024$, $d = 0.291$). This suggests that perceptual learning was impaired by onset uncertainty. Additional evidence for this interpretation of the interaction is the fact that it was driven by a lower uRP compared to cRP ($t_{62} = 2.853$, $p = 0.006$, $d = 0.359$), whereas detectability of unique patterns was not statistically different between the two uncertainty conditions (cUP versus uUP: $t_{62} = 0.191$, $p = 0.85$, $d = 0.024$). Relatedly, we found a three-way interaction between Pattern Type, Onset Timing, and Overall Performance ($F_{1,61} = 4.479$, $p = 0.038$, $\eta_G^2 = 0.012$). Follow-up rmANOVAs revealed a significant interaction between Pattern Type and Onset Timing for high performers (Above Median group: $F_{1,30} = 8.342$, $p = 0.007$, $\eta_G^2 = 0.04$) but no significant interaction for low performers (Below Median group: $F_{1,31} = 0.655$, $p = 0.424$, $\eta_G^2 = 0.005$; Figure 6C).

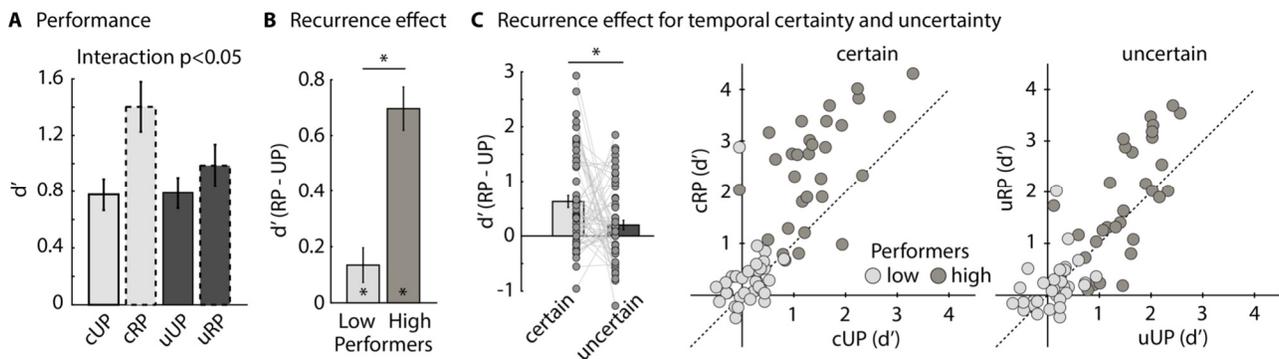


Figure 6: Results for Experiment 3B. **A:** Mean d -prime values for each condition: certain Unique Pattern (cUP), certain Recurring Pattern (cRP), uncertain Unique Pattern (uUP), and uncertain Recurring Pattern (uRP). **B:** Difference between Recurring Pattern and Unique Pattern trials grouped by above- and below-median performance. **C:** The mean difference between Recurring Pattern and Unique Pattern for certain and uncertain conditions with individual data points and connecting lines (leftmost). Individual data for certain conditions

(center) and uncertain conditions (rightmost) with 45-degree lines showing where data would fall if values were equal between conditions. Error bars reflect the standard error of the mean.

As in Experiments 1, 2A, 2B, and 3A, we found that participants were better at detecting recurring patterns than unique patterns in sounds, indicating perceptual learning of noise snippets (Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017). In Experiment 3B, we also found that, although perceptual learning occurred in both certain and uncertain contexts, perceptual learning of noise snippets was reduced when the onset of the snippet pattern was uncertain. In contrast to Experiment 3A, where we used the same frozen-noise snippet for certain and uncertain recurring patterns and found no difference in perceptual learning, in Experiment 3B, we used different snippets for certain and uncertain recurring patterns and found evidence for reduced perceptual learning in uncertain conditions.

General discussion

In the current study, we investigated whether perceptual learning of a repeated noise snippet embedded in an ongoing noise stimulus is affected by two types of temporal manipulations: the temporal regularity of snippet repetitions and the certainty about the onset of snippet sequences. We first demonstrated that our online procedure is sufficiently sensitive to detect perceptual learning of frozen noise: we showed that a noise snippet that recurred across sounds was detected better than a noise snippet that was unique for each sound. In subsequent experiments we observed that perceptual learning was diminished when the noise-snippet repetitions were temporally irregular and when the onset time of the entire snippet sequence was uncertain. We also found that these negative impacts on perceptual learning were ameliorated when the recurring noise snippet was shared across temporally manipulated and unmanipulated conditions. These findings underscore the importance of temporality

in auditory perceptual learning and show that negative consequences of temporal manipulations can be mitigated.

Perceptual learning of structure in sounds

In the current study, we adopted a previously used, frozen-noise paradigm (Andrillon et al., 2015; Andrillon et al., 2017) in an online setting. Our Experiment 1 replicated previous observations that participants were more sensitive to embedded noise patterns within a longer noise stimulus when the embedded noise snippet creating the pattern recurred across trials compared to when the snippet was unique for each trial (Andrillon et al., 2015; Andrillon et al., 2017). We found this perceptual benefit for recurring over unique patterns in each of our five experiments, demonstrating its robustness. A perceptual benefit of recurring over unique patterns has also been observed in studies using a different, but related frozen-noise paradigm (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010) and for sequences of tones containing auditory patterns (Bianco et al., 2020; Herrmann et al., 2021; but note the absence of this effect in Hodapp & Grimm, 2021). In order for participants to be more sensitive to patterns created using across-trial recurring noise snippets than to patterns created using trial-unique noise snippets, they must have learned specific aspects of the noise snippet that recurred across trials. We thus interpret this recurrence benefit as evidence of auditory perceptual learning: improved performance for recurring patterns arises from memory formation that makes recurring patterns easier to detect than unique patterns (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017; Luo et al., 2013).

We further observed that individuals who were overall better at detecting the noise-snippet repetition within a sound also had a greater perceptual benefit from recurring over unique patterns, and thus a bigger perceptual learning effect. Previous work using similar frozen noise stimuli also showed that detecting noise repetitions is difficult and performance is relatively low overall (Agus et al., 2013; Agus & Pressnitzer, 2013; Agus et al., 2010; Andrillon et al., 2015; Andrillon et al., 2017). Independent,

unpublished work in our lab, using sounds similar to those used here, further indicates that pattern-detection performance increases with increasing duration of the frozen noise snippet (see also Rajendran et al., 2016), and that some participants may benefit from a snippet duration that is longer than the 0.14 s utilized in the current study. However, due to the online format of the current study, we do not know whether participants were unwilling or unable to perform the task. An in-lab study may reduce the variability in overall performance and increase the perceptual learning benefit across participants. However, given the relatively rapid perceptual learning reported in previous work (Agus & Pressnitzer, 2013; Agus et al., 2010), it seems unlikely that our low-performing participants would improve with more training or more exposure (assuming they were willing to do the task).

Temporal irregularity reduces perceptual learning

In Experiment 2B, we found that temporally jittering a repeated noise snippet embedded in an ongoing noise stimulus reduced perceptual learning when compared with temporally isochronous repetitions of a noise snippet. That is, perceptual sensitivity was higher for recurring compared to unique patterns when the snippet repetitions in the ongoing noise stimulus were isochronous, whereas recurring and unique patterns did not differ when the snippet repetitions were jittered.

Previous work has demonstrated that temporally irregular sound presentation can reduce perceptual performance when compared with temporally regular presentation (Barnes & Jones, 2000; Henry & Herrmann, 2014; Jones et al., 2006; Jones et al., 2002; Large & Jones, 1999; Lawrance et al., 2014; Quené & Port, 2005; Werner et al., 2009). Such a performance decrement for temporal irregularity has also been observed for frozen-noise sequences similar to those used in the current study (Rajendran et al., 2016; Experiment 2A and Figure 3). However, these previous studies did not speak to the effects of temporal regularity uniquely on perceptual learning because they did not include a stimulus condition for which noise patterns recurred across trials. By including recurring pattern stimuli, we were able to demonstrate that temporal regularity affects perceptual learning, i.e., the perceptual benefit of snippet

recurrence beyond detectability of snippet repetition. We speculate that in crowded auditory scenes, temporal regularity can facilitate recognizing recurring sounds, such as calls made by an animal in nature or the faint ringing of a phone in a restaurant. Our observation that temporal irregularity reduces perceptual learning is also broadly consistent with literature on the role of temporal regularity in episodic (Hickey et al., 2020) and associative memory (Clouter et al., 2017; Roberts, Clarke, Addante, & Ranganath, 2018; Wang, Clouter, Chen, Shapiro, & Hanslmayr, 2018, but see Kulkarni & Hannula, 2021).

Conceptual (Jones, 1976; Jones, 2019; Large & Jones, 1999) and neurophysiological work (Lakatos et al., 2013; O'Connell, Barczak, Schroeder, & Lakatos, 2014; Schroeder & Lakatos, 2009) provides explanations for the effects of temporal regularity on the perceptual learning observed here. Dynamic Attending Theory suggests that internal attentional oscillations synchronize with, or entrain to, external sound rhythms, and that this entrainment is weakened by temporally irregular sound structure (Jones, 1976; Jones, 2019; Large & Jones, 1999). Better entrainment is thought to narrow the listener's expectations about future sounds, facilitating their perception. Support for this conceptual framework has come from neurophysiological work showing that neural oscillations reflect fluctuations in neuronal excitability (Lakatos et al., 2005), and that neural oscillations entrain to auditory rhythms such that the high-excitability phase of the oscillation aligns with temporally regular sounds (Lakatos et al., 2019; Lakatos et al., 2013). Alignment of the high-excitability phase with sound events facilitates their processing (Henry & Herrmann, 2014; Lakatos et al., 2013; Schroeder & Lakatos, 2009), but the alignment should be disrupted for temporally irregular sound sequences. Sounds in such irregular sequences may thus be encoded less well (Henry & Herrmann, 2014). Our results suggest that encoding of the noise snippet may have been just impaired enough by the temporal irregularity to impair perceptual learning across trials (i.e., the benefit of recurring noise snippets), while not affected detectability of patterns within trials (i.e., there was no difference between iUP and jUP in Experiment 2B; but see Experiment 2A for an overall effect of temporal regularity). Indeed, temporal irregularity in the current study was created by changing the timing of frozen-noise snippets within a sequence by

$\pm 10\%$, which is a modest jitter relative to other work using temporal irregularities (Hodapp & Grimm, 2021; Rajendran et al., 2016; ten Oever et al., 2017; although manipulations of $\sim 10\%$ jitters were sometimes included too). We speculate that a greater temporal jitter would increase the effect of temporal regularity on perceptual learning, but also lead to an overall reduction in detection performance (i.e., for jUP stimuli; Rajendran et al., 2016). In sum, our results suggest that establishing memory traces of noise structure in sounds depends on temporal regularity.

Temporal onset uncertainty reduces perceptual learning

In Experiment 3B, we found reduced perceptual learning for frozen-noise sequences in a longer noise stimulus with different onset times across trials. That is, the recurrence benefit over unique patterns was reduced for sequences in which the sequence-onset timing was uncertain compared to sequences in which the sequence-onset timing was certain. Previous work has shown that temporal certainty about when a relevant stimulus will occur facilitates perception (Herbst, Fiedler, & Obleser, 2018; Jaramillo & Zador, 2011; Los, 2010; Niemi & Näätänen, 1981; Nobre et al., 2007; Nobre & van Ede, 2018; Wilsch et al., 2018; Wilsch et al., 2015).

Previous work has also shown that temporal certainty can affect auditory memory (Wilsch et al., 2018; Wilsch et al., 2015). For example, memory for the first sound of a pair of sounds has been shown to decrease when the onset of the sound pair is temporally uncertain compared to when it is certain and thus temporally predictable across trials (Wilsch et al., 2018; Wilsch et al., 2015). We show here that perceptual learning of frozen-noise snippets and related memory processes benefit from temporal certainty about when regular noise structure (i.e., a pattern) begins in sounds. As for our temporal regularity manipulation (Experiment 2B), the encoding of the noise snippet appeared just disrupted enough by the temporal uncertainty to impair perceptual learning across trials (i.e., the benefit of recurring noise snippets), while not affecting detectability of patterns within trials (i.e., there was no

difference between cUP and uUP in Experiment 3B). The results of the current study suggest that memory traces of noise structure in sounds depend on temporal certainty.

Acquiring certainty about the pattern-onset timing in the sounds involves using the sound onset as an implicit cue relative to the temporal occurrence of the pattern. Such relation between a cue and a subsequent target stimulus is typical of studies investigating how temporal certainty affects perception and cognition (Jaramillo & Zador, 2011; Nobre et al., 2007; Nobre, 2001; Wilsch et al., 2018; Wilsch et al., 2015). Whether, in real life, a systematic relation between sound onset and patterned sound structure exists may depend on the specific context. Critically, onset certainty is only one cue that may be relevant for learning structure in sounds. Individuals can learn specific frozen-noise segments, similar to the noise snippets used here, that recur over tens of seconds based on training with a visual cue presented concurrently with the noise segments (Warren et al., 2001). Temporally co-varying rewards may further support perceptual learning of structure in noise stimuli (Seitz, Kim, & Watanabe, 2009). Certainty about recurring sound structure may thus be triggered by a variety of co-varying information in the environment that can facilitate learning.

Finally, in the current study, we independently investigated the effects of temporal regularity (Experiments 2A and 2B) and temporal certainty (Experiments 3A and 3B) on perceptual learning and demonstrate that both temporal manipulations can reduce learning. Our study was not designed to investigate the interaction between temporal regularity and temporal certainty, but we anticipate that recurring frozen-noise snippets that are presented temporally irregularly and at uncertain onset times would be even harder to learn. Future work may target the combined effects of these different timing mechanisms on perceptual learning.

Mitigating the negative impacts of temporal manipulations on perceptual learning

In the current study, temporal irregularity of a repeated noise snippet in a sound, and uncertainty about the onset of the snippet sequence across sounds, both reduced perceptual learning. However, reduced

perceptual learning only occurred when different frozen-noise snippets were used for sounds with manipulated temporal features and sounds without such manipulations (Experiments 2B and 3B). When the same frozen-noise snippet was used for sounds with and without manipulated temporal features, neither temporal regularity nor temporal onset certainty affected perceptual learning (Experiments 2A and 3A). This may suggest that the memory trace for recurring snippets formed in temporally regular or certain conditions translates to temporally irregular or uncertain conditions, mitigating reductions in perceptual learning.

Whether perceptual learning generalizes from one domain to another is still an ongoing question. Some work suggests that transfer of perceptual learning may be limited (e.g., Fahle, 1997; Fahle & Morgan, 1996), whereas other work has demonstrated perceptual learning transfer (e.g., McGovern, Webb, & Peirce, 2012; Wright, Wilson, & Sabin, 2010). It appears that the degree of transfer may depend on task aspects (Ahissar & Hochstein, 1997; Jeter, Doshier, Petrov, & Lu, 2009), training length (Aberg, Tartaglia, & Herzog, 2009; Jeter, Doshier, Liu, & Lu, 2010; Wright et al., 2010), and stimulus type (McGovern et al., 2012). The current study may suggest a unique type of transfer, such that shared stimulus content (i.e., the same frozen-noise snippet) can facilitate auditory perceptual learning across different temporal manipulations and mitigate negative impacts for perceptual learning associated with temporal regularity and temporal onset certainty.

Two additional factors could potentially also play a role. Firstly, in Experiment 2B, participants were exposed to two separate recurring noise snippets for the iRP and jRP conditions within the same block. The two recurring noise snippets may have increased the memory load relative to Experiment 2A, where the same recurring noise snippet was used for both the iRP and the jRP condition. A higher load, in turn, could have contributed to the impact of temporal irregularity on perceptual learning. However, the temporal-certainty manipulation utilized in Experiments 3A and 3B required a block design, such that the two different recurring noise snippets were presented in separate blocks. An additional memory load was thus not present in Experiment 3B, suggesting that perceptual learning was facilitated by

transfer between temporally certain and uncertain conditions in Experiment 3A, and that the absence of such transfer impairs perceptual learning.

Secondly, by utilizing different recurring noise snippets for the temporal conditions in Experiment 2B and 3B, participants were exposed to half of the instances of the specific recurring noise structure compared to Experiments 2A and 3A (although the number of trials per condition was the same across Experiments 2A and 2B and Experiments 3A and 3B). Whether the reduced exposure to a specific recurring noise snippet additionally contributed to the differences between Experiments 2A versus 2B and Experiments 3A versus 3B cannot be answered in the current study, although previous work suggests perceptual learning of noise structure occurs within a few trials (Agus & Pressnitzer, 2013; Agus et al., 2010; see also Figure 2A).

Critically, the current study does demonstrate that under specific circumstances temporal regularity and temporal certainty affect perceptual learning (i.e., when recurring patterns are distinct for different types of temporal manipulation), whereas under other circumstances these temporal manipulations do not.

Conclusions

The current study investigated whether perceptual learning of patterns in sounds is affected by temporal regularity of the pattern and temporal certainty about when the pattern occurs across sounds. In each of five experiments, we found evidence that participants were able to perceptually learn repeated noise snippets that recurred across trials. We further demonstrated that temporal irregularity and onset uncertainty reduced perceptual learning. However, it appears that this reduction in perceptual learning can be mitigated by strengthening the perceptual representation of the noise snippet. Our study highlights the importance of temporal regularity and onset certainty for auditory perception and memory.

Acknowledgements

BH was supported by the Canada Research Chair program.

Author Contributions

TD, MJH, and BH designed the study. TD and BH programmed the experiments. TD recorded and analyzed the data. TD and BH wrote the manuscript. MJH edited the manuscript.

Declaration of conflicts

The authors have no conflicts to declare.

References

- Aberg, K. C., Tartaglia, E. M., & Herzog, M. H. (2009). Perceptual learning with Chevrons requires a minimal number of trials, transfers to untrained directions, but does not require sleep. *Vision Research, 49*(16), 2087-2094. doi: 10.1016/j.visres.2009.05.020
- Agus, T. R., Carrión-Castillo, A., Pressnitzer, D., & Ramus, F. (2013). Perceptual learning of acoustic noise by dyslexic individuals. *J Speech Lang Hearing Res, 57*, 1069–1077.
- Agus, T. R., & Pressnitzer, D. (2013). The detection of repetitions in noise before and after perceptual learning. *Journal of the Acoustical Society of America, 134*(1), 464-473.
- Agus, T. R., Thorpe, S. J., & Pressnitzer, D. (2010). Rapid formation of robust auditory memories: Insights from noise. *Neuron, 66*(4), 610-618. doi: 10.1016/j.neuron.2010.04.014
- Ahissar, M., & Hochstein, S. (1997). Task difficulty and the specificity of perceptual learning. *Nature, 387*(6631), 401-406. doi: 10.1038/387401a0

- Andrillon, T., Kouider, S., Agus, T., & Pressnitzer, D. (2015). Perceptual learning of acoustic noise generates memory-evoked potentials. *Current Biology*, *25*(21), 2823-2829. doi: 10.1016/j.cub.2015.09.027
- Andrillon, T., Pressnitzer, D., Léger, D., & Kouider, S. (2017). Formation and suppression of acoustic memories during human sleep. *Nature Communications*, *8*(1), 179. doi: 10.1038/s41467-017-00071-z
- Bakeman, R. (2005). Recommended effect size statistics for repeated measures designs. *Behavior Research Methods*, *37*(3), 379-384. doi: 10.3758/bf03192707
- Barnes, R., & Jones, M. R. (2000). Expectancy, attention, and time. *Cognitive Psychology*, *41*(3), 254-311. doi: 10.1006/cogp.2000.0738
- Bianco, R., Harrison, P. M. C., Hu, M., Bolger, C., Picken, S., Pearce, M. T., & Chait, M. (2020). Long-term implicit memory for sequential auditory patterns in humans. *eLife*, *9*, 1-36.
- Clouter, A., Shapiro, K. L., & Hanslmayr, S. (2017). Theta Phase Synchronization Is the Glue that Binds Human Associative Memory. *Current Biology*, *27*(20), 3143-3148.e3146. doi: <https://doi.org/10.1016/j.cub.2017.09.001>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed ed.). Hillsdale, N.J: L. Erlbaum Associates.
- Cohen, M. A., Horowitz, T. S., & Wolfe, J. M. (2009). Auditory recognition memory is inferior to visual recognition memory. *Proceedings of the National Academy of Sciences*, *106*(14), 6008-6010. doi: 10.1073/pnas.0811884106
- Coull, J., & Nobre, A. (2008). Dissociating explicit timing from temporal expectation with fMRI. *Current Opinion in Neurobiology*, *18*(2), 137-144. doi: 10.1016/j.conb.2008.07.011
- Coull, J. T., Frith, C. D., Büchel, C., & Nobre, A. C. (2000). Orienting attention in time: Behavioural and neuroanatomical distinction between exogenous and endogenous shifts. *Neuropsychologia*, *38*(6), 808-819. doi: 10.1016/S0028-3932(99)00132-3

- Coull, J. T., & Nobre, A. C. (1998). Where and when to pay attention: The neural systems for directing attention to spatial locations and to time intervals as revealed by both PET and fMRI. *The Journal of Neuroscience*, *18*(18), 7426-7435. doi: 10.1523/JNEUROSCI.18-18-07426.1998
- de Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior Research Methods*, *47*(1), 1-12. doi: 10.3758/s13428-014-0458-y
- Fahle, M. (1997). Specificity of learning curvature, orientation, and vernier discriminations. *Vision Res*, *37*(14), 1885-1895. doi: 10.1016/s0042-6989(96)00308-2
- Fahle, M., & Morgan, M. (1996). No transfer of perceptual learning between similar stimuli in the same retinal position. *Curr Biol*, *6*(3), 292-297. doi: 10.1016/s0960-9822(02)00479-7
- Gibson, E. J. (1953). Improvement in perceptual judgments as a function of controlled practice or training. *Psychological Bulletin*, *50*(6), 401-431. doi: 10.1037/h0055517
- Gibson, E. J. (1963). Perceptual learning. *Annual Review of Psychology*, *14*(1), 29-56.
- Goldstone, R. L. (1998). Perceptual learning. *Annual Review of Psychology*, *49*(1), 585-612. doi: 10.1146/annurev.psych.49.1.585
- Goossens, T., van de Par, S., & Kohlrausch, A. (2008). On the ability to discriminate Gaussian-noise tokens or random tone-burst complexes. *The Journal of the Acoustical Society of America*, *124*(4), 2251-2262. doi: 10.1121/1.2973184
- Griffin, I. (2002). Multiple mechanisms of selective attention: Differential modulation of stimulus processing by attention to space or time. *Neuropsychologia*, *40*(13), 2325-2340. doi: 10.1016/S0028-3932(02)00087-8
- Griffin, I., C. (2001). Orienting attention in time. *Frontiers in Bioscience*, *6*(1), 660-671. doi: 10.2741/Griffin
- Guttman, N., & Julesz, B. (1963). Lower limits of auditory periodicity analysis. *Journal of the Acoustical Society of America*, *35*(4), 610.

- Hanslmayr, S., Axmacher, N., & Inman, C. S. (2019). Modulating human memory via entrainment of brain oscillations. *Trends in Neurosciences*, *42*(7), 485-499. doi: 10.1016/j.tins.2019.04.004
- Hawkey, D. J. C., Amitay, S., & Moore, D. R. (2004). Early and rapid perceptual learning. *Nature Neuroscience*, *7*(10), 1055-1056. doi: 10.1038/nn1315
- Henry, M. J., & Herrmann, B. (2014). Low-frequency neural oscillations support dynamic attending in temporal context. *Timing & Time Perception*, *2*(1), 62-86. doi: 10.1163/22134468-00002011
- Herbst, S. K., Fiedler, L., & Obleser, J. (2018). Tracking Temporal Hazard in the Human Electroencephalogram Using a Forward Encoding Model. *eNeuro*, *5*(2), ENEURO.0017-0018.2018. doi: 10.1523/ENEURO.0017-18.2018
- Herrmann, B., Araz, K., & Johnsrude, I. S. (2021). Sustained neural activity correlates with rapid perceptual learning of auditory patterns. *NeuroImage*, *238*, 118238.
- Hickey, P., Merseal, H., Patel, A. D., & Race, E. (2020). Memory in time: Neural tracking of low-frequency rhythm dynamically modulates memory formation. *NeuroImage*, *213*, 116693. doi: 10.1016/j.neuroimage.2020.116693
- Hickey, P., & Race, E. (2021). Riding the slow wave: Exploring the role of entrained low-frequency oscillations in memory formation. *Neuropsychologia*, *160*, 107962. doi: <https://doi.org/10.1016/j.neuropsychologia.2021.107962>
- Hodapp, A., & Grimm, S. (2021). Neural signatures of temporal regularity and recurring patterns in random tonal sound sequences. *European Journal of Neuroscience*, *53*(8), 2740-2754. doi: 10.1111/ejn.15123
- Irvine, D. R. F., Martin, R. L., Klimkeit, E., & Smith, R. (2000). Specificity of perceptual learning in a frequency discrimination task. *The Journal of the Acoustical Society of America*, *108*(6), 2964-2968. doi: 10.1121/1.1323465
- Jaramillo, S., & Zador, A. M. (2011). The auditory cortex mediates the perceptual effects of acoustic temporal expectation. *Nature Neuroscience*, *14*(2), 246-251. doi: 10.1038/nn.2688

- Jeter, P. E., Doshier, B. A., Liu, S.-H., & Lu, Z.-L. (2010). Specificity of perceptual learning increases with increased training. *Vision Research, 50*(19), 1928-1940. doi: 10.1016/j.visres.2010.06.016
- Jeter, P. E., Doshier, B. A., Petrov, A., & Lu, Z. L. (2009). Task precision at transfer determines specificity of perceptual learning. *Journal of Vision, 9*(3), 1-1. doi: 10.1167/9.3.1
- Jones, A., & Ward, E. V. (2019). Rhythmic Temporal Structure at Encoding Enhances Recognition Memory. *Journal of Cognitive Neuroscience, 31*(10), 1549-1562. doi: 10.1162/jocn_a_01431
- Jones, M. R. (1976). Time, our lost dimension: Toward a new theory of perception, attention, and memory. *Psychological Review, 83*(5), 323-355. doi: 10.1037/0033-295X.83.5.323
- Jones, M. R. (2019). *Time will tell: A theory of dynamic attending*. Oxford: Oxford University Press.
- Jones, M. R., Johnston, H. M., & Puente, J. (2006). Effects of auditory pattern structure on anticipatory and reactive attending. *Cognitive Psychology, 53*(1), 59-96. doi: 10.1016/j.cogpsych.2006.01.003
- Jones, M. R., Moynihan, H., MacKenzie, N., & Puente, J. (2002). Temporal aspects of stimulus-driven attending in dynamic arrays. *Psychological Science, 13*(4), 313-319. doi: 10.1111/1467-9280.00458
- Kaernbach, C. (2004). The memory of noise. *Experimental Psychology, 51*(4), 240-248.
- Kang, H., Agus, T. R., & Pressnitzer, D. (2017). Auditory memory for random time patterns. *The Journal of the Acoustical Society of America, 142*(4), 2219-2232. doi: 10.1121/1.5007730
- Kassambara, A. (2020). *rstatix: Pipe-friendly framework for basic statistical tests*.
- Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist, 73*(1), 1-2. doi: 10.1037/amp0000263
- Kraljic, T., & Samuel, A. G. (2005). Perceptual learning for speech: Is there a return to normal? *Cognitive Psychology, 51*(2), 141-178. doi: 10.1016/j.cogpsych.2005.05.001
- Kraus, N., & Banai, K. (2007). Auditory-processing malleability: Focus on language and music. *Current Directions in Psychological Science, 16*(2), 105-110. doi: 10.1111/j.1467-8721.2007.00485.x
- Kulkarni, M., & Hannula, D. E. (2021). Temporal Regularity May Not Improve Memory for Item-Specific Detail. *Frontiers in Psychology, 12*, 623402.

- Kumar, S., Bonnici, H. M., Teki, S., Agus, T. R., Pressnitzer, D., Maguire, E. A., & Griffiths, T. D. (2014). Representations of specific acoustic patterns in the auditory cortex and hippocampus. *Proceedings of the Royal Society B: Biological Sciences*, *281*(1791), 1-8. doi: 10.1098/rspb.2014.1000
- Lakatos, P., Gross, J., & Thut, G. (2019). A new unifying account of the roles of neuronal entrainment. *Current Biology*, *29*(18), R890-R905. doi: 10.1016/j.cub.2019.07.075
- Lakatos, P., Musacchia, G., O'Connell, Monica N., Falchier, Arnaud Y., Javitt, Daniel C., & Schroeder, Charles E. (2013). The spectrotemporal filter mechanism of auditory selective attention. *Neuron*, *77*(4), 750-761. doi: 10.1016/j.neuron.2012.11.034
- Lakatos, P., Shah, A. S., Knuth, K. H., Ulbert, I., Karmos, G., & Schroeder, C. E. (2005). An oscillatory hierarchy controlling neuronal excitability and stimulus processing in the auditory cortex. *Journal of Neurophysiology*, *94*(3), 1904-1911. doi: 10.1152/jn.00263.2005
- Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 1-12. doi: 10.3389/fpsyg.2013.00863
- Large, E. W., & Jones, M. R. (1999). The dynamics of attending: How people track time-varying events. *Psychological Review*, *106*(1), 119-159. doi: 10.1037/0033-295X.106.1.119
- Lawrance, E. L., Harper, N. S., Cooke, J. E., & Schnupp, J. W. H. (2014). Temporal predictability enhances auditory detection. *Journal of the Acoustical Society of America*, *135*(6).
- Litman, L., Robinson, J., & Abberbock, T. (2017). TurkPrime.com: A versatile crowdsourcing data acquisition platform for the behavioral sciences. *Behavior Research Methods*, *49*(2), 433-442. doi: 10.3758/s13428-016-0727-z
- Los, S. A. (2010). Foreperiod and sequential effects: theory and data. In A. C. Nobre & J. T. Coull (Eds.), *Attention and Time* (pp. 289–302): Oxford University Press.
- Luo, H., Tian, X., Song, K., Zhou, K., & Poeppel, D. (2013). Neural response phase tracks how listeners learn new acoustic representations. *Current Biology*, *23*(11), 968-974. doi: 10.1016/j.cub.2013.04.031

- Macmillan, N. A., & Creelman, C. D. (2005). *Detection theory: A user's guide* (2nd ed.). Mahwah, N.J: Lawrence Erlbaum Associates.
- McGovern, D. P., Webb, B. S., & Peirce, J. W. (2012). Transfer of perceptual learning between different visual tasks. *Journal of Vision, 12*(11), 1-11. doi: 10.1167/12.11.4
- Meyer, M. (1899). Is the memory of absolute pitch capable of development by training? *Psychological Review, 6*(5), 514-516. doi: 10.1037/h0069034
- Miniussi, C., Wilding, E. L., Coull, J. T., & Nobre, A. C. (1999). Orienting attention in time. *Brain, 122*(8), 1507-1518. doi: 10.1093/brain/122.8.1507
- Morillon, B., Schroeder, C. E., Wyart, V., & Arnal, L. H. (2016). Temporal prediction in lieu of periodic stimulation. *The Journal of Neuroscience, 36*(8), 2342-2347. doi: 10.1523/JNEUROSCI.0836-15.2016
- Niemi, P., & Näätänen, R. (1981). Foreperiod and simple reaction time. *Psychological Bulletin, 89*(1), 133-162. doi: 10.1037/0033-2909.89.1.133
- Nobre, A., Correa, A., & Coull, J. (2007). The hazards of time. *Current Opinion in Neurobiology, 17*(4), 465-470. doi: 10.1016/j.conb.2007.07.006
- Nobre, A. C. (2001). Orienting attention to instants in time. *Neuropsychologia, 39*(12), 1317-1328. doi: 10.1016/S0028-3932(01)00120-8
- Nobre, A. C., & van Ede, F. (2018). Anticipated moments: temporal structure in attention. *Nature Reviews Neuroscience, 19*(1), 34-48. doi: 10.1038/nrn.2017.141
- Norris, D., McQueen, J. M., & Cutler, A. (2003). Perceptual learning in speech. *Cognitive Psychology, 47*(2), 204-238. doi: 10.1016/S0010-0285(03)00006-9
- O'Connell, M. N., Barczak, A., Schroeder, C. E., & Lakatos, P. (2014). Layer Specific Sharpening of Frequency Tuning by Selective Attention in Primary Auditory Cortex. *The Journal of Neuroscience, 34*(49), 16496. doi: 10.1523/JNEUROSCI.2055-14.2014

- Olejnik, S., & Algina, J. (2003). Generalized eta and omega squared statistics: Measures of effect size for some common research designs. *Psychological Methods, 8*(4), 434-447. doi: 10.1037/1082-989X.8.4.434
- Overath, T., Cusack, R., Kumar, S., von Kriegstein, K., Warren, J. D., Grube, M., . . . Griffiths, T. D. (2007). An information theoretic characterisation of auditory encoding. *PLoS Biology, 5*(11), e288. doi: 10.1371/journal.pbio.0050288
- Quené, H., & Port, R. F. (2005). Effects of timing regularity and metrical expectancy on spoken-word perception. *Phonetica, 62*(1), 1-13. doi: 10.1159/000087222
- Rajendran, V. G., Harper, N. S., Abdel-Latif, K. H. A., & Schnupp, J. W. H. (2016). Rhythm facilitates the detection of repeating sound patterns. *Frontiers in Neuroscience, 10*(9), 1-7. doi: doi: 10.3389/fnins.2016.00009
- Roberts, B. M., Clarke, A., Addante, R. J., & Ranganath, C. (2018). Entrainment enhances theta oscillations and improves episodic memory. *Cognitive Neuroscience, 9*(3-4), 181-193. doi: 10.1080/17588928.2018.1521386
- Schroeder, C. E., & Lakatos, P. (2009). Low-frequency neuronal oscillations as instruments of sensory selection. *Trends in Neurosciences, 32*(1), 9-18. doi: 10.1016/j.tins.2008.09.012
- Seitz, A. R., Kim, D., & Watanabe, T. (2009). Rewards Evoke Learning of Unconsciously Processed Visual Stimuli in Adult Humans. *Neuron, 61*(5), 700-707. doi: 10.1016/j.neuron.2009.01.016
- Shinn-Cunningham, B. G. (2008). Object-based auditory and visual attention. *Trends Cogn Sci, 12*(5), 182-186. doi: 10.1016/j.tics.2008.02.003
- Team, R. C. (2018). *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing.
- ten Oever, S., Schroeder, C. E., Poeppel, D., van Atteveldt, N., Metha, A. D., Megevand, P., . . . Zion-Golumbic, E. (2017). Low-Frequency Cortical Oscillations Entrain to Subthreshold Rhythmic Auditory Stimuli. *The Journal of Neuroscience, 37*, 4903-4912.

- Thavabalasingam, S., O'Neil, E. B., Zeng, Z., & Lee, A. C. H. (2016). Recognition Memory is Improved by a Structured Temporal Framework During Encoding. [10.3389/fpsyg.2015.02062]. *Frontiers in Psychology, 6*, 2062.
- Viswanathan, J., Rémy, F., Bacon-Macé, N., & Thorpe, S. J. (2016). Long term memory for noise: evidence of robust encoding of very short temporal acoustic patterns. *Frontiers in Neuroscience, 10*. doi: 10.3389/fnins.2016.00490
- Wang, D., Clouter, A., Chen, Q., Shapiro, K. L., & Hanslmayr, S. (2018). Single-trial phase entrainment of theta oscillations in sensory regions predicts human associative memory performance. *The Journal of Neuroscience, 38*(28), 6299-6309. doi: 10.1523/JNEUROSCI.0349-18.2018
- Warren, R. M., Bashford, J. A., Cooley, J. M., & Brubaker, B. S. (2001). Detection of acoustic repetition for very long stochastic patterns. *Perception & Psychophysics, 63*(1), 175-182. doi: 10.3758/BF03200511
- Werner, L. A., Parrish, H. K., & Holmer, N. M. (2009). Effects of temporal uncertainty and temporal expectancy on infants' auditory sensitivity. *The Journal of the Acoustical Society of America, 125*(2), 1040-1049. doi: 10.1121/1.3050254
- Wilsch, A., Henry, M. J., Herrmann, B., Herrmann, C. S., & Obleser, J. (2018). Temporal expectation modulates the cortical dynamics of short-term memory. *The Journal of Neuroscience, 38*(34), 7428-7439. doi: 10.1523/JNEUROSCI.2928-17.2018
- Wilsch, A., Henry, M. J., Herrmann, B., Maess, B., & Obleser, J. (2015). Alpha oscillatory dynamics index temporal expectation benefits in working memory. *Cerebral Cortex, 25*(7), 1938-1946. doi: 10.1093/cercor/bhu004
- Wright, B. A., Wilson, R. M., & Sabin, A. T. (2010). Generalization lags behind learning on an auditory perceptual task. *Journal of Neuroscience, 30*(35), 11635-11639. doi: 10.1523/JNEUROSCI.1441-10.2010