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Stability of Neural Oscillations Supports Auditory-Motor Synchronization

Rebecca Scheurich | Valentin Bégel | Ella Sahlas | Caroline Palmer

Department of Psychology, McGill University, Montreal, Quebec, Canada

Correspondence: Caroline Palmer (caroline.palmer@mcgill.ca)

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ABSTRACT

Previous findings suggest that auditory-motor synchronization is supported by increased coactivation of auditory and motor brain networks. Here, we compare synchronization accuracy and consistency with the temporal dynamics of neural signals during auditory-motor synchronization. Recurrence quantification analysis, a nonlinear technique for characterizing the temporal dynamics of complex systems, was applied to participants' neurophysiological activity recorded via electroencephalography (EEG) during an auditory-motor synchronization task. Changes in participants' neural predictability and stability were compared with their behavioral synchronization accuracy and consistency. EEG was recorded while participants produced a familiar melody at a comfortable rate as a measure of optimal temporal stability. Then, participants synchronized their taps with an auditory metronome presented at each participant's optimal rate and at rates 15% and 30% slower. EEG-based outcomes of determinism (predictability) and meanline (stability) were compared with behavioral synchronization measures. Participants showed decreased synchronization accuracy and higher EEG-based determinism at slower rates, consistent with lower flexibility. Furthermore, neural stability measures correlated with synchronization consistency across stimulus rates; as neural stability increased, so did behavioral synchronization consistency. Recurrence-based measures of neural stability may indicate a general mechanism supporting the maintenance of auditory-motor synchronization.

1 | Introduction

Synchronizing one's body movements with an auditory beat requires fine temporal coordination between auditory and motor systems. The development of auditory-motor synchronization abilities is accompanied by corresponding changes in brain networks. The movements required in auditory-motor synchronization, such as musicians' finger movements, recruit several motor-related areas, including the primary motor cortex, premotor cortex, cingulate cortex, supplementary motor cortex, basal ganglia, and thalamus (Hsu et al. 2016). Structural and functional changes in these areas can accompany auditory-motor synchronization skills, including changes in auditory and motor cortices as well as their interactions (Palomar-García et al. 2017; Zatorre et al. 2007). Synchronization skill is associated with improvements in both temporal accuracy and precision, which have been attributed to increased dorsal pre-motor cortex activation (Miyata et al. 2022). Accuracy and precision measures of synchronization can be dissociated by different factors including stimulus

Abbreviations: EEG, electroencephalography; RQA, recurrence quantification analysis; SPR, spontaneous production rate.

rate, task difficulty, and skill level (Caramiaux et al. 2018; Palmer 2005; Pollok et al. 2023). Overall, these findings suggest the presence of multiple neural mechanisms that support auditory-motor synchronization.

Despite a widely held view that neural oscillations play an important role in information flow between brain regions (cf. Varela et al. 2001), few studies have focused on the nonlinear properties of those oscillations in EEG signals. Recurrence quantification analysis, a tool from dynamical systems theory, examines repeating EEG activity in terms of the underlying system that generated the time-series (Coco and Dale 2014; Marwan and Webber 2015; Wallot 2017). We apply recurrence quantification analysis (RQA) to EEG signals to study the complex dynamics of repeating patterns of brain activity as musicians perform synchronization tasks. RQA techniques allow researchers to characterize changes in brain states over time, particularly in situations where traditional linear analysis methods may not be sufficient, such as temporal drift nonlinearities in EEG signals that are typically treated as noise to be filtered or removed. We extract quantitative measures that reflect the *predictability* of the EEG signal through the frequency (density) of recurrent points (called *determinism*) and the *stability* of the signal through the length of contiguous repetitions (*meanline*) as individuals performed easier and more difficult synchronization tasks. RQA metrics such as predictability and stability have distinguished among individuals of different skill levels in timed tasks such as reading fluency (Wallot et al. 2013) and music performance (Scheurich et al. 2018; Tranchant et al. 2022). Although several studies have addressed EEG changes in musical synchronization tasks, none have addressed RQA-based predictability and stability metrics for repeating brain states during synchronization tasks.

Most RQA applications to EEG signals address clinical populations, such as the classification of epilepsy (Acharya et al. 2011) or evaluations of patients' consciousness levels (Becker et al. 2010). Clinical RQA applications in individuals with epilepsy suggest that determinism in the EEG signal tends to increase before and during epileptic seizures (Lopes et al. 2021). Similar to patterns of increased determinism in body sway by individuals with postural difficulties (Kobel et al. 2023), these findings suggest that higher determinism values reflect a physiological rigidity or lack of flexibility typical of normal healthy adults. Thus, one prediction is that EEG-based determinism measures may be smaller during easier synchronization tasks than during more difficult tasks. Another prediction concerns meanline, a measure of stability: RQA measures of EEG dynamics during a joint (duet) rhythm synchronization task suggested that the stability (meanline) of cortical signals increased when participants heard their partner produce a less-frequent rhythm, relative to when their partner produced a more-frequent rhythm (Scheurich, Demos, et al., 2019); this study did not, however, examine behavioral synchronization. We examine here the related prediction that EEG signals should be more stable (larger meanline values) in rhythmic tasks for which participants show the most behavioral consistency.

The current study investigated nonlinear complexity metrics of individuals' neural signals as they performed easier and more difficult auditory-motor synchronization tasks. EEG measures of cortical activity were collected as individuals synchronized melodies with a regular stimulus beat presented at different rates. To calibrate synchronization rates to each individual, we used a standardized spontaneous production rate (SPR) task that measures an individual's rate of optimal temporal stability (Zamm et al. 2015, 2019). Participants synchronized their melody productions with a cued signal whose rate was set to their SPR and to slower rates expected to increase in difficulty, based on previous findings of increased synchronization difficulty at slower rates than at faster rates (Repp and Doggett 2007; Scheurich et al. 2018). Neural dynamics were analyzed with RQA at electrode sites previously shown to elicit the highest spectral power during auditory-motor synchronization tasks (Nozaradan 2014; Nozaradan et al. 2015). We predicted that synchronization accuracy and consistency would decrease as the production rates slowed (moved away from individuals' SPR values). Determinism measures of EEG signals were predicted to increase (show less flexibility) as production rates slowed (as synchronization was expected to become more difficult). We also predicted that individuals' EEG meanline values (indicating neural stability) should be negatively correlated with their behavioral variability in synchronization timing.

2 | Methods

2.1 | Participants

Twenty-four participants (mean age = 24.1, SD = 3.87, range = 18–33) from a broad range of musical backgrounds (mean years of music instruction = 5.7, SD = 6.14, range = 1–15 years) provided written consent to participate in the experiment. Percussionists were excluded based on evidence suggesting differences between percussionists and non-percussionists in auditory-motor tasks (Slater et al. 2018). All participants were right-handed as determined by the Edinburgh Handedness Inventory (Oldfield 1971), had normal hearing in the frequency range of experimental stimuli as determined by an audiometry screening (< 30 dB HL threshold for 250–1000 Hz), reported no neurological disorders, and were not taking medication affecting the central nervous system at the time of participation. All participants were informed about the study's procedures and gave written informed consent. The study protocol was approved by the McGill University Research Ethics Committee.

2.2 | Stimulus Materials and Equipment

Participants' hearing thresholds were determined using a Maico MA 40 audiometer. During all tasks, participants tapped on the force-sensitive resistor (FSR) of an Arduino that measured participants' taps and delivered sounded tones in a piano timbre from an Edirol Studio-Canvas SD-80 tone generator through EEG-compatible earphones (Etymotic ER-1, Etymotic Research Inc.). In addition, a metronome sound was delivered with a woodblock timbre (pitch = E5) to signal the stimulus rate in the synchronization task. Participants heard the metronome and the auditory feedback from their tapping of a familiar melody, "Twinkle, Twinkle Little Star" in G Major. The timing of participants' taps was collected from the Arduino with FTAP, a Linux-based open-source program for collecting MIDI data synchronized with stimulus presentation with millisecond accuracy and precision, on a Dell computer running Linux (Finney 2001). The FTAP software integrated Lab Streaming Layer (LSL; Kothe 2014) so that FTAP triggers, synchronized with the EEG signals, were sent to a second Dell computer running LSL in Windows 10 over the local area network, as previously implemented (Zamm et al. 2017).

2.3 | EEG Data Recording

EEG data were recorded at a 512 Hz sampling rate with a 64-channel BioSemi ActiveTwo system (BioSemi 2002). EEG was grounded using the common mode sense (CMS) and driven right leg (DRL) electrodes. Sixty-four scalp electrodes were placed according to the 10–20 system.

2.4 | Design

Each participant performed the spontaneous production rate and auditory-motor synchronization tasks in a fixed order. The within-subjects design included the independent variable of stimulus rate, set equal to each participant's SPR (computed as the mean inter-onset interval, IOI, in ms), 15% slower than their SPR, or 30% slower than their SPR. Participants completed the three rate conditions in the same order, starting with the SPR followed by the 15% slower and then the 30% Slower (i.e., from easiest to most difficult task), so that practice or learning effects would work against expected rate differences (Mathias et al. 2020; Wright and Palmer 2023).

2.5 | Procedure

After participants provided written informed consent, they underwent an audiometry screening. Participants who passed the screening and reported familiarity with the experimental melody were outfitted with the EEG cap, electrodes, and earphones and were seated in front of a fixation cross. Participants rested their arm on a table that held the force sensing resistor. Following previous methods (Loehr and Palmer 2011; Zamm et al. 2015), participants completed the SPR task in which they were instructed to tap the melody "Twinkle, Twinkle Little Star" using the index finger of their dominant hand while focusing their gaze on the fixation cross in front of them. They were told that each time they tapped, the next tone of the melody would sound, and that they had control over when the melody tones would sound. Participants completed two practice trials and three experimental trials in which they tapped the melody at a comfortable and steady rate until they no longer heard the sound of their taps, indicating the end of each trial. Following the SPR task, participants completed musical background and handedness questionnaires while their SPRs were computed (see Section 2.6).

Participants next completed the synchronization task. They were instructed that they would be producing "Twinkle, Twinkle Little Star" as before, but that they would now hear a metronome and that their goal was to synchronize their melody productions with the metronome while focusing their gaze on the fixation cross on a wall in front of them. Participants first completed a practice trial in which they began synchronizing with the metronome after the first eight metronome clicks and continued to synchronize with the metronome for 3.5 repetitions of the melody, until they no longer heard the sound of their taps. Participants then completed three experimental trials. This procedure was repeated for all rate conditions. Participants were debriefed following the synchronization task and given a small compensation for their time. The study lasted approximately 2.5 h.

2.6 | Behavioral Data Analysis

Participants' SPRs were calculated as the mean IOI for the middle two repetitions across trials, to avoid tempo changes typically seen at melodic phrase beginnings and endings (Loehr and Palmer 2011; Zamm et al. 2015). Half notes were interpolated, and outlier IOIs more than three standard deviations away from the mean were removed (1.98% of total IOIs removed).

Synchronization performance was measured by first aligning taps with metronome onsets using a nearest neighbor approach (e.g., Pecenka and Keller 2011; Scheurich, Pfordresher, et al., 2019). Signed asynchronies were calculated as the participant's tap onset time minus metronome onset time, with negative values indicating that a tap preceded the metronome. Signed asynchrony outliers more than three standard deviations from the mean were removed (2.06% of total signed asynchronies). To assess whether participants' synchronization was above chance in each trial, the Rayleigh test for circular non-uniformity was conducted; a significant Rayleigh test indicates a significant mean direction (i.e., unimodal synchronization pattern; Fisher 1993). Following previous work (Dalla Bella and Sowiński 2015; Pecenka and Keller 2011), trials in which the Rayleigh test did not reach significance were removed from subsequent behavioral and EEG analyses (8 or 3.71% of total trials). Three additional trials were removed due to technical issues, leaving a total of 205 trials. The mean signed asynchronies and standard deviations of the signed asynchronies were then computed for each trial.

2.7 | EEG Preprocessing and Data Analysis

EEG data were preprocessed using EEGLAB v2021.0 (Delorme and Makeig 2004). Data for all trials and tasks were first concatenated together and re-referenced to the common average across electrodes. Electrodes with poor signal quality were detected by visually inspecting distributions of deviations from mean activity. Those with no deviation or very large deviations from mean activity were identified as flat and noisy electrodes, respectively, and were removed. The data were then filtered between 1 Hz and 40 Hz using a Hanning windowed sinc FIR filter (high and low pass filter order = 1000), segmented into 1-s epochs solely for the pre-processing stage, and pruned for non-stereotypical artefacts including eye movements and eye blinks, temporal muscle activity, and line noise. Data were then submitted to extended infomax Independent Component Analysis (ICA). Resulting ICA components reflecting eyeblink and lateral eye movement artefacts were visually identified from component topomaps and removed from the unfiltered data. Finally, electrodes removed due to poor signal quality were spherically interpolated.

EEG data were then prepared for recurrence quantification analysis. Following previous research showing maximal power at C1 during an auditory-motor tapping synchronization task (Nozaradan 2014; Nozaradan et al. 2015), C1 was selected as input to the recurrence quantification analysis. C1was also reported to have the strongest coherence with MEG activity related to movements of the index finger in right-handed individuals (Chakarov et al. 2009), as used in the current task. Data recorded from C1 during the synchronization task were first filtered at the beat frequency corresponding to the metronome rate in each subject's rate conditions. Filter cutoffs were defined as two standard deviations above and below the production frequency in the corresponding rate condition for each participant to account for timing deviations from the metronome beat frequency. A Hanning windowed sinc FIR filter was used (high and low pass filter order = 1000). EEG analyses were based on a 14.5 s epoch from each trial, corresponding to the shortest melody repetition produced by the fastest participant in the SPR task, extracted from the start of the second melody repetition to capture participants' most stable performance. Data were finally *z*-scored per epoch for normalization to permit comparison of RQA metrics across different datasets or conditions (Coco et al. 2021).

Auto-recurrence analyses were conducted using the Cross Recurrence Plot Toolbox in MATLAB (Marwan et al. 2007). Parameters were optimized per rate condition and participant. The optimal delay parameter, determined using average mutual information (AMI), was selected by identifying the first local minimum (the first delay at which the least information is shared). The optimal number of embedding dimensions was determined by identifying the number of dimensions for which the number of false nearest neighbors in the phase space was minimized. This number was determined to be the same across rate conditions and participants (selected embedding dimensions = 4), consistent with a previous study that implemented the same pipeline (Scheurich, Demos, et al., 2019). The recurrence rate was fixed at 10% (Marwan et al. 2007; Scheurich, Demos, et al., 2019; Wallot 2017) when rate manipulations were compared, in order to avoid a potential confound in the interpretation of recurrence outcomes (the same-sized time window applied to slower and faster rates may yield greater recurrence at the faster rate simply because more cycles at fast rates fall within the analysis window). The Theiler window and minimum diagonal line lengths were set to 23 samples for all rate conditions and participants, corresponding to 1/2 of the smallest optimal delay across rate conditions and participants (approximately 1/8 of the cycle of the fastest rate).

Sample recurrence plots are shown in Figure 1 alongside the time series EEG data, for one participant's trial in the SPR rate condition (Figure 1A) and in the 30% Slower rate condition (Figure 1B) as a visual depiction. The RQA outcomes of interest were determinism and meanline. Determinism describes the proportion of recurrent points that fall along diagonal lines in the recurrence plot and represents predictability in periodic systems (Marwan and Webber 2015). Determinism is computed as shown in Equation (1) (Marwan et al. 2007), where l refers to the diagonal line length, $P(l)$ refers to the histogram of the diagonal lines of length l, and l_{min} refers to the minimum diagonal line length.

$$DET = \frac{\sum_{l=l_{min}}^{N} l\,P(l)}{\sum_{l=1}^{N} l\,P(l)} \tag{1}$$

Meanline describes the average diagonal line length (# samples) in the recurrence plot and corresponds to the average length or period of repeating patterns (Marwan and Webber 2015). Meanline, computed as in Equation (2) (Becker et al. 2010), is an index of a system's stability (Demos et al. 2017; Laudańska et al. 2022; Rosen et al. 2013): Longer lines (larger values) indicate greater stability. The distinction between Equations (1) and (2) is the denominator: The denominator in Equation (2) represents the total number of diagonal lines, whereas in Equation (1), it represents the total number of recurrent points.

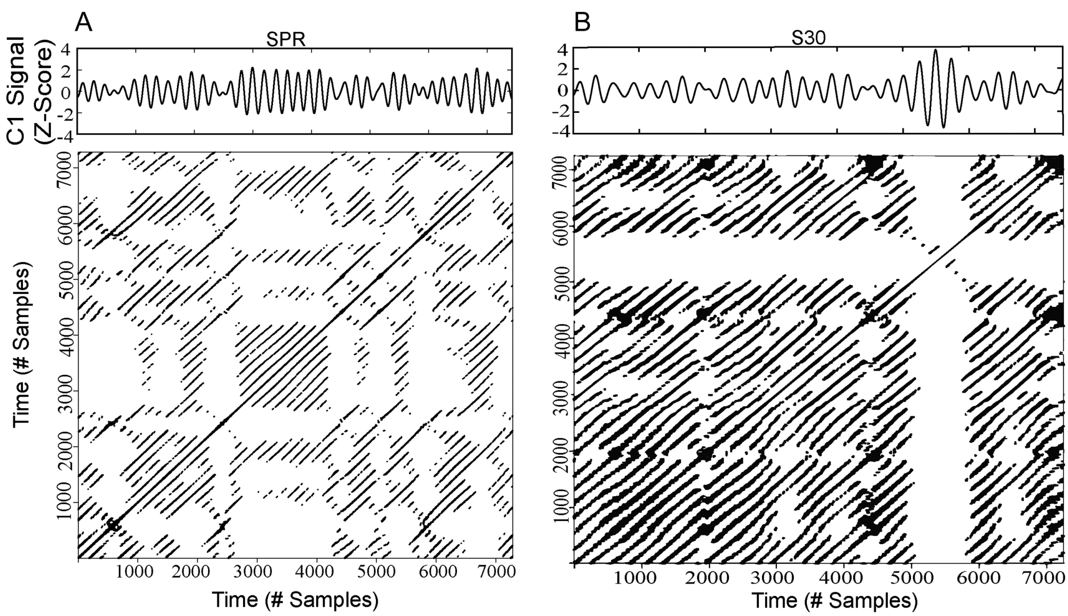

FIGURE 1 | Sample auto-recurrence plots and corresponding time series from one participant's EEG signal (C1 electrode). (A) A single trial at the participant's spontaneous production rate. (B) A single trial at the 30% slower rate.

$$L = \frac{\sum_{l=l_{min}}^{N} l\,P(l)}{\sum_{l=l_{min}}^{N} P(l)} \tag{2}$$

2.8 | Statistical Analysis

Analyses of variance (ANOVA) conducted by rate are reported for behavioral and neural measures with effect sizes. Post hoc comparisons are reported with Holm's (1979) correction for the number of tests. Robust ANOVAs are reported when tests of homogeneity of variance fail. Pearson correlations are reported to examine brain–behavior relationships between synchronization stability (standard deviation of the signed asynchronies) and neural stability (meanline).

3 | Results

3.1 | Spontaneous Rates

Figure 2 shows participants' mean SPR values, computed as mean IOI, ordered from fastest to slowest (minimum = 302.95 ms IOI; maximum = 752.84 ms IOI). Similar to previous studies, large individual differences in SPRs were observed across participants (a 2.5-fold increase from fastest to slowest participant) with small disparities across trials within participant (indicated by the standard error bars). Thus, the participants' spontaneous rates provided a wide range of individual stimulus rates that were incorporated in the synchronization task.

3.2 | Synchronization Accuracy

3.2.1 | Behavioral Measures

Participants' synchronization accuracy was measured by the mean signed asynchrony (participant's tap onset minus metronome stimulus onset), where a negative value indicates the participant preceded the metronome cue. As Levene's (1960) test indicated that homogeneity of variances was violated at the 15% slower rate, $F(1, 22) = 4.89$, $p = 0.038$, a robust ANOVA using the trimmed means method (Mair and Wilcox 2020) was conducted on the mean signed asynchronies by Rate (SPR, 15% Slower, and 30% Slower). The significant main effect of rate, $Q = 6.32$, $p = 0.017$, shown in the top of Figure 3, indicated that signed asynchronies became larger (more negative) as the rate became slower than each participant's SPR.

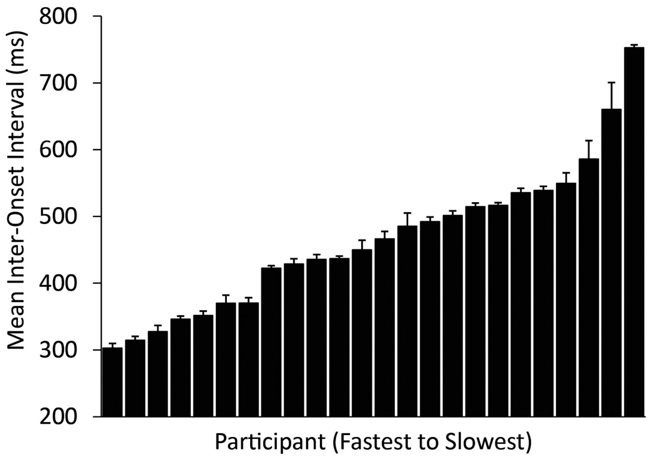

FIGURE 2 | Distribution of participants' SPR values (mean IOI in ms) ordered from fastest to slowest. Error bars represent standard error.

3.2.2 | Neural Recurrence Measures

We assessed the predictability of EEG activity during the synchronization task. A one-way ANOVA on participants' neural determinism values showed a significant effect of rate, $F(2, 44) = 161$, $p < 0.001$, $\eta^2_G = 0.17$. As shown in the bottom of Figure 3, determinism was higher at the 15% and 30% slower rates than at the SPR and higher at the 30% Slower rate than at the 15% Slower rate (Holm-adjusted p's < 0.001). Consistent with previous findings, determinism values indicated most flexibility (lowest values) at each individual's SPR.

3.3 | Synchronization Consistency

3.3.1 | Behavioral Measures

Synchronization consistency was measured via the mean standard deviation of the signed asynchronies in each trial. A one-way ANOVA on the standard deviations indicated no significant effect of rate, $F(2, 44) = 0.70$, $p = 0.5$, $\eta^2_G = 0.06$.

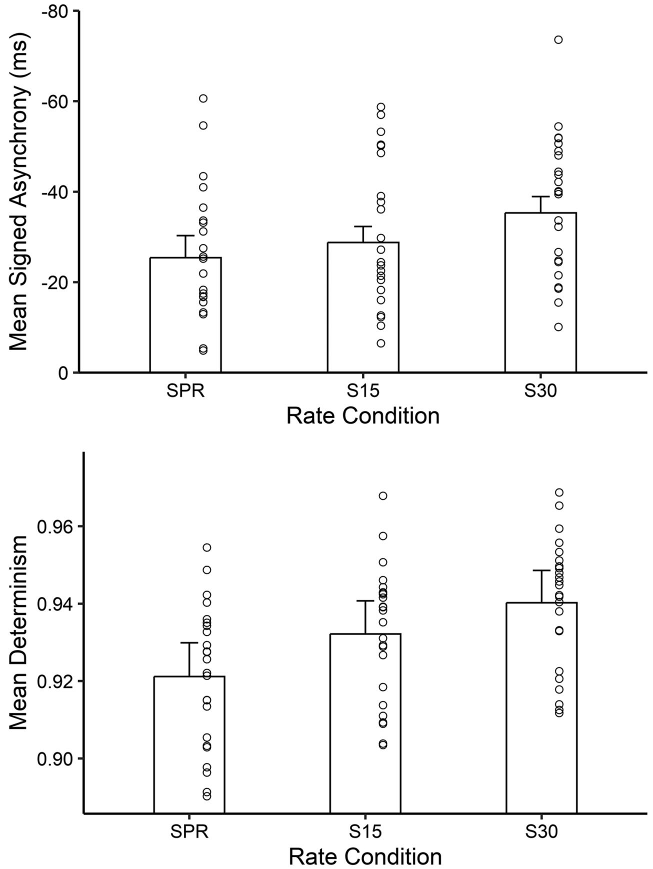

FIGURE 3 | Behavioral and neural effects of synchronization rate. Top: Mean signed asynchrony (ms) by rate condition; points indicate individual values. Error bars indicate standard errors. Bottom: Mean determinism (predictability) in EEG signal by rate condition; points indicate individual values. Error bars indicate standard errors.

3.3.2 | Neural Recurrence Measures

We assessed the stability (consistency) of EEG activity during the synchronization task. A one-way ANOVA on participants' meanline values showed no significant effect of Rate, $F(2, 44) = 2.27$, $p = 0.11$, $\eta^2_G = 0.04$.

3.4 | Brain–Behavior Correlations

Finally, we examined the relationship between synchronization consistency (standard deviation of the signed asynchronies) and neural stability (meanline) for each individual. Figure 4 shows the simple correlations between the behavioral and neural stability metrics for each rate condition. Correlations were significant at all rates (SPR: $r(22) = -0.43$, $p = 0.039$; 15% slower: $r(22) = -0.65$, $p < 0.001$; 30% slower: $r(22) = -0.43$, $p = 0.038$). Figure 4 indicates that as individuals' EEG-based meanline values increased, the standard deviation of their signed asynchronies decreased. Consistent with our predictions, individuals' neural stability increased as their synchronization variability decreased.

4 | Discussion

We compared performance in an auditory-motor synchronization task, measured by participants' accuracy and consistency, with the temporal dynamics of their EEG signals. The stability of participants' EEG signals, measured with recurrence quantification methods, corresponded with their behavioral consistency. Novel to this study, each participant produced melodies in synchrony with a range of stimulus rates titrated to participant-specific spontaneous production rates. As the stimulus rates became slower, synchronization accuracy decreased, confirming the increase in task difficulty. Most importantly, brain–behavior comparisons showed significant negative correlations between a metric of neural stability and the temporal variability of participants' asynchronies across all stimulus rates. Recurrence quantification techniques successfully identified EEG temporal regularities that corresponded to behavioral change, findings that expand the small but growing number of nonlinear analysis applications to neurophysiological signals that do not meet the assumptions of stationarity and linearity (Eqlimi et al. 2023; Lopes et al. 2021; Pitsik et al. 2020).

A major finding was the correspondence between individuals' neural and behavioral stability that increased both within and between stimulus rates. These results are consistent with general findings that the strength of neural entrainment increases as synchronization performance improves (Bouvet et al. 2020; Nozaradan et al. 2016) but go beyond those studies as stimulus rates were titrated to each participant's preferred rate of melody production only in the current study. Thus, these findings suggest that neural stability may be a critical mechanism supporting auditory-motor synchronization as individuals deviate from their preferred performance rates. An advantage of recurrence quantification measures such as meanline and determinism is their sensitivity to recurring patterns typical of EEG signals (cf. Figure 1) as well as their robustness to nonlinearity and nonstationarity.

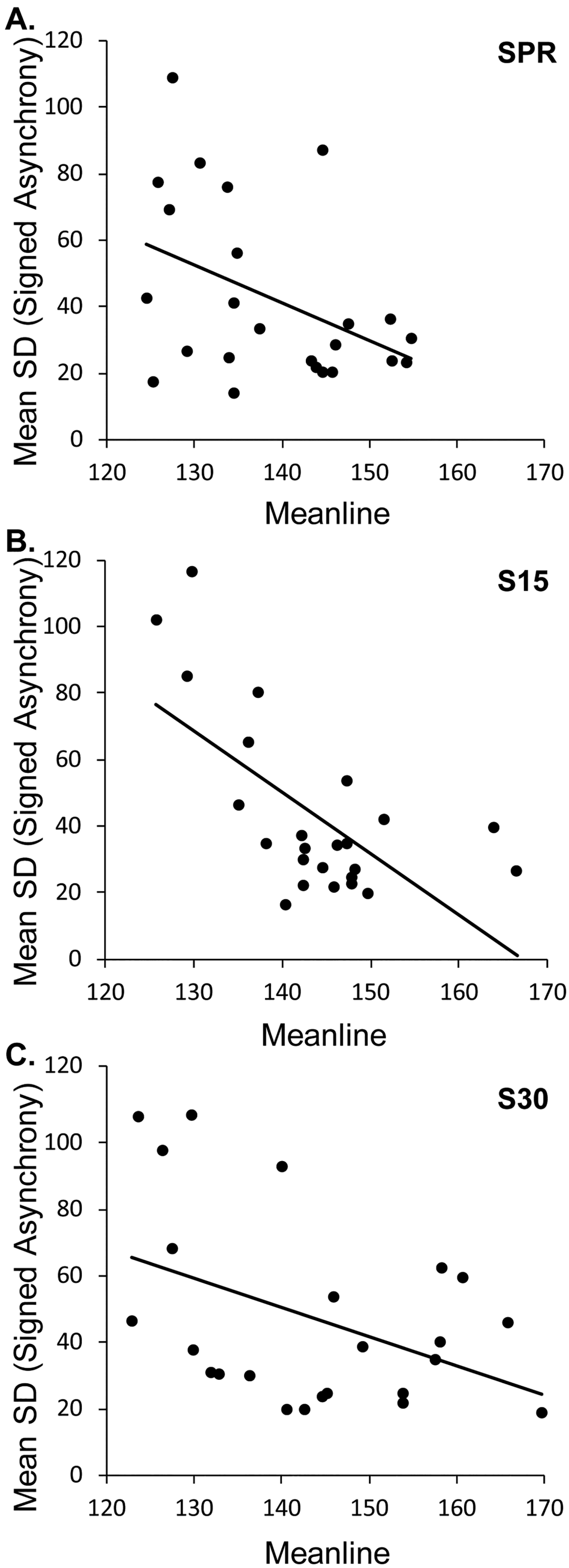

FIGURE 4 | Correlations between meanline (stability) in EEG signal and standard deviation of participants' asynchronies by rate condition. (A) Spontaneous production rate; (B) 15% slower rate; and (C) 30% slower rate. Points indicate individual values.

Another key finding was the impact of slower stimulus rates on behavioral and neural dynamics; that is, synchronization accuracy decreased and neural predictability.

(measured by determinism) increased as individuals performed rates became slower. These findings are consistent with previous reports that movement coordination becomes more demanding and less flexible at slower rates (Fujiyama et al. 2013; Scheurich et al. 2018). The current study tailored the task demands to each individual by determining the stimulus rates relative to each participant's spontaneous (uncued) rate of melody production. Task demands are typically lowest at stimulus rates equivalent to the individual's SPR, representing the individual's optimal temporal stability; synchronization task demands tend to increase as the stimulus rate becomes slower (Repp and Doggett 2007; Scheurich et al. 2018). Previous research has similarly shown that increased task demands result in increased determinism (minimal or slow change, interpreted as greater rigidity) in postural sway measures (Balasubramaniam et al. 2000; Mazaheri et al. 2010) and in temporal synchronization behaviors (Scheurich et al. 2018). Future incorporation of participant-specific measures (such as task difficulty or musical training) can address whether musical training increases neural flexibility (lowered determinism) in synchronization tasks.

Recurrence quantification analysis of individual EEG electrode measures requires a conceptual shift away from traditional EEG techniques that alter or remove properties of the original time series in order to boost the desired signal relative to the noise. Previous studies of EEG signals collected during auditory-motor synchronization tasks have focused on linear indices that collapse across time. Examples include the spectral power present in the EEG response at the stimulus frequency (Bouvet et al. 2020; Nozaradan et al. 2016; Nozaradan et al. 2015; Varlet et al. 2020) and the phase coherence or consistency in phase between MEG signals and auditory stimuli (Fujioka et al. 2010, 2012). The novel correspondences reported here between nonlinear neural and behavioral metrics may also exist in the tasks studied previously. To our knowledge, this study is the first to contrast the recurrence quantification dynamics of individual (non-averaged) EEG time series with the synchronization behavior in the same trials.

In sum, participants showed decreased synchronization accuracy at slower stimulus rates titrated to each participant's spontaneous rate, as well as differences in synchronization variability across all stimulus rates. These behavioral patterns were indexed in the EEG time series by nonlinear metrics of determinism (predictability) and meanline (stability), respectively. Future studies may extend the behavioral tasks to faster as well as slower production rates and to different condition orders, and extend EEG analyses to multivariate techniques (Hall et al. 2023; Wallot et al. 2016; Zamm et al. 2018) such as multidimensional RQA, which can uncover relationships among time series measured across electrodes. Furthermore, applications of RQA to event-related potentials (ERPs) may distinguish the roles of alpha and beta oscillations that accompany changes in rhythmic movements (Hsu et al. 2016). Finally, recurrence quantification analyses can be applied to source activity associated with auditory and motor networks, as extracted from EEG-based source localization techniques. Overall, these novel findings indicate that individual differences in the consistency of behavioral synchronization were associated with the stability of their neural signals across a range of stimulus rates, while their synchronization accuracy and neural predictability were differentially affected by individual-specific stimulus rates.

Author Contributions

Rebecca Scheurich: conceptualization, data curation, formal analysis, methodology, supervision, validation, writing – original draft, writing – review and editing. **Valentin Bégel:** data curation, validation, writing – original draft, writing – review and editing. **Ella Sahlas:** data curation, methodology, validation, writing – review and editing. **Caroline Palmer:** conceptualization, funding acquisition, project administration, resources, writing – original draft, writing – review and editing.

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Ethics Statement

The research was reviewed by the McGill University Research Ethics Board and the study was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets for the current study are available online in an open-source format at OSF (https://osf.io/ake49/files/osfstorage).

Peer Review

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/ejn.70127.

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