

Full Length Article

Early learning differences between intra- and interpersonal interlimb coordination

Colin T. Annand^{a,b,*}, Francis M. Grover^a, Paula L. Silva^a, John G. Holden^{a,b}, Michael A. Riley^a^a Center for Cognition, Action, & Perception, Department of Psychology, University of Cincinnati, Cincinnati, OH, USA^b The Complexity Group, Department of Psychology, University of Cincinnati, Cincinnati, OH, USA

A B S T R A C T

Intrinsic coordination patterns exist between limbs such that 1) coordination at these states is inherently stable, 2) any other pattern requires learning to produce, and 3) this learning is subject to interference from a systemic bias towards intrinsic patterns. The dynamics that govern intrapersonal interlimb coordination also govern interpersonal coordination. However, intrapersonal coordination exhibits greater coupling strength and thus more stable intrinsic dynamics than interpersonal coordination. Because the strength of intrinsic coordination tendencies has consequences for learning coordination patterns, the differences in coupling strength between intra- and interpersonal coordination should impact the ability to perform new coordination patterns via greater or less interference from intrinsic dynamics. This was investigated by measuring participants' performance as they learned a new coordination pattern alone (intrapersonal) or in pairs (interpersonal). Participants were implicitly tasked with learning the pattern as they separately controlled the vertical and horizontal position of an on-screen cursor to trace a circling target. We observed better performance of dyads on first trial and steeper learning trajectories for individuals. Overall, these results indicate that individuals experienced greater interference from stronger intrinsic coordination dynamics during early learning but could overcome this interference and achieve similar performance to that of dyads with very little practice.

1. Introduction

To successfully perform a number of daily activities, individuals have to coordinate the movements of their upper and lower limbs in a variety of patterns. Coordination occurs during rhythmic activities, such as walking and clapping, where the effectors have roughly symmetric roles, and also during activities requiring different contributions from each limb, such as playing the guitar or loading the dish washer. Many daily activities occur in conjunction with other people, and thus appropriate coordination patterns must be produced not only intra- but interpersonally to achieve desired task goals. The ease with which trained individuals perform these activities (alone or with a partner) hides an underlying complexity: Even the simplest rhythmic pattern involves the regulation of many heterogeneous components (neural, muscular, skeletal) whose states change at different time scales. A robust body of research has given expression to the dynamical processes that underlie the compression of these indefinitely many degrees of freedom into task-appropriate patterns that reflect underlying stable states (i.e., attractors) in a behavioral state space (Kelso, 1995; Schöner, Zanone, & Kelso, 1992; Zanone & Kelso, 1992 & Zanone & Kelso, 1997). At issue in the present research is how the process of establishing stable behavioral patterns plays out during practice of a challenging coordination pattern: from an initial period, where learners become acquainted with the essential nature of the target pattern, to a subsequent intermediate learning period, where they standardize and stabilize the performance of that pattern (Fitts, 1964; see also Mitra, Amazeen, & Turvey, 1998).

* Corresponding author at: Department of Psychology Edwards Center 1, University of Cincinnati Cincinnati, OH 45221-0376, USA.
E-mail address: annandct@mail.uc.edu (C.T. Annand).

Certain patterns of rhythmic interlimb coordination are easily producible and others are not. Typically, 0° and 180° relative phase differences (denoted by φ , with $\varphi = 0^\circ$ and $\varphi = 180^\circ$ referred to respectively as *in-phase* and *anti-phase*) between the limbs are readily attainable, inherently stable patterns (i.e., attractors) exhibiting relatively low within-trial variability (i.e., low standard deviation—SD φ), at least at certain movement frequencies (Kelso, 1984). In contrast, other patterns (e.g., $\varphi = 90^\circ$) are inherently unstable and are difficult to achieve without substantial practice. Learning a new coordination pattern such as $\varphi = 90^\circ$ requires modifying the attractor landscape defining the intrinsic interlimb coordination dynamics (Haken, Kelso, & Bunz, 1985) such that the to-be-learned pattern becomes a new attractor (Schöner et al., 1992; Zanone & Kelso, 1992 & Zanone & Kelso, 1997). This process is subject to interference from a systematic bias towards the intrinsic dynamics depending on the strength of pre-established attractors (Fontaine, Lee, & Swinnen, 1997; Kostrubiec, Zanone, Fuchs, & Kelso, 2012; Wenderoth & Bock, 2001; Wenderoth, Bock, & Krohn, 2002), which is shaped by various control parameters (e.g., movement frequency or coupling strength; Schöner & Kelso, 1988).

While untrained individuals have difficulty achieving intrinsically unstable interlimb patterns spontaneously, they are able to do so relatively quickly with the help of visual feedback that provides simplified information about the relative motion of their limbs (Fowler & Turvey, 1978; Kovacs, Buchanan, & Shea, 2010; Mechsner, Kersel, Knoblich, & Wolfgang, 2001; Newell, Morris, & Scully, 1985; Swinnen, Lee, Verschueren, Serrien, & Bogaerds, 1997; Wenderoth et al., 2002). These types of relative motion feedback map unstable patterns onto simple visual effects (e.g., $\varphi = 90^\circ$ as a circle; see Method below). Individuals can then focus on producing the visual effect, which may reduce (but probably not eliminate; Amazeen, DaSilva, & Amazeen, 2008) the effect of biases towards intrinsically stable patterns and promote relatively quick acquisition of challenging interlimb coordination patterns (Kovacs et al., 2010).

It is unknown how much the bias towards intrinsically stable coordination patterns affects learning of new, challenging patterns in the context of extended practice with this type of simplified, higher-order feedback. This issue may be examined by manipulating the relative strength of intrinsic attractor landscapes, which can be accomplished by exploiting natural differences in stability that exist between intrapersonal and interpersonal coordination patterns. The dynamics that govern intrapersonal interlimb rhythmic coordination also govern interpersonal coordination (Schmidt, Carello, & Turvey, 1990; Schmidt & Turvey, 1994). However, intrapersonal coordination patterns are more stable than interpersonal coordination patterns, a finding that has been attributed to greater coupling strength between effectors (Black, Riley, & McCord, 2007; Schmidt, Fitzpatrick, Bienvenu, & Amazeen, 1998). This is likely due to the influence of neuromechanical and haptic (proprioceptive) mechanisms that cannot be used to couple body motions of different individuals who are not otherwise mechanically linked to each other. Bernstein (1996) identified proprioception as the most fundamental perceptual system for coupling the many components involved in the production of stable, large scale rhythmic patterns and emphasized that visual information (which enables interpersonal coordination) is a poor substitute for it (Kugler & Turvey, 1987; Mitra, Riley, Schmidt, & Turvey, 1998; Turvey & Fonseca, 2014).

Because the strength of intrinsic coordination tendencies has consequences for learning coordination patterns (Fontaine et al., 1997; Wenderoth et al., 2002; Wenderoth & Bock, 2001), the differences in coupling strength between intrapersonal and interpersonal coordination should impact the ability to perform new coordination patterns. For example, the greater coupling strength associated with intrapersonal coordination would be expected to result in greater initial interference from intrinsically stable patterns (in-phase and anti-phase), increasing the initial difficulty of producing an inherently unstable new pattern corresponding to $\varphi = 90^\circ$.

Our focus in this study was on the potential disparities in initial performance and subsequent learning (early to intermediate-stages; Bernstein, 1996; Fitts, 1964; Mitra, Amazeen, & Turvey, 1998; Mitra, Riley, et al., 1998) between intra- and interpersonal coordination that might arise due to differential interference from intrinsic coordination patterns. We investigated this question using a coordination task that transformed relative effector motion into a simplified visual feedback display. Participants tracked a target that moved in a circular trajectory by manipulating hand-held dials to respectively control the x (horizontal) and y (vertical) displacement of a digital cursor on a screen. This implicitly required participants to learn to produce an intrinsically unstable coordination pattern—continuous 1:1 frequency locking with $\varphi = 90^\circ$. Participants engaged in the task either individually (i.e., controlling one dial with each hand) or as part of a dyad (i.e., each person controlling one dial).

We quantified learning trajectories in terms of task performance (i.e., tracking accuracy) over time. We hypothesized that dyads would, at least initially, perform better than individuals because the relatively weaker coupling of interpersonal coordination would result in less bias toward the intrinsically stable coordination patterns. We additionally sought to determine whether learning trajectories differed for individuals and dyads. If individuals performed worse initially, as hypothesized, then their performance might consistently lag that of dyads over trials. Alternatively, they might exhibit a different rate of performance change than dyads across trials. Research has shown that learning to produce an intrinsically unstable pattern is predicated on learning to discriminate the perceptual information that specifies the required coordination and control of the relevant degrees of freedom (Wilson, Collins, & Bingham, 2005; Wilson, Snapp-Childs, & Bingham, 2010; Wilson, Snapp-Childs, Coats, & Bingham, 2010). As noted, haptic proprioception is the most fundamental perceptual system underlying this achievement. Thus, the same feature that led us to hypothesize initially worse performance in individuals—greater coupling strength giving rise to stronger intrinsic coordination dynamics—could, over the course of learning, be harnessed to achieve more rapid stabilization (and hence better performance) of the new $\varphi = 90^\circ$ coordination pattern.

As an ancillary aim, we tested the additional possibility that manipulating intrinsic attractor strength by varying required movement frequency would affect the rate of learning. During interlimb coordination, increasing movement frequency notably reduces the strength and stability of intrinsic attractors (Haken et al., 1985; Schmidt et al., 1990; Schöner & Kelso, 1988), which would reduce the degree of bias toward those attractors. Thus, we hypothesized that higher movement frequencies would elicit less of a bias and thus learning should occur with less interference (and therefore yield better initial performance) than at lower movement frequencies.

2. Method

2.1. Participants

Undergraduate psychology students from the University of Cincinnati participated in the experiment in exchange for course credit. Participants provided written consent prior to completing the study. The University of Cincinnati Institutional Review Board approved all study procedures.

We calculated sample size using G*Power statistical software (Faul, Erdfelder, Lang, & Buchner, 2007) based on the critical analysis in the current study which focused on the interaction of test (pre- vs. post-training comparison) and group (performing as an individual vs. dyad). To obtain the expected effect size of the test \times group interaction, we analyzed the data from an initial sample composed of 5 individuals and 5 dyads using a 2 (group) \times 2 (test) analysis of variance (ANOVA). Power calculation indicated that a sample size of 48 (24 individuals and 24 dyads) was sufficient to detect an expected, medium-sized effect ($\eta^2 = 0.22$) with a power of 80% and the traditional .05 statistical significance criterion. We recruited a total of 28 individuals and 28 dyads. Initial data inspection revealed recording issues stemming from equipment malfunction in four individuals and two dyads, so we removed their data yielding a final sample of 24 individuals and 26 dyads. With this final sample size, we were sufficiently powered to test the main study hypothesis.

All participants had normal or corrected-to-normal vision and were free of any neurological, motor, or balance disorders or recent injuries.

3. Materials and apparatus

An apparatus was designed that presented an on-screen cursor whose horizontal and vertical positions could be independently manipulated via two hand-turned dials (Fig. 2). Each dial was connected to a potentiometer which communicated a scalar value to the computer program based on its angular position (mapping 110° of possible angular displacement to an arbitrary unit ranging from 1 to 1024). The scalar values were then converted to pixel units, yielding the x (for the left dial) and y (for the right dial) screen coordinates. This mapping resulted in the on-screen cursor moving ~ 9.31 pixels along each axis per degree of angular displacement from the respective dial.

When the dials were moved concurrently, the shape of the cursor's trajectory resulted from the phase relation (ϕ) between the dials (i.e., a Lissajous curve). The trajectory formed a circle when the dials were moved at $\phi = 90^\circ$ (Fig. 1). A "target" indicator traced the

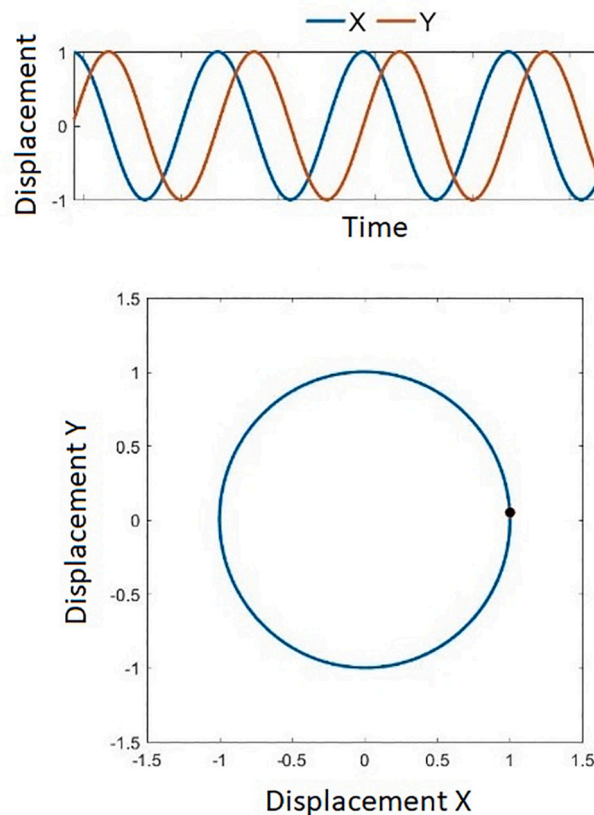


Fig. 1. Target coordination pattern. Displacement along each axis (X and Y) must synchronize at a 90° phase-lag to produce a circle.

shape of a circle continuously at a constant oscillation frequency and amplitude. The circle that the target traced was also continuously indicated on the screen in a thin, black line. Participants were tasked with controlling the cursor to follow the target along the circle as closely as possible by manipulating the dials in the appropriate fashion, which they had to discover—they were not explicitly instructed to produce a 90° phase relation. Participants not only had to reproduce the trajectory of the target but had to move in time with it (Fig. 2). The *implicit* task for participants at the coordination level was thus to learn to oscillate their cursor's *x* and *y* positions (via the angular position of each dial) at a 1:1 frequency ratio with a 90° phase offset—to learn to stabilize an inherently unstable bimodal coordination pattern.

Two different target frequencies were used (0.19 and 0.38 Hz). The target's peak-to-peak amplitude (i.e., circle diameter) remained fixed with an on-screen displacement of 7.50 cm and requiring 55° of angular displacement from each dial. Individual participants were given both dials to turn, while in the dyadic condition each participant was randomly assigned to either dial (Fig. 3). Dyad participants were visually occluded from each other by a curtain and viewed identical displays, and each dyad member was allowed to turn their respective dial with their preferred hand. The dial positions (i.e., the *x* and *y* positions of the cursor) as well as the *x* and *y* positions of the target cursor were sampled synchronously at a rate of 42 Hz.

4. Procedure

Participants sat in front of the apparatus facing a monitor. A cursor (a blue dot) was displayed on the screen and participants were shown how each dial controlled its position along the horizontal and vertical axes. Participants were then presented with the target (a red dot) and shown how it would continuously trace the indicated circle. Participants grasped (either one or both of, depending on if performing individually or dyadically) the dials and turned them in order to move their cursor to keep it “as close to on top of the target” as possible. Participants were instructed to remain silent for the duration of the study. Experiment started with a pre-test that lasted 120 s, followed by 20 practice trials of 60 s each, with a voluntary break in between each trial. Participants concluded the experiment with a 120 s post-test. Longer durations were used for the pre- and post-test to allow for a more precise assessment of average performance to aid follow-up analyses of group differences before and after training. The pre- and post-test trials along with 20 practice trials resulted in 22 total trials per participant, with a total experimentation time of approximately 24 min.

4.1. Design

Our study employed a mixed design with two between-subjects manipulations—group (individual and dyad) and target speed (fast and slow)—and one within-subjects manipulation—training (trial repetitions).

5. Measures

5.1. Assessment of task performance

As instructions to participants were to match the position of their cursor with that of the target, task success was contingent not only on a proper phase relation between the dials, but also on dial amplitude and synchrony with the target. To gauge task performance, a metric was required that could encapsulate all three factors.¹ We therefore calculated the instantaneous error as the Euclidean distance from the participant's cursor to the target (in normalized units such that circle radius = 1) at each time step. We then calculated the root mean square (RMS) of this measure over each trial to submit to statistical analysis. A reduction in this error metric indicates, *ipso facto*, the following changes in coordination between the two dials: 1) convergence toward $\phi = 90^\circ$, 2) reduced variability about $\phi = 90^\circ$, 3) proper movement amplitude, and 4) better coordination in time with the target.

5.2. Statistical analysis

We employed growth curve modeling (GCM) to determine whether and how tracking accuracy (i.e., RMS tracking error) changed with practice and, most critically, whether and how the described changes differed between groups (individual vs. dyad) and task conditions (slow vs. fast target speed). GCM is a maximum likelihood multiple regression technique appropriate for modeling the time-varying character of behavioral variables—here the improvement in performance over practice trials. Like an ordinary least-squares regression model, it weights a set of predictors (as main effects and interactions) to model a continuous dependent measure. GCM was appropriate for this study because, unlike ordinary least squares, it does not assume similar changes across time and participants. Instead, it includes random effects to capture individual differences over time, which yields more reliable estimates of fixed effects.

The model in this study tested for fixed effects of training (change in performance over trials, including pre- and post-test), group (individual vs. dyad), and target speed (fast vs. slow), as well as interactions between these three variables. Initial visual inspection of the data suggested nonlinearity in the change in performance over trials. To examine the exact nature of this trend, we considered that nonlinearity could be expressed quadratically or cubically, and thus included linear, quadratic, and cubic fixed effects of learning in building the model.

¹ We were unable to utilize explicitly phase-based measures of performance, as participants' movements—specifically during early trials when they were still exploring the task-space—were not always oscillatory.

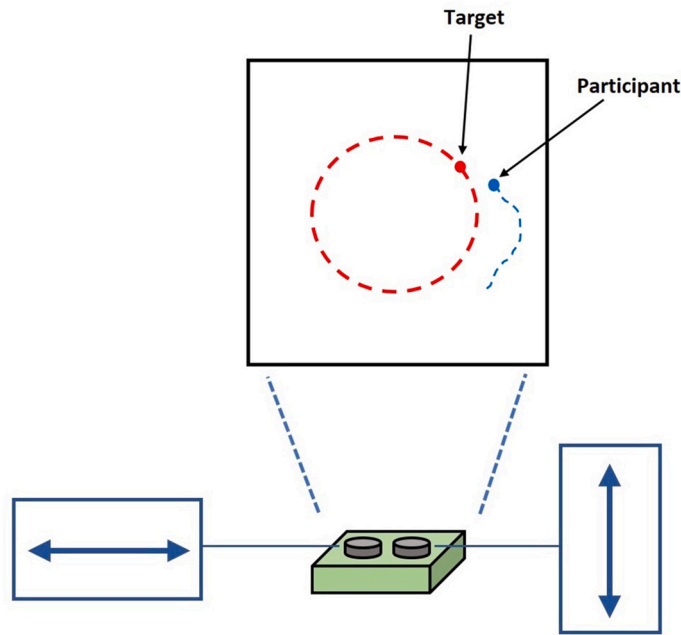


Fig. 2. Experimental apparatus. Each hand-turned dial controlled the position of the participant cursor along a respective axis (X and Y). A target cursor oscillated at fixed amplitude and frequency to trace the shape of a circle of fixed size. Perfect performance would be indicated by zero difference in the positions of the participant and target cursor over time.

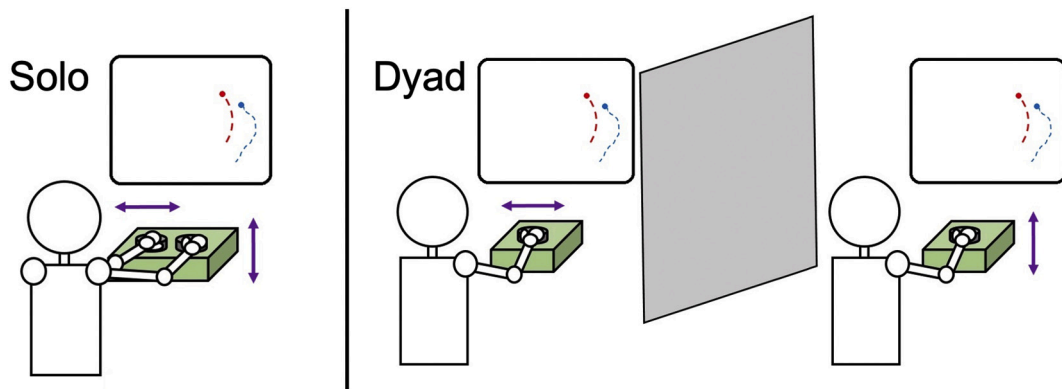


Fig. 3. Grouping paradigm. (Left) Individuals controlled both dials with each hand. (Right) Dyad participants were assigned one dial to turn and were occluded from each other as they viewed identical displays.

We started the analysis process with a “loaded” model including all fixed effects (main effect of group, speed, and trial—linear, quadratic, cubic—and the interactions between these factors). Random effects were selected to control for differences between individuals/dyads in initial performance (random intercept) and differences between participants in performance changes over time (random slopes for main effects). The model did not converge when random slopes for quadratic and cubic trends were included along with random slopes for linear trends. Thus, the full model only included random intercepts and random slopes for linear trends. The random portion of the model was fixed before the trimming of fixed effects. This general strategy used for modeling in this study follows recommendations in the literature (Gelman & Hill, 2007; Zuur, Ieno, Walker, Saveliev, & Smith, 2009). We then compared the fit between the full model and more conservative (trimmed) nested models by assessing change in -2 log likelihood (-2LL). Change in -2LL is distributed as chi-square with degrees of freedom equal to the difference in the number of parameters between nested models allowing tests for statistical significance. Only interactions that significantly improved fit were kept in the final model. An outline of the final model can be found in [Table 1](#).

Table 1
Effects on RMS error while attempting to coordinate with target.

	Predictor	Estimate	SE	p
Fixed Effects	Intercept	1.42	0.08	<.001
	Training (linear)	−0.07	0.01	<.001
	Training (quadratic)	3e-3	1e-3	<.01
	Training (cubic)	−7e-5	3e-5	<.05
	Group (individual = 1, dyad = 2)	−0.30	0.11	<.05
	Training (linear) × Group	0.02	5e-3	<.001
Random Effects	Intercept	0.15	0.03	<.001
	Training (linear)	2e-4	7e-5	<.001

Note. SE = standard error.

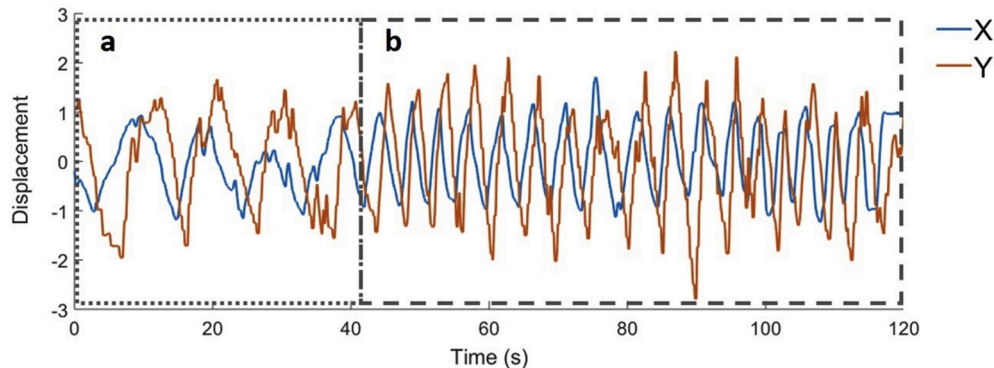


Fig. 4. Different learning stages. (a) Participants began by exploring and gaining an appreciation for the basic oscillatory nature of the task. (b) Participants eventually discovered the relevant coordination pattern and began following the target more closely in time.

6. Results

Participants typically discovered the coordination pattern required for task success early on (either within the pre-test or the first few practice trials) after an initial period of exploratory action (Fig. 4a). During that early learning period prior to discovery of the task solution, the participant cursor typically moved erratically, with any oscillations occurring at a much slower frequency than the target. This resulted in an error time series that was oscillatory, reflecting the relation of the periodic target trajectory to the aperiodic participant trajectory (Fig. 5, trial 1). However, once the proper coordination solution was discovered (Fig. 4b), the participants' cursor movements became much more coordinated with the target in time, reflected by an error time series that was noisy but exhibited no clear oscillatory structure (Fig. 5, trial 5). From that point forward, learning appeared to consist of attempting to increase the precision and stability of the coordination pattern to track the target with increasing accuracy (Fig. 5, trials 5-20), consistent with what Fitts (1964) described as *intermediate learning*.

7. Learning differences

There was a significant linear effect of training on error, $F(1, 311.17) = 47.67, p < .001$, with error decreasing overall with practice (Table 1). There was also a significant fixed quadratic effect of training, $F(1, 248.71) = 8.40, p < .01$, and cubic effect of training, $F(1, 252.15) = 4.18, p < .05$, indicating that the rate of learning across trials was not fixed. There was a fixed effect of group, $F(1, 49.38) = 6.65, p < .05$, which indicates that dyads (group = 1) differed from solo participants (group = 0) on the reference trial (pre-test). As shown in Table 1, the magnitude of RMS error was estimated to be 0.30 lower for dyads than for individuals. There was also a significant trial × group interaction effect indicating that learning occurred at differing rates for individuals and dyads, $F(1, 49.39) = 21.07, p < .001$ (Fig. 6). Error was higher in the pre-test for individuals than for dyads, as indicated by the main effect of group and confirmed via t-test, $t(48) = 3.59, p < .001, d = 1.02$, but decreased faster for individuals over learning trials, with no difference between individuals and dyads observed in the post-test, $p > .05$.² This indicated that learning trajectories for individuals converged with those for dyads with repeated training, after which point (trial 2) performance became indistinguishable over the learning period.

² A few participants' movements (two individuals and five dyads) were persistently uncoordinated with the target's even toward the end of the experiment which raises the possibility that they were not complying with task instructions. We tested the model excluding those data but found no changes in the model's results with the exception that the cubic trend in learning trajectories no longer significantly contributed to model fit. We speculate that the "flat" learning trajectories of these participants could have been responsible for strengthening the cubic shape of the average learning trajectory. Thus, the significant effect of the cubic trend in the reported model should be interpreted cautiously.

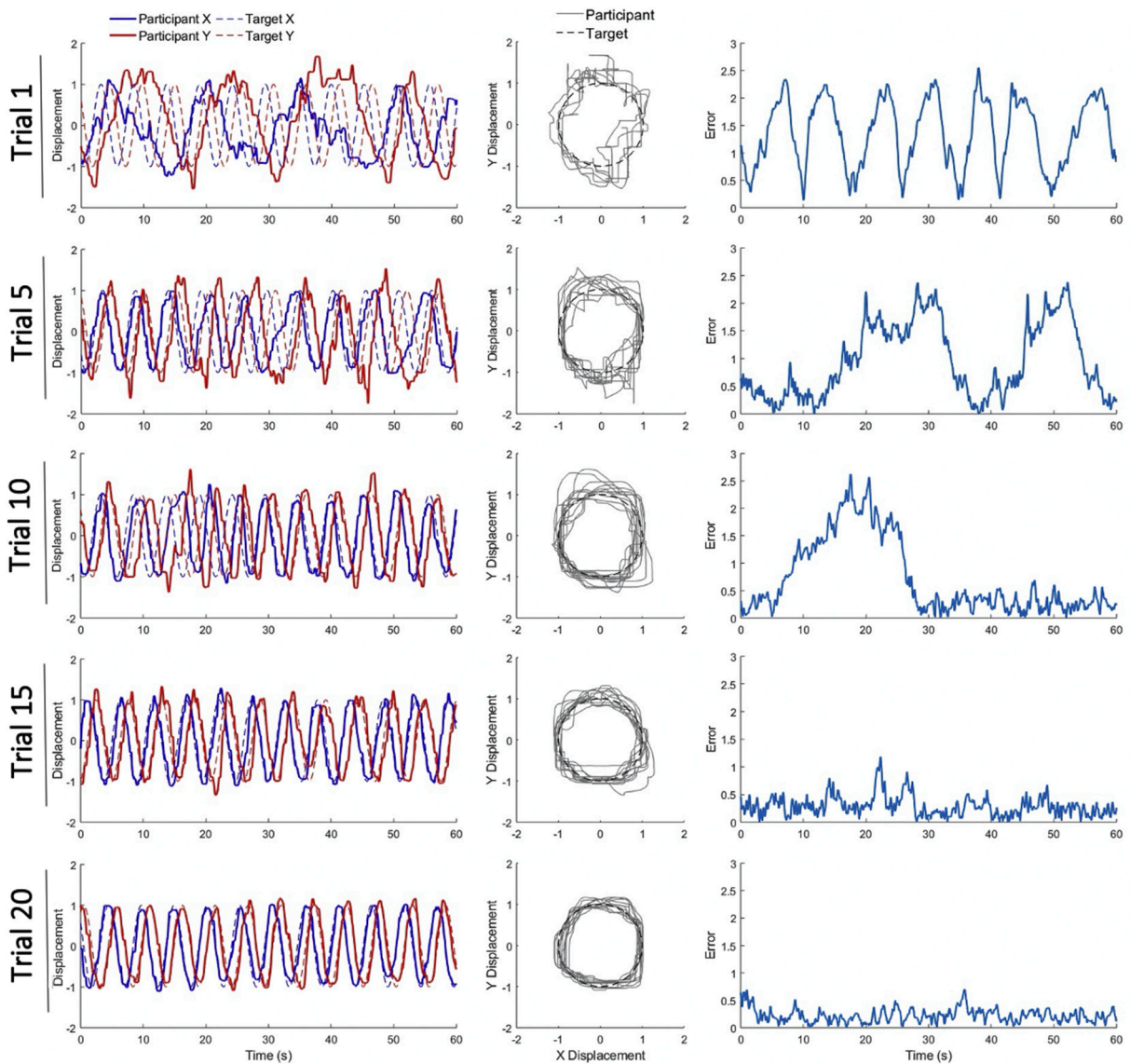


Fig. 5. Example learning trajectory. In trial 1, the participant is still in the exploratory stage, not coordinating with the target and thus producing an oscillatory error time series. By trial 5, the participant has left the exploratory stage and trials 5-20 therefore chart the participant attempting to produce more accurate and stable movements.

employed in this study.³

The group \times trial interaction indicated a higher rate of change in error for individuals than for dyads, particularly in the earliest trials. This effect, considering the longer duration of the pre-test, prompted us to determine whether there could have been differing rates of learning within the pre-test that were not captured in the model. We investigated this by splitting the two-minute pre-test trial into 60 s halves and utilized a mixed-design ANOVA to compare error across group (as in previous analyses) as well as across the first and second halves of the pre-test. This was also done for the post-test; however, no differences were expected given that the learning curves had converged much earlier in the experimental session and were indistinguishable for the final few trials of the experiment. RMS error was greater overall in the first half of the pre-test ($M = 1.34$, $SD = 0.39$) than the second half, ($M = 1.21$, $SD = 0.45$), $F(1,48) = 27.61$, $p < .001$, $\eta_p^2 = .37$. The previously reported main effect of group was confirmed again via this ANOVA, $F(1,48) = 13.1$, $p <$

³ We based our conclusion on convergence of the group learning trajectories as the point that the 95% confidence intervals overlapped, as opposed to conducting multiple corrected comparisons. This approach of interpreting overlapping confidence intervals entails a slight risk of Type 1 error (between 0.56% and 1%; Payton, Greenstone, & Schenker, 2003).

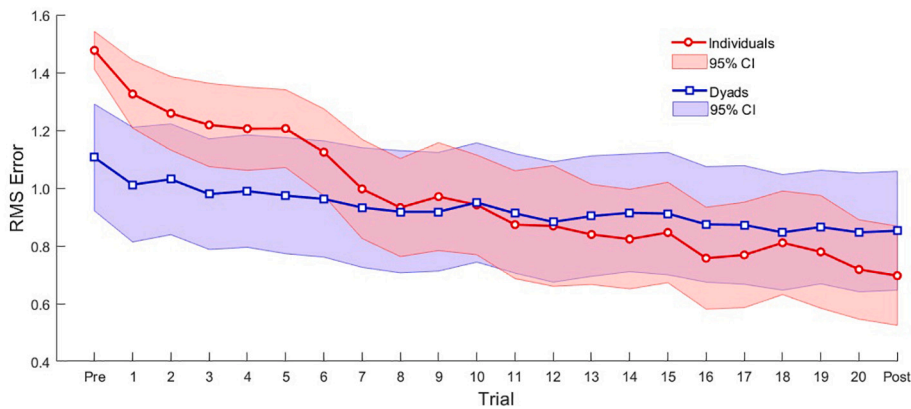


Fig. 6. RMS Error as a function of practice. Error bands constitute 95% Confidence Interval. The pre-test and post-test are the first and last trials on the X axis. The overlap of confidence intervals begins on Trial 2 which we interpreted to indicate the point of no significant difference in performance between groups (see Footnote 3).

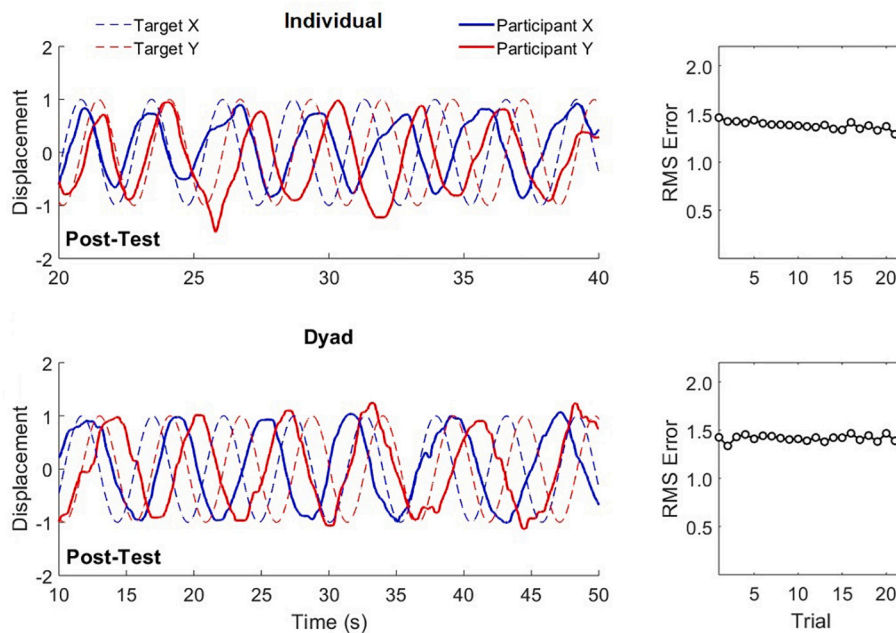


Fig. 7. Post-test trials from example participants who failed to produce stable coordination with the target by the end of the experiment, indicated by an RMS error that did not decrease or decreased only marginally over practice. This occurred for both individuals and dyads. Note that the individual shown is in the fast target condition and the dyad shown is in the slow target condition.

.001, $\eta_p^2 = .21$, but there was no significant interaction between the pre-test halves and group, $p > .1$, indicating that the rate of error reduction did not differ between groups at this very early stage. As expected, there were no differences in error between post-test halves, regardless of group, all $p > .3$.

Target speed did not emerge as a significant factor in any of the analyses.

8. Intermediate learning difficulty

Inspection of individual learning trajectories revealed a small set of both individuals and dyads who, despite attempting to follow the task instructions, persistently struggled to stably coordinate with the target in time (i.e., uncovered the proper $\phi = 90^\circ$ pattern but could not consistently produce it at the required frequency, drifting in and out of phase with the target). This was indicated by an RMS error that remained quite high, decreasing only marginally (or not at all) over practice (Fig. 7). We associated this phenomenon with the participants struggling to successfully progress from early to intermediate stages of learning as outlined by Fitts (1964). However, for these participants, error occasionally showed some initial decrease just before the end of the study (Fig. 7; top right). We found no

indication of a higher frequency of this occurrence in individuals or dyads.

9. Discussion

The GCM results confirmed the hypothesis that individuals would experience greater initial difficulty than dyads at producing the new $\varphi = 90^\circ$ coordination pattern. Dyads outperformed individuals in the first trial, supporting our hypothesis that the stability of intrinsic coordination dynamics can affect early learning. A limitation of the findings, though, is that group differences in performance were distinguishable only within the pre-trial of the experiment. We also observed steeper learning trajectories for the individuals (see Fig. 6), indicating that their performance improved at a more rapid pace. Individuals' performance at the second trial was already statistically indistinguishable from that of dyads. However, contrary to our expectation, individuals did not achieve better performance than dyads within the time scale of the current experiment. Hence, our hypothesis that individuals would reach better performance levels over time due to more effective (neuromechanical) stabilization of the 90° pattern was not supported by our present data. The steeper slope of the individuals' performance improvement curves could be an indicator that they would eventually reach higher performance than the dyads. This interpretation is based on an extrapolation that would only be valid if performance of participants did not reach ceiling (which may or may not be the case). Given that group differences in performance distinguishable within the pre-test were not overcome during the course of the task, the current study's findings motivate follow-up research that extends the training period to address this possibility.

The lack of influence of target speed did not support our hypothesis that different oscillation frequencies would influence the intrinsic attractor strength and thus influence initial performance and subsequent learning. The null effect was surprising in light of previous literature showing a strong effect of frequency on coordination dynamics (e.g., Amazeen, Schmidt, & Turvey, 1995; deGuzman & Kelso, 1991; Haken et al., 1985). The range of frequencies used in such studies were, however, considerably higher than the ones we used here. Thus, it is possible that the difference in target speed in the present study was simply not salient enough to induce an effect. Increasing target speed further might elicit more substantial changes in the stabilities of intrinsic coordination dynamics and reduce their interference on early learning, as hypothesized.

10. Variation in learning trajectories

There was considerable variation in the learning trajectories across individual participants as well as among the different dyads that participated in the present study. The finding that greater strength of attraction toward the intrinsic coordination dynamics (by virtue of greater coupling strength) led to greater initial learning difficulty suggests that an investigation of attractor strength at the scale of individual participants could lend further insight into individual learning trajectories. That is, if a participant or dyad was instructed to produce in-phase or anti-phase patterns prior to the study, the relative stability of those patterns (which would indicate the strength of the in-phase or anti-phase attractors) might predict the subsequent rate of learning and account for variance across learning trajectories not addressed in this study (this technique is referred to as *scanning* the intrinsic dynamics; see Zanone & Kelso, 1992). Moreover, the initial stability of intrinsic patterns might predict which future subjects fail to discover the task solution, and those which discover but cannot stably produce the required movement pattern (such as the subgroup which exhibited relatively flat learning trajectories).

The variance across learning trajectories was greater for dyads than individuals. This motivates inquiry into possible sources of variance for dyadic learning that would not apply to individual learning. For example, leader/follower dynamics that emerge during joint action (Bosga, Meulenbroek, & Cuijpers, 2010; Graf, Schütz-Bosbach, & Prinz, 2009; Richardson et al., 2015) or other types of social-psychological factors (e.g., Schmidt, Christianson, Carello, & Baron, 1994) could manifest as greater asymmetry in interlimb coupling for dyads than the asymmetry expected for individuals due to handedness (Treffner and Turvey, 1995) or other sources of functional asymmetry in intrapersonal rhythmic interlimb coordination such as directed visual attention (Amazeen, Amazeen, Treffner, & Turvey, 1997; Riley, Amazeen, Amazeen, Treffner, & Turvey, 1997). Amazeen et al. (1997) found that asymmetric coupling can impact the stability of interlimb rhythmic coordination patterns, suggesting that asymmetries might therefore have an impact on the rate of learning a new coordination pattern. Differences in the strength of the two individuals' intrinsic coordination dynamics could also potentially give rise to asymmetric coupling at the interpersonal scale which might impact dyadic learning trajectories. An investigation is underway to address these issues.

11. Conclusion

The findings of the present study offer the novel insight that early learning (i.e., initial performance) in interlimb coordination is differentially constrained for intra- or interpersonal coupling. Our results suggest this disparity was due to differential interference from intrinsic coordination dynamics arising from differences in coupling strength. In doing so they advance the potential of integrating a coordination dynamics framework with related theoretical perspectives on motor learning, such as Fitts' (1964) classical view of distinguishable motor learning stages (i.e., early, intermediate, and late; cf. Mitra, Amazeen, & Turvey, 1998, Mitra, Riley, et al., 1998).

Additionally, we anticipate the learning paradigm employed in this study can be usefully adapted to probe many different hypotheses of interlimb coordination and motor learning, such as (but not limited to) coupling asymmetries, task complexity (e.g., simple or polyrhythmic coordination; Deutsch, 1983; Fraise, 1946; Treffner & Turvey, 1993), or the nature of available task-relevant information (Bingham, 2004; Mechsner et al., 2001; Wilson et al., 2005; Wilson, Snapp-Childs, & Bingham, 2010).

References

- Amazeen, P. G., Schmidt, R. C., & Turvey, M. T. (1995). Frequency detuning of the phase entrainment dynamics of visually coupled rhythmic movements. *Biological Cybernetics*, 72(6), 511–518. <https://doi.org/10.1007/BF00199893>.
- Amazeen, E. L., Amazeen, P. G., Treffner, P. J., & Turvey, M. T. (1997). Attention and handedness in bimanual coordination dynamics. *Journal of Experimental Psychology: Human Perception and Performance*, 23(5), 1552–1560. <https://doi.org/10.1037/0096-1523.23.5.1552>.
- Amazeen, E. L., DaSilva, F., & Amazeen, P. G. (2008). Visual-spatial and anatomical constraints interact in a bimanual coordination task with transformed visual feedback. *Experimental Brain Research*, 191(1), 13–24. <https://doi.org/10.1007/s00221-008-1490-x>.
- Bernstein, N. A. (1996). On dexterity and its development. In M. L. Latash, & M. T. Turvey (Eds.), *Dexterity and Its Development* (pp. 3–237). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Bingham, G. P. (2004). A perceptually driven dynamical model of bimanual rhythmic movement (and phase perception). *Ecological Psychology*, 16, 45–53.
- Black, D. P., Riley, M. A., & McCord, C. K. (2007). Synergies in intra- and interpersonal interlimb rhythmic coordination. *Motor Control*, 11(4), 348–373. Retrieved from. <http://www.ncbi.nlm.nih.gov/pubmed/18042965>.
- Bosga, J., Meulenbroek, R. G. J., & Cuijpers, R. H. (2010). Intra- and interpersonal movement coordination in jointly moving a rocking board. *Motor Control*, 14(4), 440–459.
- deGuzman, G. C., & Kelso, J. A. S. (1991). Multifrequency behavioral patterns and the phase attractive circle map. *Biological Cybernetics*, 64(6), 485–495. <https://doi.org/10.1007/BF00202613>.
- Deutsch, D. (1983). The generation of two isochronous sequences in parallel. *Perception & Psychophysics*, 34(4), 331–337. <https://doi.org/10.3758/BF03203045>.
- Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39, 175–191.
- Fitts, P. (1964). Perceptual-motor skill learning. In A. W. Melton (Ed.), *Categories of Human Learning* (pp. 244–285). New York, NY: Academic Press.
- Fontaine, R. J., Lee, T. D., & Swinnen, S. P. (1997). Learning a new bimanual coordination pattern: reciprocal influences of intrinsic and to-be-learned patterns. *Canadian Journal of Experimental Psychology*, 51(1), 1–9. <https://doi.org/10.1037/1196-1961.51.1.1>.
- Fowler, C. A., & Turvey, M. T. (1978). Skill acquisition: An event approach with special reference to searching for the optimum of a function of several variables. In G. E. Stelmach (Ed.), *Information processing in motor control and learning* (pp. 1–40). New York: Academic Press. <https://doi.org/10.1016/B978-0-12-665960-3.50006-2>.
- Fraisse, P. (1946). Contribution à l'étude du rythme en tant que forme temporelle [Contribution to the study of rhythm as temporal figure]. *Journal de Psychologie Normale et Pathologique*, 39, 283–304.
- Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. New York, NY: Cambridge University Press.
- Graf, M., Schütz-Bosbach, S., & Prinz, W. (2009). Motor involvement in action and object perception similarity and complementarity. In G. Semin, & G. Echterhoff (Eds.), *Grounding sociality: Neurons, minds, and culture* (pp. 27–52). New York, NY: Psychology Press.
- Haken, H., Kelso, J. A. S., & Bunz, H. (1985). A Theoretical Model of Phase Transitions in Human Hand Movements. *Biological Cybernetics*, 51, 347–356. <https://doi.org/10.1007/BF00336922>.
- Kelso, J. A. S. (1984). Phase transitions and critical behavior in human bimanual coordination. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, 246(6), R1000–R1004. <https://doi.org/10.1152/ajpregu.1984.246.6.R1000>.
- Kelso, J. A. S. (1995). *Dynamic Patterns: The self-organization of brain and behavior*. Cambridge, MA: MIT Press.
- Kostrubiec, V., Zanone, P. G., Fuchs, A., & Kelso, J. A. S. (2012). Beyond the blank slate: Routes to learning new coordination patterns depend on the intrinsic dynamics of the learner—experimental evidence and theoretical model. *Frontiers in Human Neuroscience*, 6, 1–14. <https://doi.org/10.3389/fnhum.2012.00222>.
- Kovacs, A. J., Buchanan, J. J., & Shea, C. H. (2010). Impossible is nothing: 5:3 and 4:3 multi-frequency bimanual coordination. *Experimental Brain Research*, 201(2), 249–259. <https://doi.org/10.1007/s00221-009-2031-y>.
- Kugler, P. N., & Turvey, M. T. (1987). *Information, natural law, and the self-assembly of rhythmic movement*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.
- Mechner, F., Kersel, D., Knoblich, G., & Wolfzanz, P. (2001). Perceptual basis of bimanual coordination. *Nature*, 414, 69–73. <https://doi.org/10.1038/35102060>.
- Mitra, S., Amazeen, P. G., & Turvey, M. T. (1998). Intermediate motor learning as decreasing active (dynamical) degrees of freedom. *Human Movement Science*, 17, 17–65.
- Mitra, S., Riley, M. A., Schmidt, R. C., & Turvey, M. T. (1998). Vision and the level of synergies. In L. H. Harris, & M. Jenkin (Eds.), *Vision and Action* (pp. 314–331). New York: Cambridge University Press.
- Newell, K. M., Morris, L. R., & Scully, D. M. (1985). Augmented Information and the Acquisition of Skill in Physical Activity. *Exercise and Sport Sciences Reviews*, 13(1), 235–262.
- Payton, M. E., Greenstone, M. H., & Schenker, N. (2003). Overlapping confidence intervals or standard error intervals: What do they mean in terms of statistical significance? *Journal of Insect Science*, 3(1), 34–40.
- Richardson, M. J., Harrison, S. J., Kallen, R. W., Walton, A., Eiler, B. A., Saltzman, E., & Schmidt, R. C. (2015). Self-organized complementary joint action: Behavioral dynamics of an interpersonal collision-avoidance task. *Journal of Experimental Psychology: Human Perception and Performance*, 41(3), 665–679. <https://doi.org/10.1037/xhp0000041>.
- Riley, M. A., Amazeen, E. L., Amazeen, P. G., Treffner, P. J., & Turvey, M. T. (1997). Effects of temporal scaling and attention on the asymmetrical dynamics of bimanual coordination. *Motor Control*, 1(3), 263–283. <https://doi.org/10.1123/mcj.1.3.263>.
- Schmidt, R. C., & Turvey, M. T. (1994). Phase-entrainment dynamics of visually coupled rhythmic movements. *Biological Cybernetics*, 70, 369–376.
- Schmidt, R. C., Carello, C., & Turvey, M. T. (1990). Phase transitions and critical fluctuations in the visual coordination of rhythmic movements between people. *Journal of Experimental Psychology: Human Perception and Performance*, 16(2), 227–247. <https://doi.org/10.1037/0096-1523.16.2.227>.
- Schmidt, R. C., Christianson, N., Carello, C., & Baron, R. (1994). Effects of social and physical variables on between-person visual coordination. *Ecological Psychology*, 6(3), 159–183.
- Schmidt, R. C., Fitzpatrick, P. A., Bienvenu, M., & Amazeen, P. G. (1998). A Comparison of intra- and interpersonal interlimb coordination: Coordination breakdowns and coupling strength. *Journal of Experimental Psychology: Human Perception and Performance*, 24(3), 884–900. <https://doi.org/10.1037/0096-1523.24.3.884>.
- Schöner, G. S., & Kelso, J. A. S. (1988). Dynamic patterns in biological coordination: Theoretical strategy and new results. In J. A. S. Kelso, A. J. Mandell, & M. F. Schlesinger (Eds.), *Dynamic patterns in complex systems* (pp. 77–102). Singapore: World Scientific Publishing Co.
- Schöner, G., Zanone, P. G., & Kelso, J. A. S. (1992). Learning as change of coordination dynamics: Theory and experiment. *Journal of Motor Behavior*, 24(1), 29–48. <https://doi.org/10.1080/00222895.1992.9941599>.
- Swinnen, S. P., Lee, T. D., Verschueren, S., Serrien, D. J., & Bogaerds, H. (1997). Interlimb coordination: Learning and transfer under different feedback conditions. *Human Movement Science*, 16(6), 749–785. [https://doi.org/10.1016/S0167-9457\(97\)00020-1](https://doi.org/10.1016/S0167-9457(97)00020-1).
- Treffner, P. J., & Turvey, M. T. (1995). Handedness and the asymmetric dynamics of bimanual rhythmic coordination. *Journal of Experimental Psychology: Human Perception and Performance*, 21(2), 318–333. <https://doi.org/10.1037/0096-1523.21.2.318>.
- Treffner, P. J., & Turvey, M. T. (1993). Resonance Constraints on Rhythmic Movement. *Journal of Experimental Psychology: Human Perception and Performance*, 19(6), 1221–1237. <https://doi.org/10.1037/0096-1523.19.6.1221>.
- Turvey, M. T., & Fonseca, S. T. (2014). The Medium of Haptic Perception: A Tensegrity Hypothesis. *Journal of Motor Behavior*, 46(3). <https://doi.org/10.1080/00222895.2013.798252>.
- Wenderoth, N., & Bock, O. (2001). Learning of a new bimanual coordination pattern is governed by three distinct processes. *Motor Control*, 5(1), 23–35.
- Wenderoth, N., Bock, O., & Krohn, R. (2002). Learning a new bimanual coordination pattern is influenced by existing attractors. *Motor Control*, 6(2), 166–182. <https://doi.org/10.1123/mcj.6.2.166>.
- Wilson, A. D., Collins, D. R., & Bingham, G. P. (2005). Perceptual coupling in rhythmic movement coordination: Stable perception leads to stable action. *Experimental Brain Research*, 164(4), 517–528. <https://doi.org/10.1007/s00221-005-2272-3>.

- Wilson, A. D., Snapp-Childs, W., & Bingham, G. P. (2010). Perceptual Learning Immediately Yields New Stable Motor Coordination. *Journal of Experimental Psychology: Human Perception and Performance*, 36(6), 1508–1514. <https://doi.org/10.1037/a0020412>.
- Wilson, A. D., Snapp-Childs, W., Coats, R., & Bingham, G. P. (2010). Learning a coordinated rhythmic movement with task-appropriate coordination feedback. *Experimental Brain Research*, 205(4), 513–520.
- Zanone, P. G., & Kelso, J. A. S. (1992). Evolution of behavioral attractors with learning: nonequilibrium phase transitions. *Journal of Experimental Psychology: Human Perception and Performance*, 18(2), 403.
- Zanone, P. G., & Kelso, J. A. S. (1997). Coordination dynamics of learning and transfer: collective and component levels. *Journal of Experimental Psychology: H*, 23(5), 1454–1480.
- Zuur, A., Ieno, E. N., Walker, N., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R*. Springer Science & Business Media.