Human-machine trios show different tempo changes in musical tasks

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Abstract

Music-making relies on precise temporal control and mutual coordination among performers, particularly to maintain tempo. We evaluate the impact of human-machine interaction and rhythmic subdivisions on tempo change in musical trios. A synchronization-continuation task was performed by trios of human participants interacting with confederates or with algorithmic (i.e. machine) models. Sounded tone onsets were produced by a linear error-correction model, delay-coupled model, and Kuramoto model that replaced a human participant. Inter-onset intervals were examined from participants who performed rhythms in both in-phase and anti-phase conditions while a third group member was either a human or algorithmic model. Trios drifted toward faster tempi more when they contained a human than an algorithmic model. Tempo drift also increased for the aligned rhythms (in-phase) compared to rhythms with rhythmic subdivisions (anti-phase). Finally, the tested algorithmic models replicated the confederate's tempo drift without the use of any period correction mechanisms. This research advances our understanding of unintentional tempo drift, offering insights into ensemble dynamics and models of temporal coordination in groups. Implications for musical coordination and avenues for future research are discussed.

Keywords: group coordination, tempo drift, joint rushing, synchronization, oscillator models, linear error-correction

Introduction

Successful music-making places stringent requirements on performers in terms of their mutual temporal coordination. Maintaining and controlling tempo (defined as events per unit of time in musical ensembles is a crucial aspect of any cohesive performance. Maintaining tempo is challenging as group performances include both inter-individual differences and expressive nuances (Walton et al., 2018). Musical groups of up to 16 members have been shown to spontaneously adapt their tempo to others when faced with auditory feedback delays (Shahal et al., 2020).

Recent findings indicate that both musically trained and untrained individuals increase their tempo when they attempt to align their rhythmic actions in groups, called "joint-rushing" (Wolf & Knoblich, 2022), compared with when they produce these rhythms by themselves. These tempo changes are unlikely to be the result of a failing tempo memory which has been demonstrated as accurate and stable (Vigl, Talamini, Feller, Gerstgrasser, & Henning, 2023). On the other hand, the ability to maintain tempo could be related to expertise or performance accuracy as performers are able to maintain synchrony during tempo changes (Goebl & Palmer, 2009) and speed up less when variability in asynchronies is reduced (Thomson, Murphy, & Lukeman, 2018; Wolf & Knoblich, 2022). The consistent observation of tempo drift in groups has raised the question of whether tempo drift has functional significance as a sort of coordination smoother (Vesper, Butterfill, Knoblich, & Sebanz, 2010).

Most investigations of joint performance in musical ensembles control for or correct tempo drift by using shorter trials or applying detrending techniques (Dotov, Delasanta, Cameron, Large, & Trainor, 2022). Recently though, research has begun to focus on joint rushing as a behavior of interest and initial studies have ruled out individual tendencies, social facilitation, and action mirroring as potential underlying mechanisms [see (Wolf, Vesper, Sebanz, Keller, & Knoblich, 2019)].

One plausible contributor to tempo change in groups is the number of group members (Demos & Palmer, 2023). One study of musical groups documented tempo drift decreased for larger groups as a function of the nonlinear dynamics that arise in larger groups (Dotov et al., 2022). Another study showed that tempo slowed down under continuous visual coupling (Bardy et al., 2020). Explanatory accounts that rely on mutual prediction have been promoted to explain increased rushing for larger groups with linear error correction mechanisms (Thomson et al., 2018; Wolf et al., 2019). However, the impact of group size on joint rushing and its stabilization remains a debated one. The fact that tempo remains more stable in solo performance (Loehr, Large & Palmer, 2011; Okano, Shinya, & Kudo, 2017) and in larger musical groups who perform in the presence of an isochronous metronome (Ogata, Katayama, & Ota, 2019) does suggest that joint rushing seems to arise as an emergent group property from multiple coordinating humans (Demos & Palmer, 2023), rather than as a property of self-perception mechanisms (Vigl et al., 2023).

Two mechanisms have been proposed for temporal errors in synchronization: a phase correction mechanism that is automatic, unconscious, and temporary, and a period correction mechanism that is effortful, intentional, and long-

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society*.

lasting (Repp & Keller, 2004). Temporal coordination models integrating these notions have been proposed in two main categories: linear error-correction models that work in absolute time with a linear variable that is not intrinsically periodic (Van Der Steen & Keller, 2013; Wing, Endo, Bradbury, & Vorberg, 2014) and oscillator models that work in terms of (relative) phase as a circular and periodic variable (Dotov et al., 2022; Konvalinka, Vuust, Roepstorff, & Frith, 2009; Okano, Kurebayashi, Shinya, & Kudo, 2017). While several studies have put forward hypotheses on the underlying mechanisms of tempo drift, to our knowledge only one has made a direct comparison of different temporal coordination models. This study showed that solo participants' tempo change could be approximated better by a nonlinear oscillator model than by a linear timekeeper model in solo performance (Loehr, Large, & Palmer, 2011).

The current study compares the behavior of two human participants coordinating with a linear error-correction model, a delay-coupled model or a Kuramoto model in a trio synchronization-continuation task. The linear model adapts future onset timing using discrete corrections based on previous inter-onset asynchronies. It has been used to match asynchronies of tapping data and to estimate correction gains in musical ensembles (Wing et al., 2014). The delay-coupled oscillator model compares its own time-delayed behavior, which implicitly includes past information about the other system's behavior, with the other system's instantaneous behavior and adapts future onset timing using instantaneous phase adjustments and small feedback delays. It allows for mutual anticipation and adaptation between coordinating performers and has been used to explain anticipatory synchrony in musical duets (Demos, Layeghi, Wanderley, & Palmer, 2019) and in continuous movement control tasks (Washburn et al., 2019). Finally, the Kuramoto model relies on sinusoidal coupling between two oscillators and was chosen as a well-known model of synchronization that applies across a broad range of coordination behaviors (Acebrón, Bonilla, Vicente, Ritort, & Spigler, 2005; Shahal et al., 2020). It has captured the synchronization differences between dyad members (Heggli, Cabral, Konvalinka, Vuust, & Kringelbach, 2019) as well as the behavioral changes occurring in larger groups (Zhang, Beetle, Kelso, & Tognoli, 2019).

The current study measured tempo change in trio performances as participants attempted to maintain an initially cued tempo in a synchronization-continuation task. Tempo change was considered unintentional as participants were given explicit instructions to maintain the cued tempo. The algorithmic models thus contained only phase correction model terms and no period correction as the latter is considered an effortful, intentional, and long-lasting process (Repp & Keller, 2004). Model comparisons were applied to inter-onset intervals rather than to synchrony measures as the focus of this study was on tempo drift.

The tempo changes across each trial were measured in two of the trio members as they produced simple melodies in coordination with a human confederate or with an algorithmic model (the third member). Both in-phase (three simultaneous productions) and anti-phase rhythms (two simultaneous productions together with a confederate or model in anti-phase) were included. The influence of the number of in-phase participants was evaluated by manipulating the rhythmic relationships formed between the participants' parts. The first hypothesis was that tempo drift would be smaller when two participants performed with models that adapted in a regular (algorithmic) manner to the participants' behavior, compared with the confederate's adaptation. A second hypothesis was that tempo drift would be smaller during the anti-phase performance as compared to the in-phase performance (Repp, 2003), as a function of the increased temporal information given by the trio's combination of in-phase and anti-phase rhythms (Vesper, Van Der Wel, Knoblich, & Sebanz, 2011).

Methods

Participants

Data from 48 participants aged 18-30 years old with at least 6 years of individual instruction on a musical instrument and with no self-reported hearing problems was included. Participants were randomly paired for the study. Two research confederates with more than 6 years of formal musical instrument training were recruited to perform the experiment with participants in 12 trios each. All trio members passed a perceptual test (see Procedure below) to participate. The experimental protocol was approved by an Ethics Review Board of McGill University.

Equipment and Materials

Participants produced tone onsets via taps on force-sensing resistors connected to a Bela ultra-low latency platform[1]. Tap onsets were recorded using a custom Pure Data patch running on the Bela platform. Algorithmic models that produced tone onsets in response to the taps were also implemented in the Pure Data patch (see Model Implementations below). Audio was generated by the Bela platform and distributed to participants using Sennheiser HD 280 Pro headphones connected to a Motu 828 MkII audio interface. Experimental trials were launched using a Pure Data patch running on a Linux PC connected to the Bela platform over a USB connection.

Stimulus Materials and Design

The within-trio design contained 8 conditions from the crossed independent variables of Rhythm (in-phase and anti-phase) and Agent (human confederate, linear error correction model, delay-coupled model, and Kuramoto model). The order of conditions was counterbalanced. Participants always performed the in-phase, then the anti-phase conditions with the confederate first before performing them with the algorithmic models.

[1] The Bela platform: https://bela.io

Each participant's taps generated sinewave tones that formed one of the arpeggiated chords (Part1: G2-C3-E3-C3, Part2: C4-E4-G4-E4, Part3: E5-G5-C6-G5). The 3 melodies were designed to be harmonious when sounded simultaneously. Each of the melodies was produced in a different octave to ensure participants could discriminate their own tone onsets. Tone amplitudes were set to have equal loudness using the Fletcher-Munson equal-loudness contours.

The two Rhythm conditions, shown in Figure 1, required all participants to tap simultaneously with each other in the in-phase condition, and the pair of participants to tap out-of-phase with the confederate or model in the anti-phase condition. As shown in Figure 1, the two participants thus produced the same tone patterns at the same rate in both conditions; only the confederate or model changed its tone onsets relative to the participants.

	Time (ms)	0	300	600	900	1200	1500	1800	2100
IN-PHASE	Participant 1	X		X		X		X	
	Participant 2	X		X		X		X	
	Agent (confederate/model)	X		X		X		X	
ANTI-PHASE	Participant 1	X		X		X		X	
	Participant 2	X		X		X		X	
	Agent (confederate/model)		X		X		X		X

Figure 1: Rhythmic structure (in-phase, anti-phase) and third participant (confederate, model) stimulus manipulations in the trio study. X indicates tapping onsets.

Procedure

Trio participants were seated on 3 sides of a square table so they had a full view of their partners. Participants' hands were hidden from other group members by screens so they could not see each other's finger movements and had to rely on sound to coordinate their performances.

Each trial began with an 8-metronome-beat cue that signaled the intended tempo, which was set to 600ms for the entire study. The trial then continued in a synchronization-continuation task. Participants first listened to 4 isochronous beats, then tapped along for 4 isochronous beats, and then continued synchronizing their performances with their trio members until they heard no more sound over headphones, signaling the end of the trial. Participants were instructed to maintain the tempo and synchronize their taps as a group. In the anti-phase condition, the third group member (confederate or algorithmic model) alternated taps with the other two participants (see Figure 1). Tone onsets of this alternating member were muted for the first 4 taps of each trial to make it easier for them to "jump in" between the two other synchronizing group members. Thus, the Inter-Onset Intervals (IOIs) were analyzed starting with the fifth tap after the metronome was turned off, yielding 43 IOIs per trial or 11 melody repetitions.

One practice trial and three experimental trials were included in each of the 8 conditions. Halfway through the experiment, the confederate left the room, and the participants were told they would hear the confederate's part being controlled by an algorithmic model. The remainder of the conditions were completed, and the total experiment lasted about 75 minutes. Participants received a small honorarium or course credit for their time.

Model Implementations

As mentioned above, the third trio part was performed by a confederate or by one of three algorithmic models. The first model consisted of a linear error correction model based on a timekeeper-based account of temporal coordination (Wing et al., 2014). The second model was based on a delay-coupled oscillator model (Demos et al., 2019) and the third model was based on a Kuramoto model (Acebrón et al., 2005). Parameter values for each model are presented in Table 1.

The linear error correction model was adapted from (Wing et al., 2014) in a simple implementation that did not include a noise term, had uniform all-to-all correction gains, and was adapted to incorporate contributions from three instead of four group members. It consisted of a first-order linear phase correction model applying discrete corrections to tone onsets:

$$t_{i,n} = t_{i,n-1} + T_{i,n} - \frac{1}{N} \sum_{j=1, j\neq i}^{N} \alpha_{ij} \cdot \left(t_{i,n-1} - t_{j,n-1}\right),$$

where i = 1,2,3, N = 3, $t_{i,n}$ and $t_{i,n-1}$ are current and previous observed tone onset times for player i, $T_{i,n}$ represents the timekeeper interval, and α_{ij} refers to the correction gain applied by player i for the asynchrony $\left(t_{i,n-1} - t_{j,n-1}\right)$ with player j.

The delay-coupled oscillator model was adapted from (Demos et al., 2019). Like the Kuramoto model, it consisted of three phase oscillators with uniform all-to-all coupling. However, this model also included a time-delay term that fed a copy of its time-delayed behavior (which implicitly includes the system's past behavior) back into itself. The model is formalized as

$$\dot{\theta}_i = \omega_i + \frac{1}{N} \sum_{j=1, j\neq i}^{N} k_{ij} \cdot (\theta_j - \theta_{i,\tau}),$$

with N = 3, k_{ij} is coupling between player i and j, τ_i the time-delay of player i, and player j being the partner.

The Kuramoto oscillator model was adapted from (Acebrón et al., 2005) and consisted of three phase oscillators with uniform all-to-all coupling parameter strengths and a sinusoidal coupling term:

$$\dot{\theta}_i = \omega_i + \frac{1}{N} \sum_{j=1, j\neq i}^{N} k_{ij} \cdot sin(\theta_j - \theta_i).$$

i = 1,2,3, N = 3, θ_i is phase of player i, ω_i is intrinsic frequency of player i, and k_{ij} is coupling between player i and j, with player j being the partner.

Table 1: Algorithmic model parameters

Linear error correction		Delay-coupled		Kuramoto	
T	600ms	ω	1.666Hz	ω	1.666Hz
α_{ij}	1	k_{ij}	3	k_{ij}	3
		τ	15ms		

Data Analysis

All analyses were run in R Statistical Software (v4.3.1).

43 IOIs of each participant in each trial from each of the 24 trios were collected and analyzed. IOIs were collected 4 beats after the 8-beat metronome cue-in as these were muted for the anti-phase player. Only the tone onsets of the two participants whose melody productions stayed the same across conditions were included (see Fig 1). IOIs in each trial were divided into quintiles containing 8, 9, 9, 9, and 8 IOIs respectively. Tapping onsets for 1 trial were lost due to a technical issue, and trial sections where IOIs exceeded the cued-in tempo ± 50% were excluded (n = 5 / 192 trials or 2.6%). Outlier IOI values (defined as being larger or smaller than 3 standard deviations from the overall IOI mean) were removed (0.6% of all data). This resulted in 1920 IOI quintile values that formed the unit of analysis.

Mixed models with second-order orthogonal polynomials were applied to the IOI quintiles using the Afex (v1.3-0) and lme4 packages in R (v1.1-34). A random structure was determined by starting with a maximal structure and removing components based on Principal Component Analysis and Inter-Class Correlations of the random effects. We report Type III F-tests with Saitherwaith degrees of freedom using the LmerTest package (v3.1-3). Linear contrasts (Tukey posthocs) were run with the emmeans package (v1.8.9).

Two mixed models were defined and applied to the data set (see Table 2). The first model tested the 2 (Rhythm: in-phase and anti-phase) by 4 (Agent: confederate, linear error-correction, delay-coupled, Kuramoto) full design. Rhythm and Agent were dummy coded as fixed effects on both linear and quadratic time terms. Trios were included as a random variable (intercept). The linear time term and the interaction between Rhythm and a two-level Agent variable (confederate or algorithmic model) were included as random slopes per trio. The second mixed model tested Agent, linear, and quadratic time terms separately for each Rhythm level (the in-phase and anti-phase conditions). Interactions of linear and quadratic time terms with Agent were included as fixed effects. Trios were included as a random intercept. Interactions between the linear time term and Agent were included as a random slope per trio.

Table 2: Mixed model equations

Mixed models	Equation
Full model	IOI ~ (ot1 + ot2) * Rhythm * Agent + (1 + ot1 + Rhythm * Agent2|trio)
Rhythm condition models	IOI ~ (ot1 + ot2) * Agent + (1 + ot1 * Agent|trio)
ot1 = linear time term, ot2 = quadratic time term Agent2 = 2-level Agent (confederate, model)	

Results

We first tested tempo change by examining the first and last quintiles of each trial. The first IOI quintile values showed that participants immediately sped up following the 600-ms metronome cue, one-sample t-test: $t(47) = -16.639$, $p < .001$, $d = -2.40$. We then tested the mean tempo change from the first quintile of each trial (n = 8 events) to the last quintile (n = 8 events) for evidence of joint rushing. As shown in Figure 2 for all conditions, participants continued to speed up across the trial, $t(47) = 11.989$, $p < .001$, $d = 0.67$.

Full statistical model

Table 2 shows the mixed model conducted on each participant's mean IOIs per quintile by Rhythm (in-phase, anti-phase) and Agent (Confederate, linear, Kuramoto, delay-coupled), with both linear and quadratic time terms. Figure 2 shows the mean IOIs by trial plotted by quintiles as points and the regression model fits from the full statistical model plotted as lines.

Rhythm was significant as a main effect, $F(1,23) = 135$, $p < .001$, as were the interactions of Rhythm with the linear trend, $F(1,1781) = 113$, $p <.001$, with the quadratic trend, $F(1,1781) = 6.16$, $p = 0.013$, and with the Agent variable, $F(3,63.6) = 4.97$, $p = .004$. The three-way interaction of Rhythm with linear trend and Agent was also significant, $F(3,1781) = 11.1$, $p < .001$. Given the complexity of the Rhythm interactions, we conducted the analysis for the in-phase and anti-phase conditions separately.

In-Phase Conditions

Participants' mean IOIs per trial quintile from the in-phase conditions, analyzed with the second mixed model shown in Table 2, indicated significant main effects of the linear trend, $F(1,20.01) = 69.9$, $p < .001$, the quadratic trend, $F(1,738) = 85.4$, $p < .001$, and the Agent variable, $F(3,23) = 17.8$, $p < .001$. As shown in Figure 2, the confederate trios showed the largest tempo drift, followed by the delay-coupled model, and then the linear and Kuramoto models. There was a significant interaction of linear trend and Agent, $F(3,23.5) = 35.4$, $p < .001$. There was no interaction of quadratic trend with Agent ($p = .365$). Linear contrasts on the means from the Agent variable indicated significant differences (seen in Table 3) between the Confederate and all other models except the delay-coupled model. The delay-coupled model also differed from the Kuramoto model and approached a significant difference in comparison with the linear model.

Table 3: Linear contrasts for the in-phase condition for Agent (significant contrasts in bold)

Contrast	Estimate	SE	df	t ratio	p-value
Confed – Lin	**-7.730**	**1.38**	**23**	**-5.621**	**<.001**
Confed – Delay	-3.472	1.83	23	-1.894	.2580
Confed – Kura	**-8.054**	**1.76**	**23**	**-4.574**	**<.001**
Lin – Delay	4.258	1.60	23	2.655	.0632
Lin – Kura	-0.323	1.77	23	-0.182	.9978
Delay – Kura	**-4.581**	**1.39**	**23**	**-3.289**	**.0158**

Anti-Phase Conditions

Participants' mean IOIs per trial quintile from the anti-phase conditions, analyzed with the second mixed model shown in Table 2, indicated a significant main effect of the linear trend, $F(1,23) = 10.6$, $p = 0.003$, and of Agent, $F(3,23) = 3.49$, $p = 0.032$. The quadratic trend was not significant ($p = 0.890$) and neither were the interactions between Agent and linear trend ($p = 0.741$) or Agent and quadratic trend ($p = 0.125$). Participants thus showed similar drift trends in presence of the confederate and the algorithmic models.

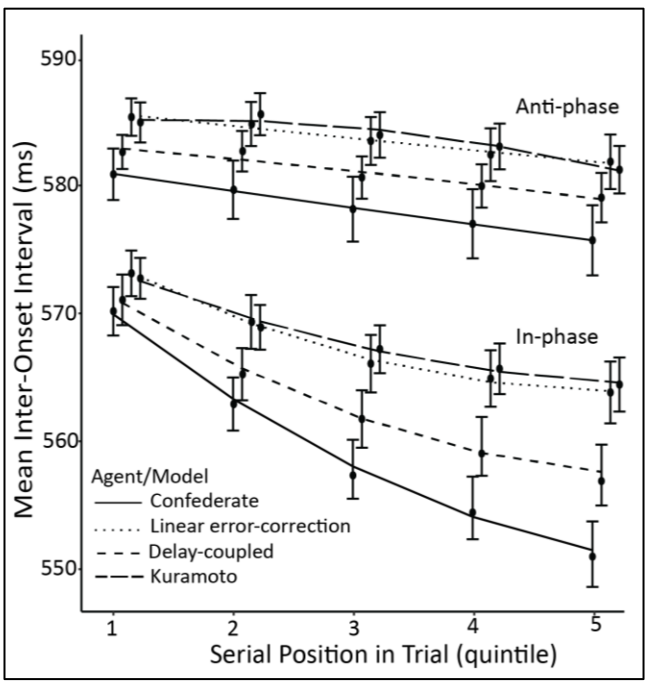

Figure 2: Mean inter-onset intervals with standard error values (points and error bars) and model fits (lines) by condition.

Discussion

Musical trios, formed with 2 participants and a confederate or an algorithmic model, showed significant tempo drift in all conditions. Surprisingly, tempo drift took different forms in situations when three performers were aligned (in-phase) in their rhythms, versus when two performers were aligned (anti-phase). The in-phase alignment led to the largest tempo drift, regardless of whether the trio included a confederate or an algorithmic model. Less surprisingly, trios with a confederate as the third performer showed larger tempo drift compared to trios performing with an algorithmic model. This might be expected due to the optimizing nature of the algorithms, which adapted each tone onset based on the previous tone onsets and the fact that the models did not implement any period correction.

The study replicates and extends the findings of Wolf (Wolf & Knoblich, 2022), who demonstrated tempo drifts for dyads across 60-second trials. The overall tempo drift values from trios in the current study (5.3%) were larger than perceptual sensitivity estimates (Drake & Botte, 1993). In the current study, trio participants sped up more in the in-phase condition (when 3 members produced the same rhythm) than in the anti-phase condition (when 2 members produced the same rhythm). This observation seems to support an increased tempo drift with increased group size.

Rhythmic subdivisions seemed to help reduce joint rushing over time; tempo drift in the anti-phase condition was smaller compared to the in-phase condition. Rhythmic subdivisions might thus effectively have reduced tempo drift by reducing variability (Repp, 2003) and increasing predictability (Vesper et al., 2011) by offering increased temporal information to coordinating participants. It is important to note that rhythmic subdivisions are unlikely to account for the larger tempo drift in the anti-phase condition by the first quintile of the trials, as the third group member (confederate or algorithmic model) did not yet alternate in anti-phase with the two players before quintile 1 (its tone onsets were muted).

Tempo drift was largest when the participants interacted with a human confederate compared to the algorithmic models. The three algorithmic models were able to adapt to tempo drift in all conditions and were distinguished by their approximations. The delay-coupled oscillator model performed most like the confederate as demonstrated by linear contrasts on the Agent variable in the in-phase condition. The linear error correction and Kuramoto models performed similarly and exhibited significantly less tempo drift compared to the confederate. Previous modelling efforts have relied on explicit and intentional period corrections to explain tempo drift using symmetric phase adjustments based on previous asynchronies (Van Der Steen & Keller, 2013; Wing et al., 2014), direct phase adjustments using early and late taps (Konvalinka et al., 2009) or by including an intentional term to maintain tempo (Okano, Kurebayashi, et al., 2017). Yet in our study, all models successfully approximated the trios' tempo drifts with a human confederate (linear and quadratic terms) despite the absence of period correction in the model implementations.

Interestingly, the delay-coupled model generated timing that best approximated the observed tempo drift of the confederate in model comparisons. The 15ms time delays in this model might serve as a crucial component to properly capture tempo drift in groups and mimic the (human) capability for anticipatory synchronization (Demos et al., 2019; Palmer & Demos, 2022; Washburn et al., 2019). The Kuramoto model also operates as an oscillator model with instantaneous phase corrections and does not incorporate any feedback delays. Previous explanations of tempo drift based on early vs late taps (Konvalinka et al., 2009) or phase advancement mechanisms (Wolf et al., 2019) may have to incorporate time delays to better explain unintentional tempo drift or joint rushing in groups.

Tempo drift curves in the anti-phase condition were linear, while tempo curves in the in-phase condition contained both linear and quadratic components. The presence of a quadratic trend yields the prediction of a faster move toward a stable tempo (indicated by a zero slope). Furthermore, the quadratic trend was greatest in the human-confederate trios. Other studies have demonstrated stabilization of unintentional tempo drift in synchronization-continuation paradigms but have not analyzed the tempo drift curves themselves (Ogata et al., 2019; Thomson et al., 2018; Wolf et al., 2019). The stabilization of tempo drift has been reported in previous studies (Thomson et al., 2018) and raises the question of an emerging tempo attractor balancing tempo drifts in the human and human-machine trios.

Future work may investigate the relationship between tempo drift and synchronization measures to evaluate the possible role of joint rushing in coordination improvement (Vesper et al., 2010). Another factor that may influence tempo drift is inter-individual differences in spontaneous production rates that are known to influence group dynamics in both synchronization and tempo change (Palmer, Spidle, Koopmans, & Schubert, 2019; Tranchant, Scholler, & Palmer, 2022; Zamm, Wang, & Palmer, 2018). An important question from this work is whether tempo attractors can be predicted from group members' endogenous rhythms (Zamm et al., 2018). These factors combined may address how temporal coordination arises and whether tempo attractors emerge from group dynamics to facilitate improved coordination. Algorithmic models such as the ones presented in this work could then be tuned individually to allow for a better performance. Finally, an investigation of algorithmic models with and without period correction in (un)intentional tempo maintenance tasks may answer the question of whether period correction terms are required in human temporal coordination mechanisms (Calabrese, Bardy, De Lellis, & Di Bernardo, 2022).

References

Acebrón, J. A., Bonilla, L. L., Vicente, C. J. P., Ritort, F., & Spigler, R. (2005). The Kuramoto model: A simple paradigm for synchronization phenomena. *Reviews of Modern Physics*, *77*, 137–185.

Bardy, B. G., Calabrese, C., De Lellis, P., Bourgeaud, S., Colomer, C., Pla, S., & Di Bernardo, M. (2020). Moving in unison after perceptual interruption. *Scientific Reports*, *10*, 18032.

Calabrese, C., Bardy, B. G., De Lellis, P., & Di Bernardo, M. (2022). Modeling frequency reduction in human groups performing a joint oscillatory task. *Frontiers in Psychology*, *12*, 753758.

Demos, A. P., Layeghi, H., Wanderley, M. M., & Palmer, C. (2019). Staying together: A bidirectional delay–coupled approach to joint action. *Cognitive Science*, *43*, e12766.

Demos, A. P., & Palmer, C. (2023). Social and nonlinear dynamics unite: Musical group synchrony. *Trends in Cognitive Sciences*.

Dotov, D., Delasanta, L., Cameron, D. J., Large, E. W., & Trainor, L. (2022). Collective dynamics support group drumming, reduce variability, and stabilize tempo drift. *Elife*, *11*, e74816.

Drake, C., & Botte, M.-C. (1993). Tempo sensitivity in auditory sequences: Evidence for a multiple-look model. *Perception & Psychophysics*, *54*, 277–286.

Goebl, W., & Palmer, C. (2009). Synchronization of timing and motion among performing musicians. *Music Perception*, *26*, 427–438.

Heggli, O. A., Cabral, J., Konvalinka, I., Vuust, P., & Kringelbach, M. L. (2019). A Kuramoto model of self-other integration across interpersonal synchronization strategies. *PLoS Computational Biology*, *15*, e1007422.

Konvalinka, I., Vuust, P., Roepstorff, A., & Frith, C. D. (2009). A coupled oscillator model of interactive tapping. *ESCOM 2009: 7th Triennial Conference of European Society for the Cognitive Sciences of Music*.

Loehr, J. D., Large, E. W., & Palmer, C. (2011). Temporal coordination and adaptation to rate change in music performance. *Journal of Experimental Psychology: Human Perception and Performance*, *37*, 1292.

Ogata, T., Katayama, T., & Ota, J. (2019). Cross-feedback with partner contributes to performance accuracy in finger-tapping rhythm synchronization between one leader and two followers. *Scientific Reports*, *9*, 1–12.

Okano, M., Kurebayashi, W., Shinya, M., & Kudo, K. (2017). A coupled oscillator model for acceleration of a paired tapping through mutual timing adjustment for synchronization. *Studies in Perception and Action XIV: Nineteenth International Conference on Perception and Action*, 21–24. Psychology Press.

Okano, M., Shinya, M., & Kudo, K. (2017). Paired synchronous rhythmic finger tapping without an external timing cue shows greater speed increases relative to those for solo tapping. *Scientific Reports*, *7*, 43987.

Palmer, C., & Demos, A. P. (2022). Are we in time? How predictive coding and dynamical systems explain musical synchrony. *Current Directions in Psychological Science*, *31*, 147–153.

Palmer, C., Spidle, F., Koopmans, E., & Schubert, P. (2019). Ears, heads, and eyes: When singers synchronise. *Quarterly Journal of Experimental Psychology*, *72*, 2272–2287.

Repp, B. H. (2003). Rate limits in sensorimotor synchronization with auditory and visual sequences: The synchronization threshold and the benefits and costs of interval subdivision. *Journal of Motor Behavior*, *35*, 355–370.

Repp, B. H., & Keller, P. E. (2004). Adaptation to tempo changes in sensorimotor synchronization: Effects of intention, attention, and awareness. *The Quarterly Journal of Experimental Psychology Section A*, *57*, 499–521.

Shahal, S., Wurzberg, A., Sibony, I., Duadi, H., Shniderman, E., Weymouth, D., … Fridman, M. (2020). Synchronization of complex human networks. *Nature Communications*, *11*, 3854.

Thomson, M., Murphy, K., & Lukeman, R. (2018). Groups clapping in unison undergo size-dependent error-induced frequency increase. *Scientific Reports*, *8*, 808.

Tranchant, P., Scholler, E., & Palmer, C. (2022). Endogenous rhythms influence musicians' and non-musicians' interpersonal synchrony. *Scientific Reports*, *12*, 12973.

Van Der Steen, M. C., & Keller, P. E. (2013). The ADaptation and Anticipation Model (ADAM) of sensorimotor synchronization. *Frontiers in Human Neuroscience*, *7*, 253.

Vesper, C., Butterfill, S., Knoblich, G., & Sebanz, N. (2010). A minimal architecture for joint action. *Neural Networks*, *23*, 998–1003.

Vesper, C., Van Der Wel, R. P. R. D., Knoblich, G., & Sebanz, N. (2011). Making oneself predictable: Reduced temporal variability facilitates joint action coordination. *Experimental Brain Research*, *211*, 517–530.

Vigl, J., Talamini, F., Feller, A., Gerstgrasser, S., & Henning, H. (2023). Accuracy and stability of musical tempo memory and the role of musical expertise. *Music Perception: An Interdisciplinary Journal*, *41*, 15–35.

Walton, A. E., Washburn, A., Langland-Hassan, P., Chemero, A., Kloos, H., & Richardson, M. J. (2018). Creating time: Social collaboration in music improvisation. *Topics in Cognitive Science*, *10*, 95–119.

Washburn, A., Kallen, R. W., Lamb, M., Stepp, N., Shockley, K., & Richardson, M. J. (2019). Feedback delays can enhance anticipatory synchronization in human-machine interaction. *PloS One*, *14*, e0221275.

Wing, A. M., Endo, S., Bradbury, A., & Vorberg, D. (2014). Optimal feedback correction in string quartet synchronization. *Journal of The Royal Society Interface*, *11*, 20131125.

Wolf, T., & Knoblich, G. (2022). Joint rushing alters internal timekeeping in non-musicians and musicians. *Scientific Reports*, *12*, 1190.

Wolf, T., Vesper, C., Sebanz, N., Keller, P. E., & Knoblich, G. (2019). Combining phase advancement and period correction explains rushing during joint rhythmic activities. *Scientific Reports*, *9*, 9350.

Zamm, A., Wang, Y., & Palmer, C. (2018). Musicians' Natural Frequencies of Performance Display Optimal Temporal Stability. *Journal of Biological Rhythms*, *33*, 432–440.

Zhang, M., Beetle, C., Kelso, J. S., & Tognoli, E. (2019). Connecting empirical phenomena and theoretical models of biological coordination across scales. *Journal of the Royal Society Interface*, *16*, 20190360.