INTRODUCTION

To organize and make meaning of our sound environment, auditory objects need to be extracted from the acoustic input. Forming memory-traces of complex auditory patterns that occur repeatedly is key to auditory object formation and can aid sound source segregation (McDermott et al., 2011). The brain shows a remarkable ability to detect repeating patterns (Agus et al., 2010; Kaernbach, 1992; Viswanathan et al., 2016) and memory traces shape the way repeating sound sequences...
are perceived (Agus et al., 2010; Viswanathan et al., 2016). In paradigms presenting repeated patterns of unstructured and random stimulus material (e.g., periodic white noise or periodic sequences of tones with randomly varying pitch), electroencephalography (EEG) reveals an increase in the sustained response to the repetition onset (Barascud et al., 2016) and a characteristic negativity, which is time-locked to each occurrence of the repeating pattern (Andrillon et al., 2015; Berti et al., 2000; Kaernbach et al., 1998). The latter is suggested to only be evoked once a memory trace for the pattern is formed, which led to their interpretation as memory-evoked potentials (Andrillon et al., 2015).

One characteristic of repetitive sounds in nature is that not seldom they are rhythmic (e.g., locomotion sounds such as bird wings or footsteps), a characteristic that is exploited in a variety of different auditory tasks. Temporal regularity can be used as a cue to stabilizing streams (Bendixen et al., 2010), especially when other cues (e.g., frequency) are insufficient (Andreou et al., 2011) and can help establish higher-order sensory predictions (Tavano et al., 2014). Perceptual benefits of rhythm have also been reported to affect pitch discrimination (Chang et al., 2019; Jones et al., 2002), perception of intensity (Geiser et al., 2012) and duration (Barnes & Jones, 2000; McAuley & Jones, 2003) and to facilitate detection of near threshold stimuli (Lawrance et al., 2014). Interestingly, temporally regular presentation of repeating sound sequences also seems advantageous for repetition perception (Rajendran et al., 2016). Non-rhythmic repetitions can still be perceived as such, however, rhythm significantly facilitates repetition detection. The temporally regular contexts allow neural entrainment (Calderone et al., 2014; Lakatos et al., 2008) which results in highest neural excitability (Lakatos et al., 2009) in the critical time window and can optimize performance in auditory tasks (Henry & Obleser, 2012). Selective attention can additionally guide entrainment of oscillations (Bolger et al., 2013; Calderone et al., 2014; Lakatos et al., 2008; Sameiro-Barbosa & Geiser, 2016). This cortical sensitivity to temporal regularity seems diminished in older people (Herrmann et al., 2019), making a focus on these regularities even more crucial.

However, the effect rhythmic (isochronous) presentation has on the neural correlates of repeating complex sound patterns has received little attention so far. To this day, most pattern repetition paradigms exhibit an inherent temporally regular structure (e.g., periodic noise paradigms), so that neural entrainment through temporal regularity and tracking of recurring patterns through memory processes will need to be disentangled to understand repetition processing. In favour of a memory-related origin, Andrillon et al. (2015) report an increased magnitude of the memory-related potential (accompanied by an improvement of participants’ performance in detecting repetitions), when the same repeated pattern is presented in various trials of the experiment. Furthermore, these learned patterns already elicit the memory-related potential in response to an initial presentation, before any within-trial repetition (or temporal regularity) would occur. Yet, this first position differs mostly in the overall sustained potential and does not display the characteristic phasic negative potential. It can therefore not be ruled out that the reported negative potentials in response to a pattern’s onset are shaped by the temporal predictability. The effect of temporal regularity on the neural correlates of repeating sound patterns can only be differentiated from memory-effects by comparing them to temporally irregular repetitions. If the negative potential corresponds to the presented patterns, it should be visible in a temporally irregular condition also. If there is in fact a memory process underlying these memory-evoked potentials, we would additionally expect repeated exposure (in various trials) to modulate the ERP.

Therefore, this study examines the effect of temporal regularity on EEG correlates of repetition detection. It examines if induced temporal regularity shapes the ERP response and investigates the neural correlates of repetition processing in a temporally irregular (jittered) context. The repeated exposure to a pattern within a block in both temporal conditions will additionally help to disentangle temporal predictability, the recurrence of the pattern and perceptual learning.

## 2 | MATERIALS AND METHODS

### 2.1 | Participants

The experiment was part of a research project whose protocols were approved by the Ethical Committee of the Leipzig University. All participants gave written informed consent before the experimental session in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki). 35 naive volunteers (eight male) participated in the experiment. Subjects were compensated by either course credits or money (8€/h). Age ranged from 18 to 43 years ($M = 25.06; SD = 6.02$). All participants had self-reported normal hearing and two participants were left-handed. Five participants had to be discarded from the analysis, as they performed at chance level ($n = 5$) and one due to a poor signal to noise ratio of the EEG data (less than 50% artefact-free epochs). This left data from $n = 29$ participants for the final analysis.

### 2.2 | Experimental design and procedure

For the experiment, a noise-learning paradigm adapted for EEG recordings (see, e.g., Agus et al., 2010; Andrillon et al., 2015; Kaernbach et al., 1998) was implemented using tonal sound sequences as stimuli. Sound sequences consisted
of 50 ms complex sound segments (including a 5 ms rise and a 5 ms fall time) that were drawn from a pool of 25 tones with fundamental frequencies between 220 and 880 Hz in semitone spacing. Harmonics were added to the fundamental frequency, with their intensities reducing as a function of frequency following a linear slope starting at 2000 Hz until reaching the cut-off at 4000 Hz. Additionally, uneven harmonics were attenuated to 20% of their intensity. To equalize intensity between tonal segments in a sequence, we assured that the root mean square (RMS) of all segments’ complex signal was equal.

Each of the 14 experimental blocks consisted of three different types of trials: 20 trials of continuous random sounds (Rand) that contained no recurring patterns, 10 trials with repeated patterns (Pat) for which patterns of fixed tonal segments were repeated within-trial, and 10 trials with reference repeated patterns (refPat) for which patterns of fixed tonal segments were repeated within and also across-trial.

2.3 | Temporally regular condition

In the seven blocks of the temporally regular condition (isochronous condition, see Figure 1), Rand trials consisted of a 2.8 s tonal sequence with 52 segments of random frequency. For both of the other trial types (Pat, refPat) tonal patterns lasting 0.3 s (6 tonal segments of random frequency) were generated, each presented either 4 or 5 times in a continuous sequence. The occurrences of this fixed pattern were separated by 0.2 s (4 tonal segments) of tones with random frequency, which resulted in an isochronous appearance of the pattern every 0.5 s. All Pat and refPat sequences started with a 0.15 s interval consisting of randomly selected tones before the first presentation of the fixed pattern and ended with a 0.15 s interval of randomly selected tones before sequence offset. In half of the trials of each repetition type (Pat and refPat), the pattern was only presented four times (compared to 5 in the other half of the trials). In that case, the final pattern position was replaced with random tonal segments. The Pat and refPat trials differed only in that the same 0.3 s sound pattern was used for all refPat trials within a block ($n = 10$), while a different random pattern was generated for each Pat trial ($n = 10$). The patterns used were different for each participant.

2.4 | Temporally irregular condition

The seven experimental blocks of the temporally irregular condition (jittered condition, see Figure 1) differed only in their temporal structure. In Pat and refPat trials, the fixed patterns were repeated with a temporal jitter. The time interval between recurring fixed patterns could vary between 0 and 0.4 s (corresponding to 0–8 tones). The length of the interval was randomly chosen. Due to this procedure, the individual trials in this condition varied slightly in length. The first pattern was always presented 0.15 s after the sequence onset. Note that for refPat trials, only the pattern was repeated across trials, while the number of random sound segments in between individual patterns varied between trials. The number of Rand ($n = 20$), Pat ($n = 10$) and RefPat ($n = 10$) sequences within each block was the same as in the temporally regular condition.

2.5 | Procedure

Participants were asked to discriminate between continuous sequences of randomly selected tonal segments (Rand) and sequences including repeated sound patterns (Pat and refPat). The distinction between Pat and refPat was unknown to the participants. Participants were to give their response at the end

FIGURE 1 Trials consisted of 52 randomly drawn tonal sound segments. Pat trials contain recurring patterns that were repeated within a trial (red). RefPat patterns were additionally repeated across trials (blue). Patterns were repeated 4 or 5 times within a trial sequence.
of each sequence. A response time window of maximally 4 s assured that participants had enough time to respond. The response was followed immediately by the feedback "Richtig" or "Falsch" (right or wrong) that was displayed instead of the fixation cross. If the participants did not respond within the time window given, "zu langsam" (too slow) was presented on the screen. The trial's setup was adjusted to the participants' response time, so that the onset of the next sequences was 0.5 s after the feedback presentation. After each block, participants were given feedback on the overall percentage of correct responses. Sounds were presented binaurally at approximately 64 dB SPL via headphones (Sennheiser HD 25) and stimulation was controlled by running the Psychophysics Toolbox (Brainard, 1997; Kleiner et al., 2007) in Matlab R2019a (MathWorks Inc. Natick, MA, USA).

2.6 Data acquisition

The EEG was recorded continuously from 64 active Ag/AgCl electrodes positioned according to the extension of the international 10–20 system and mounted in a nylon cap (BioSemi headcap) while participants performed the behavioural task. Additionally, electroocular activity was recorded from two electrodes placed at the outer canthi of both eyes for the horizontal electrooculogram (HEOG) and two electrodes placed above and below the right eye for the vertical electrooculogram (VEOG). Two electrodes were positioned at the right and left mastoid and an electrode on the tip of the nose served as reference electrode. EEG data were acquired at a sampling rate of 512 Hz and amplified using a BioSemi ActiveTwo amplifier (BioSemi, Amsterdam, The Netherlands). EEG data were pre-processed and analysed with MATLAB R2019a using EEGLab (Delorme & Makeig, 2004) and fieldtrip (Oostenveld et al., 2011) toolboxes.

2.7 Analysis

EEG was high-pass filtered at 0.25 Hz using a windowed sinc FIR filter (0.5 Hz transitional bandwidth, Blackman window, order = 5,632) and low-pass filtered at 40 Hz (windowed sinc FIR filter, 10 Hz transitional bandwidth, Blackman window, order = 282). All filters were applied in a zero-phase forward-backward manner. For Figure 3 the data were high-pass filtered at 0.1 Hz (windowed sinc FIR filter, 0.2 Hz transitional bandwidth, Blackman Window, order = 14,080). Bad channels were identified by their variance in case it exceeded an absolute z-score value of 3.0 and were removed from the dataset (removed channels per person: \(M = 1.2, SD = 0.9\)). Data were epoched from −0.5 to 3.7 s around sequence onset. To improve signal-to-noise ratio, an independent component analysis (ICA) was conducted. For this, a copy of the EEG data was high-pass filtered at 1 Hz using a windowed sinc FIR filter (0.5 Hz transitional bandwidth, Blackman window, order = 5,632) prior to epoching and artifactual epochs were removed with amplitude differences exceeding 750 \(\mu V\) (excluded trials per person: \(M = 12.1, SD = 23.3\)). EEGLab's runica function was used to calculate the IC weights. The weights were transferred to the pre-processed EEG data after the same channels and epochs were removed as for the ICA pre-processing. Independent components were classified using EEGLab's IClabe plug-in (Pion-Tonachini et al., 2019). Only components of the categories brain and other, as well as those that could only be classified with a likelihood of less than 25%, were used for further analysis (removed IC components per person: \(M = 15.4, SD = 7.6\)). Previously rejected channels were interpolated using a spherical spline function (Perrin et al., 1989) after the data cleaning procedure.

To extract pattern-related ERPs, shorter epochs were cut from the sequence-related data ranging from −200 to 500 ms relative to individual pattern onsets. A baseline correction with respect to the interval from −200 to 0 ms was applied. All epochs in which the difference between the minimum and the maximum amplitude exceeded 250 \(\mu V\) were excluded (trials rejected per participant: \(M = 15, SD = 16.7\)).

For a comparison of trials that contain a pattern to random trials, ERPs were averaged across Pat and refPat trials to create an overall Pattern average. Pattern trials were averaged over positions 2–5 (position 5 was only included if it contained a pattern presentation), respectively. ERPs in the Rand condition were extracted from corresponding temporal windows (at positions 2–5) within the Rand sequences. For a comparison of the different repetition types, position 2–5 was averaged for Pat, refPat and Rand trials separately. All three trial types were also averaged separately for the first position. For the last pattern position (at which a pattern was presented in only 50% of the trials), Pat and refPat trials in which a pattern was presented (Pattern) and trials that were initially Pat or refPat sequences but had no pattern presentation at this last position (no Pattern) were averaged separately. There was no differentiation between refPat and Pat trials for this comparison. In general, epochs were averaged for each temporal condition (isochronous and jittered) separately and for correct trials only. Both also applied to random trials, so that any pattern data was always compared to all random trials in the respective temporal condition.

2.8 Statistics

A non-parametric cluster-based permutation approach (CBP; using Monte-Carlo method; 1,000 permutations; alpha level = 0.05, cluster \(\alpha = 0.05\); Maris & Oostenveld, 2007) was used to assess electrode-time clusters with differential...
activity between conditions (Pattern vs. Rand; Pat vs. refPat difference waves; Pattern vs. no Pattern). Significant time clusters informed on likely relevant time windows in which conditions could show different activation. Parametric statistics were used to confirm differences in mean amplitude within the respective time windows. All mean values are reported in Table 1. Thus, for the pattern versus random comparison, a two-way repeated measures ANOVA (rmANOVA) on mean ERP amplitudes was calculated with the factors trial type (pattern and random) and temporal condition (isochronous and jittered). For the comparison of Pat and refPat, the rmANOVA was calculated on mean amplitudes of Pat – Rand and refPat – Rand difference waves with the two repetition types (Pat and refPat) and the temporal conditions as factors. An analogous rmANOVA on mean difference wave amplitude was calculated for the first pattern position. Regarding the last pattern position an rmANOVA was calculated on mean amplitude with Pattern and no Pattern as trial type factors and isochronous and jittered as temporal condition factors. Paired sample Student’s t-tests were calculated for pairwise comparisons. Generalized eta squared statistics ($\eta_g^2$) and Cohens’s d are reported as estimates of effect size. All frequentist analyses were performed using R 3.6.3.

Frequentist analyses were complemented by estimating Bayes Factors (BF$_{10}$) using JASP 0.13.1.0. For the Bayesian repeated measures ANOVA all alternative models were tested against the null model. BF$_{10}$ for each model are reported in Table 2. The Bayes factor was calculated using 10,000 sample repetitions and using a default Cauchy prior centred around 0 with scale parameter of 0.5 for fixed effects (scale parameter = 1 for random effects). For an additional evaluation of main effects and interactions, BF Inclusion (BF$_{incl}$) was calculated across matched models (i.e., models that include and models that do not include the effect) to provide a measure of change odds from prior to posterior distributions (Mathôt, 2017). Data were interpreted as being in favour of the null hypothesis if BF$_{10}$/BF$_{incl}$ Values $\leq$1/3. Values $\geq$3 were seen as evidence in favour of the alternative hypothesis, whereas values close to 1 were considered inconclusive (Jeffreys, 1961; Lee & Wagenmakers, 2014). If the alternative hypotheses were best supported by an interaction model, the analyses were followed up with Bayesian t-tests (default Cauchy prior centred around 0 with a scale parameter of 0.707).

2.9 | Behaviour

Participants were instructed to discriminate between a sequence containing a repetition and a random sequence via button press (RTbox, Suzhou Litong Electronic Co., Li et al., 2010). To quantify participants’ repetition detection performance across blocks, the sensitivity index $d'$

### Table 1

| Overview of measures and analyses reported in this publication including type of analysis (first column), analysed measure and position (second column), type of effect (third column), analysed ERP time window (fourth column), condition (fifth column), mean values (with their respective SD) of the retrieved measure in the isochronous (sixth column) and in the jittered condition (seventh column) |
|-------------------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| **Behavioural data** | $d'$ | Repetition-detection | Pat | 1.57 (0.54) | 1.22 (0.42) |
|                    |     |                  | refPat | 1.59 (0.53) | 1.27 (0.47) |
| **ERP data** | **Position 2–5** | Mean amplitude in $\mu$V | Periodicity-effect | $-30–130$ ms | Pattern | 0.76 (0.60) | 0.06 (0.42) |
|                  |     |                  | Random | 0.05 (0.49) | 0.01 (0.40) |
|                  |     |                  | Reoccurrence-effect | $250–420$ ms | Pattern | $-0.51$ (0.68) | $-0.62$ (0.57) |
|                  |     |                  | Random | 0.22 (0.52) | $-0.03$ (0.63) |
|                  |     |                  | Pat versus refPat | Reoccurrence-effect | $270–339$ ms | Pat-Rand | $-0.77$ (0.78) | $-0.74$ (0.60) |
|                  |     |                  | refPat-Rand | $-0.39$ (0.93) | $-0.32$ (0.85) |
| **Position 1** | Mean difference amplitude in $\mu$V | Pat versus refPat | Reoccurrence-effect | $250–420$ ms | Pat-Rand | 0.78 (1.71) | 0.96 (1.89) |
|                  |     |                  | refPat-Rand | 0.65 (1.94) | 0.86 (1.68) |
|                  |     |                  | 350–450 ms | Pat-Rand | 0.97 (1.82) | 0.96 (1.67) |
|                  |     |                  | refPat-Rand | 0.43 (2.02) | 0.72 (1.52) |
| **Position 5** | Mean amplitude in $\mu$V | Periodicity effect | $-30–130$ ms | Pattern | 1.05 (0.97) | $-0.08$ (0.78) |
|                  |     |                  | no Pattern | 0.89 (0.75) | $-0.00$ (0.87) |
|                  |     |                  | Reoccurrence effect | $250–420$ ms | Pattern | $-0.82$ (1.50) | $-1.05$ (1.34) |
|                  |     |                  | no Pattern | 0.13 (1.79) | $-0.52$ (1.30) |
for refPat and Pat trials was calculated independently and for each of the conditions. To avoid infinite d’ values due to extreme performances, parameters were adjusted to the equivalent of half of a single correct and incorrect response (Hautus & Lee, 2006). A two-way rmANOVA was used to test for differences in sensitivity between the factors trial type (refPat and Pat) and temporal condition (isochronous and jittered). Equivalent to the analyses of EEG data, the behavioural analyses were complemented by estimating Bayes Factors (BF10).

### RESULTS

**Behaviour.** Behavioural performance measures d’ (Figure 2) showed a significant main effect of condition
Participants’ discrimination performance of random versus pattern sequences was increased for isochronously repeated patterns. However, behavioural performance did not differ between newly generated patterns that were repeated within the sequence (Pat) and those that were additionally repeated across trials (refPat).

**Sequence overview.** The sequence overview of the grand average waveform evoked by the trial types Rand, Pat and refPat in the isochronous and jittered conditions revealed clear modulations of the ERP with temporal regularity (Figure 3). The onset response is followed by a sustained potential. In all conditions, a steady-state oscillatory response at 20 Hz is visible on top of the sustained potential corresponding to the presentation rate of the individual tonal segments within each sequence (every 50 ms). In the isochronous condition, Pat and refPat trials are characterized by a series of additional waveform modulations superposed onto the sustained slow-wave potential.

**General pattern at position 2–5.** In Figure 4, the Pattern (all trials containing a pattern combined) and Rand grand average waveform are depicted time-locked to pattern onset and averaged across pattern presentations 2 to 5 for the isochronous and jittered condition, respectively. In both conditions, a clear ERP waveform corresponds to the pattern presentation when compared against the random condition. The CBP test revealed that isochronously recurring patterns were accompanied by an early frontal positivity ranging from −30 to 130 ms and a later frontal negative component ranging from 250 to 420 ms. In the jittered condition, pattern repetition elicited only a later frontal negativity but in a time range comparable with the one in the isochronous condition. As the Fz electrode is at the centre of the clusters of activation, all further analysis is based on this electrode.

For the mean amplitudes in the early time window (−30 to 130 ms), a rmANOVA with the factors condition (isochronous vs. jittered) and trial type (pattern vs. random) showed a significant effect of condition \( F_{(1, 28)} = 12.95, p < .001, \eta_g^2 = 0.128; BF_{incl} = 297.78 \) and trial type \( F_{(1, 28)} = 20.55, p < .001, \eta_g^2 = 0.138; BF_{incl} = 524.48 \). Critically, the effect of the trial type depended on the temporal condition (Trial type × Condition: \( F_{(1, 28)} = 21.93, p < .001, \eta_g^2 = 0.106; BF_{incl} = 152.68 \)). The amplitude of Pattern...
FIGURE 4 The left column illustrates the isochronous and the right column the jittered condition. (a) Individual subject ERPs and grand-averaged \( n = 29 \) ERP waveform (across pattern positions 2–5) at Fz time-locked to pattern onset. Horizontal green lines illustrate significant differences indicated by the CBP test. Bars shaded in grey indicate the time windows used for statistical analysis. The oscillatory response at 20 Hz that is visible on top of the ERP is corresponding to the presentation rate of the individual tonal segments within each sequence (every 50 ms). (b) Individual subject and grand-averaged difference waveform (Pattern minus Rand). (c) Topographies of the difference (Pattern minus Rand) for the indicated time window.
trials was significantly more positive than Rand trials in the isochronous condition ($t(28) = 5.43, p < .001, d = 1.009; BF_{10} = 2.475.10 \pm 1.74x10^4$), whereas no significant difference was found in the jittered condition ($t(28) = 0.64, p = .53, d = 0.119; BF_{10} = 0.24 \pm 0.002$). Note that also in the CBP test, a difference between Pattern and Rand trials in this time window was only visible in the temporally regular condition. Therefore, we will refer to this effect as the early periodicity-effect.

For the late time window (250–420 ms), a main effect of condition ($F(1, 28) = 5.38, p = .028, \eta_g^2 = 0.022; BF_{Incl} = 1.75$) and trial type ($F(1, 28) = 72.15, p < .001, \eta_g^2 = 0.236; BF_{Incl} = 4.43 \times 10^9$) reached significance. There was no significant interaction between condition and trial type ($F(1, 28) = 0.63, p = .433, \eta_g^2 = 0.003; BF_{Incl} = 0.36$). ERPs seem to be more negative in the jittered condition, yet the data are not conclusively more probable under models including condition as a predictor than under those without the factor condition. Trials containing a pattern elicit a significantly greater negative potential in both temporal conditions. We will refer to this effect as the recurrence-effect of a pattern. Scalp topographies indicate a frontocentral distribution of the potential.

**Trial type difference waves at position 2–5.** Pat and refPat difference waves are visualized in Figure 5. The CBP test showed a significant cluster in the 270–330 ms time range for the isochronous condition and in the 200–250 ms time range for the jittered condition. These time windows were combined for a general time window of interest. The rmANOVA for a 200 to 330 ms time window revealed a significant main effect of trial type ($F(1, 28) = 14.52, p < .001, \eta_g^2 = 0.060; BF_{Incl} = 15.97$). There was no effect of condition ($F(1, 28) = 0.11, p = .745, \eta_g^2 = 0.001; BF_{Incl} = 0.21$) and no interaction ($F(1, 28) = 0.04, p = .847, \eta_g^2 = 0.000; BF_{Incl} = 0.27$). Pat and refPat trials differ thus in mean amplitude in the time window of the late recurrence-related negativity in both temporal conditions.

**First position.** For the first pattern presentation, the CBP test did not find any differences between Pat and refPat trials, when comparing Pat-Rand and refPat-Rand difference waves. There were no effects found in a rmANOVA comparing mean amplitudes in the time window of the recurrence-effect from 250 to 420 ms (Condition: $F(1, 28) = 0.28, p = .603, \eta_g^2 = 0.003; BF_{Incl} = 0.24$; Trial type: $F(1, 28) = 0.20, p = .657, \eta_g^2 = 0.001; BF_{Incl} = 0.20$; Condition x Trial type: $F(1, 28) = 0.00, p = .517, \eta_g^2 = 0.000; BF_{Incl} = 0.31$). To address the possibility that the latency of the recurrence-effect could differ at the first presentation, the analysis was rerun with a manually selected time window (350–450 ms), based on the visual inspection of potential differences, which is depicted in Figure 6 and yielded no significant results either. Bayesian analysis yielded moderate evidence against any effects of condition or trial type (Condition: $F(1, 28) = 0.13, p = .725, \eta_g^2 = 0.002; BF_{Incl} = 0.25$; Trial type: $F(1, 28) = 2.35, p = .136, \eta_g^2 = 0.013; BF_{Incl} = 0.22$; Condition x Trial type: $F(1, 28) = 0.43, p = .517, \eta_g^2 = 0.002; BF_{Incl} = 0.30$).

**Last position.** The last possible pattern position (Figure 7) was analysed by comparing Pattern trials to no Pattern trials. For the mean amplitude in the early time window of the periodicity effect, a rmANOVA showed a significant main effect of condition ($F(1, 28) = 39.90, p < .001, \eta_g^2 = 0.267; BF_{Incl} = 1.86 \times 10^9$). There was no effect of trial type ($F(1, 28) = 0.10, p = .751, \eta_g^2 = 0.000; BF_{Incl} = 0.20$) and no interaction ($F(1, 28) = 0.97, p = .333, \eta_g^2 = 0.005; BF_{Incl} = 0.36$). In the early time window, significantly more positive potentials were elicited in the isochronous compared to the jittered condition. In line with the frequentist approach, the model including only condition as a predictor was the preferred model according to the Bayesian account (see Table 2), suggesting that ERPs were not affected by whether the pattern was actually presented at position 5 or not (see, evidence against a trial type effect). The absence of an interaction was more probable than its inclusion, yet this was not fully conclusive ($BF_{Incl} = 0.36$).

The CBP test found a negative cluster in case of actual pattern presentations in a 200–350 ms time range in the isochronous condition, overlapping to a considerable extent with the time window of the recurrence-related effect. For comparison, the time windows for further analysis were based on the time window of interest for these recurrence-related potentials. For this late time window a significant main effect of trial type was found ($F(1, 28) = 7.01, p = .013, \eta_g^2 = 0.060; BF_{Incl} = 7.13$). There was no effect of condition ($F(1, 28) = 3.07, p = .090, \eta_g^2 = 0.022; BF_{Incl} = 0.70$) and no interaction ($F(1, 28) = 0.56, p = .461, \eta_g^2 = 0.005; BF_{Incl} = 0.35$), whereas evidence for those null effects was weak. Altogether, compared to no pattern trials, trials with a pattern presentation at position 5 elicited a significantly more negative potential in the late time window in both temporal conditions.

### 4 | DISCUSSION

The current study disentangled EEG correlates of repetition processing, temporal regularity and memory-effects in a tone pattern learning paradigm. The introduction of repetitions with jittered time intervals allowed us to demonstrate that there are ERP markers for recurring patterns independent from an isochronous presentation of pattern stimuli. This recurrence-effect was further influenced by learning through across-trial repetitions of the pattern. We additionally showed a modulating effect of periodicity on the overall ERP response.
FIGURE 5 The left column illustrates the isochronous and the right column the jittered condition. (a) Individual subject ERPs and grand-averaged (n = 29) ERP waveform (across pattern positions 2–5) for Pat-Rand and refPat-Rand difference waves at Fz time-locked to pattern onset. Red horizontal lines illustrate significant differences indicated by the CBP test. Bars shaded in grey indicate the time window used for statistical analysis. (b) Individual subject and grand-averaged difference waveform (Pat minus refPat). (c) Topographies of the difference (Pat minus refPat) for the indicated time window.
The effect of temporal regularity

Rhythmic presentation of the repeated patterns led to a better detection of the repetitions (Figure 2). The difference in perception between temporally regular and jittered stimuli is in line with findings of a rhythm benefit in the detection of repeated white noise (Rajendran et al., 2016) and the enhanced perception of various other stimulus characteristics (Barnes & Jones, 2000; Chang et al., 2019; Jones et al., 2002; Lawrance et al., 2014) for temporally regular presentation that can be explained by neural entrainment (Calderone et al., 2014; Lakatos et al., 2008).

In that line of thinking, entrained phase-aligned brain oscillations accompanying rhythmic sensory stimulation have been shown to result in periodic EEG activity (Calderone et al., 2014). Others, however, have emphasized ERPs that are associated with the occurrences of a unique pattern, held in sensory memory. For instance, Andrillon et al. (2015) argue...
FIGURE 7  The left column illustrates the isochronous and the right column the jittered condition. (a) Individual subject ERPs and grand-averaged (n = 29) ERP waveform for Pattern and no Pattern (Random at position 5 only) trials at Fz time-locked to stimulus onset of the last possible pattern presentation (position 5) of a trial. The green horizontal line illustrates a significant difference indicated by the CBP test. Bars shaded in grey indicate the time window used for statistical analysis. The oscillatory response at 20 Hz that is visible on top of the ERP is corresponding to the presentation rate of the individual tonal segments within each sequence (every 50 ms). (b) Individual subject and grand-averaged difference waveform (Pattern minus no Pattern). (c) Topographies of the difference (Pattern minus no Pattern) for the indicated time window.
that their recurrence-related ERP component is memory-evoked by nature. Mainly, this claim is based on the fact that the component can already be observed at the first occurrence of a pattern within a sequence (once the specific pattern has been heard several times throughout the block), that is before EEG activity could start to entrain to the periodicity of the current trial.

So, is the described ERP a correlate of sensory entrainment or a memory-related process? Our results corroborate previous findings of a negative potential associated with the pattern presentation (Andrillon et al., 2015; Berti et al., 2000; Kaernbach et al., 1998). Critically, we could substantiate that these negative deflections do not depend on the temporal condition and are present in response to temporally irregular pattern presentation also (Figure 4). This can be seen as evidence towards an evoked-response to a repeated pattern, which is independent of temporal regularity. We found the negative potential to differ in amplitude between a pattern presentation and a replacement with random sound segments, even after the pattern rhythm should have led to sensory entrainment (Figure 7). This points further towards a recurrence-related pattern response rather than a correlate of neural sensory entrainment or attentional processes per se, which should have continued for one or several cycles after the last presentation of the isochronous stimulus (Calderone et al., 2014; Hickok et al., 2015).

The temporal properties of the pattern recurrence do however change the morphology of the ERP response. Only the temporally regular condition is characterized by an early positive deflection, with an onset before the pattern’s onset (Figures 4, 5 and 7). This periodicity-related positive component is immediately followed by the discussed negative recurrence-related potential in a cyclic manner, which resembles the overall waveform described by Berti et al. (2000). The cyclic response to repeating patterns has been reported to persist in the absence of attention (Berti et al., 2000), in line with other findings of attention-independent ERP responses in repeated white noise (Andrillon et al., 2015). Differences in waveform compared to the results of Andrillon et al. can at least partly be explained by baseline differences. In our data, a shorter baseline (e.g., –100 to 0 s; as in Andrillon et al., 2015) would result in a higher amplitude for the negative component, while reducing the early positive part of the waveform. Crucially, the positive component is not found when the pattern is repeated with a temporal jitter. When taking the literature findings on ERPs in absence of attention into account, the positive component seems to depend on temporal regularity but not direct attention. It could be part of a pre-attentive tracking of regularities, which are predictable in time. The proposed sensory neural entrainment to isochronous stimuli could underlie this process, as the positive component was shown to be independent of an actual pattern presentation after a temporal regularity was induced. Within the framework of predictive processing (Friston, 2005, 2010) it was repeatedly shown that information about regularities in sound input are acquired automatically (Bendixen, 2014). This could be translated to periodic noise where upcoming patterns can be temporally predicted (Kaernbach et al., 1998). Behavioural performance would benefit from such an automatic tracking and can explain easier detection of a repeating pattern in an isochronous condition. This hypothesis will have to be tested in upcoming experiments with attentional modulation and in studies that directly focus on the role of neural entrainment.

4.2 Perceptual benefit for repeated tonal patterns

The finding of a late negative ERP component regardless of the temporal properties of the repetition, suggests that the potential is not dependent on temporal regularity. This indicates that it could be a reflection of establishing a memory trace for a specific pattern (Andrillon et al., 2015). Interestingly, tonal patterns that could have been perceptually learned across trials, elicited an ERP whose negative potential was smaller in amplitude in both temporal conditions (Figure 5). Per se, a response modulation would be in line with previous studies using EEG (Andrillon et al., 2015), MEG (Luo et al., 2013) or fMRI (Kumar et al., 2014), that suggest the formation of specific memory traces for repeated patterns. However, the direction of our ERP modulation differs from reports on white noise pattern learning (Andrillon et al., 2015). Reasons for such discrepancies could lie in the stimulus material used, emphasizing that results from repeated white noise stimuli cannot easily be transferred to tonal stimuli. This is important to note, because white noise is an often used stimulus in auditory memory research, since it is stripped of spectral cues and semantic content (Cohen et al., 2009). White noise requires the listener to learn idiosyncratic features from an array of acoustic characteristics, whereas for tonal stimuli the order of a small number of successive pitch intervals needs to be learned. In the latter case, learning might be faster, opening the path for speculations whether an attenuation of the negative ERP component could reflect reduced perceptual effort with repeated exposure across trials. On the other hand, two successive tones or even longer parts of the repeated sequence can randomly occur outside the actual pattern when patterns are separated by random pitch intervals, probably resulting in greater (or at least a differential form of) interference, rendering the explanation of an effort reduction only partially tenable. Besides those differences regarding how and how fast learning occurs for specific types of material, the brain sources of representations of repeated patterns could vary also, with changes in ERP amplitude rather reflecting changes in dipole orientation than in strength of activation. Further research will be needed to clarify which explanation might hold. Additionally, one should note that there was no evidence for a behavioural effect of learning and moderate evidence for the
absence of an ERP at the first pattern presentation (Figure 6), which would have been critical cues for an interpretation of the late recurrence-related ERP as the correlate of a memory trace. So, the differential ERP activation neither translates into an increased explicit perception of the pattern nor is there a (strong enough) memory representation which would enable a recognition of the pattern on its first reappearance. So far, our findings suggest that there is a clear ERP effect for across-trial repetition, which generalizes to temporally irregular stimuli but does not translate to behaviour.

5 | CONCLUSION

The current study investigated the relationship between temporal regularity and neural signatures of repeating tonal patterns. We could demonstrate a late negative recurrence-related potential independent of the temporal context, which was modulated by repeated exposure to a pattern, potentially reflecting facilitated processing. Temporal regularity results in a behavioural benefit in repetition detection and induces an additional positive periodicity-related component, coalescing with the later negative peak to a response that appears to oscillate with pattern recurrences. Thus, while temporal regularity is not crucial to forming sensory memory traces for recurring patterns, the periodicity may induce processes of neural entrainment that can aid memory-related operations to be more effective.

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CONFLICT OF INTEREST

The authors have no conflict of interest.

AUTHOR CONTRIBUTION

AH and SG designed the study. AH collected the data. AH and SG analysed the data. AH and SG wrote the manuscript.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The data and scripts that support the findings of this study are openly available in Open Science Framework (OSF) at https://doi.org/10.17605/OSF.IO/XJGSF.

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