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**Collaborative Creativity: Information-driven coordination dynamics and prediction in
movement and musical improvisation**

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Abstract

Humans collaborate with a large number of people in order to create and accomplish incredible feats. We argue that rich coordination dynamics underpin our capacity for collaborative creativity. These dynamics characterize the ways in which people are able to covary their thoughts, actions, behavior etc. for functional purposes. We investigated the coordination dynamics of improvisation as a special case of collaborative creativity from two openly available datasets: a movement-based mirror game (Noy et al., 2011) and jazz piano improvisation (Setzler & Goldstone, 2020). By focusing on improvisation, the tasks elicit the need for real-time adaptation and mutual prediction based on information exchange between interacting individuals, with the creative ‘product’ being the behavioral performance itself. For each dataset, we performed a transfer entropy analysis as well as an estimate of predication decay. The combination of these two methods allows us to understand the dynamics as information-driven coordination flow and to differentiate unidirectional influence from mutual influence as well as the predictability of signals exhibited during collaborative creativity. We observed that for the mirror game, experts and novices exhibited unidirectional and bidirectional influence on each other’s movements largely, independent of their improvisational experience level. Further, movement improvisation signals generated by experts were generally more predictable than those of novices. In terms of the jazz improvisation, our results showed evidence of bidirectional influence between the onset densities of coupled *and* one-way improvisational dyads and the predictability of the signal did not vary systematically across these conditions. We discuss these findings in terms of differences between improvisational contexts, methodical challenges, and future directions.

1. Introduction

Humans are able to collaborate with a large number of people in order to create and accomplish feats that were previously only imaginable. How is it that we successfully engage in these highly collaborative activities such as creating and performing an orchestral composition to developing rockets that can land on floating platforms? Each example of human creative potential is wildly different, yet can often be equally powerful at bringing together and moving groups of individuals. Here we provide computational approaches that boost the strong claim that low-level coordination dynamics may provide a fundamental mechanism that scaffolds the way humans are able to work together (Nowak et al., 2017) during a wide range of creative processes (Miles et al., 2017). Specifically, we will focus on the special case of improvisation suggesting that the coordination mechanisms that underpin our ability to “play” together more flexibly, may form the foundation from which humans are able to employ more predictive capacities that allow us to better understand and coordinate with other social agents (Teufel & Fletcher, 2020). Indeed, this coordination “might scaffold the human ability to represent complex (structured) actions and to entrain multiple agents—via reciprocal prediction and adaptation—in the pursuit of shared goals” (Novembre & Keller, 2014, p. 1). Crucially, it is these more flexible interactions like improvisation that allow for novel, creative output to be generated collaboratively.

Coordination is actually a defining characteristic for how the many components of complex systems change together over time (Butner et al., 2014), often in goal-directed ways (Turvey, 1990), and evidence of these patterns can be seen across physical, biological, and social systems (Amazeen, 2018). *Interpersonal* coordination as an area of inquiry is growing and advancing our understanding of which modalities (e.g., physiology, kinematics, social behavior, language, etc.) we coordinate with others in (Delaherche et al., 2012; Palumbo et al., 2017;

Wiltshire et al., 2020), what mechanisms make this coordination possible (Hoehl et al., 2020; Koole & Tschacher, 2016), how we move in and out of synchrony with others (Likens & Wiltshire, 2020; Mayo & Gordon, 2020; Wiltshire et al., 2019), and what the interactional benefits of coordination are (Rennung & Göritz, 2016). In cases of joint action, coordination can be *emergent* or *planned* and would subsequently draw on a variety of perceptuo-motor and/or cognitive processes (see Knoblich et al., 2011 for a detailed review). In this work, we review the fundamentals of interpersonal coordination dynamics with a focus on how coordination emerges in modalities related to a particular type of collaborative creativity: *improvisation*. Improvisation is an interesting, special case of interpersonal coordination because it involves being able to adapt to one another in real time and could require an ability to predict what the other might do (Knoblich et al., 2011; Richardson et al., 2007).

Toward this end, our chapter provides a comparison of coordination dynamics in two improvisational settings: a movement-based improvisation known as the mirror game and in a dyadic musical improvisation on a digital keyboard. Although we investigate coordination in two empirical dyadic contexts, we aim to set the stage for further work that can scale up to larger groups. To do so, we employ methods that can apply to multiple data modalities and that prior work has applied beyond the dyadic (or bivariate) level (Borge-Holthoefer et al., 2016; Clark et al., 2015; Ye & Sugihara, 2016). We envision that the key to this is understanding interpersonal coordination in terms of information flow and signal predictability. And, we elaborate on this later in the coordination section as well as the methods. We conclude this chapter with a discussion of some unanswered questions to set the stage for future research that investigates the role of coordination dynamics in collaborative and creative contexts.

2. Coordination Dynamics, Creativity, and Improvisation

2.1 Coordination Dynamics

Coordination dynamics, as an area of inquiry “describes, explains and predicts how patterns of coordination form, adapt, persist and change in living things” (Kelso, 2009, p. 1537,). Coordination dynamics is focused on spanning theoretical, empirical, and modeling approaches that can connect dynamics across levels of explanation (Tognoli et al., 2020; Zhang et al., 2019) from, for example, brain to behavior in individuals and in social interactions. Importantly, during human interactions, coordination may be fundamentally multi-scale (i.e., coordination may span and behave differently at different levels of a system and differently at different temporal resolutions), yet lawful patterns that govern the functional coordination of systems components to facilitate goal-directed activity should exist (Amazeen, 2018; Tognoli et al., 2020). By combining empirical observations of the dynamics, particularly with tools for modeling non-linearly coupled equations, a key strength of coordination dynamics as an approach is that it can allow for the characterization of phenomena that hold potential to transcend scales of analysis, for example, identifying functionally equivalent coordination patterns in the oscillations of finger movements as well as in neural activity (Tognoli et al., 2020; Tognoli & Kelso, 2014).

One of, if not the, fundamental example from this field is the Haken-Kelso-Bunz (HKB) model (Haken et al., 1985), which was originally developed to capture nonlinear, oscillatory motor coordination of individual limbs. This model, or variants of it, have since been adapted to model interpersonal motor coordination in primarily rhythmic tasks as well as neural oscillations (Tognoli et al., 2020) and coordination in larger social groups (Zhang et al., 2018). One of the key challenges for this area though is when coordination might take on other, non-rhythmic forms (Amazeen, 2018; Butler, 2011). While work that follows a formal coordination dynamics approach including

both empirical observation, equation-based modeling, and recursive development is only conducted by a handful of research groups, studies of interpersonal coordination supporting the empirical component with attempts to link coordination with an interactional functionality have flourished in recent years (Hoehl et al., 2020; Palumbo et al., 2017; Rennung & Göritz, 2016; Wiltshire et al., 2020).

In coordination dynamics, much of the relevant research focuses on tasks that are clearly rhythmic and involve some form of tapping, swinging of pendulums, or limb oscillations, for example. Such cases can readily be characterized by mathematical models and logical extensions of the HKB model (Zhang et al., 2019). However, considering cases of collaborative creativity and improvisation, which are not necessarily rhythmic (discussed in the next section), we can instead look for model-free informational drivers and informational flow of the system by utilizing measures based on transfer entropy and empirical dynamic modeling (see Methods Section).

2.2 Collaborative Creativity and Improvisation

In order to explicate the potential underpinnings of coordination dynamics with collaborative creativity and improvisation specifically, we need some further definitions. *Collaboration* implies that there are multiple individuals that interact with each other in order to accomplish a shared goal (Bedwell et al., 2012), which in the case of creativity, is often directed towards solving novel problems (Fiore et al., 2010) and generating new products, ideas, and content (Paulus et al., 2012). What that novelty may be in the case of improvisation is not the central focus of this offering; however, during a skilled performance such as in improvisation, the performance itself is actually the creative product. As such, the variability in the performance itself may serve as a marker of collaborative improvisational creation (cf., Gray & Lindstedt, 2017; Torrance & Schumann, 2019).

One assumption that we make here is that collaborative creativity requires a shared goal (i.e., to create together) and as such, we distinguish this from other forms of emergent coordination, such as spontaneous entrainment (Dumas & Fairhurst, 2019; Knoblich et al., 2011). How these two types of coordination types vary in terms of more fine scale dynamics is not yet well detailed as current computational approaches typically focus on quantifying overall coordination (cf., Likens & Wiltshire, 2020; Wiltshire et al., 2019). Regardless, shared goals require interacting agents, like a group of jazz musicians, to both anticipate actions and respond to each other in meaningful ways so as to coordinate their behavior (Phillips-Silver & Keller, 2012; Wöllner, 2020). The assumption would therefore be that across time one might observe more complex, interactive patterns with multiple, informative phase shifts. Figure 1 aims to highlight this distinction where on the one hand, spontaneous, emergent coordination is characterized by an uncoupled pair of signals becoming coupled. On the other hand, in cases of collaborative creativity, there are likely multiple informative phase shifts in the coordination patterns from coupled to uncoupled and back again as the creative context demands. Due to this higher degree of variability, it is likely individuals track the dynamics as well as employ predictive mechanisms (anticipating what another might do). Indeed, previous work in the sensorimotor synchronization literature (in dyads), has identified different synchronization strategies as a function of individual differences where, in order to adapt and coordinate behavior with another, one either simply tracks moment to moment changes or forms internal models based on more complex prediction (Pecenka et al., 2013; Pecenka & Keller, 2011).

Spontaneous, emergent coordination		Convergent dynamical process towards synchrony. Single phase change from uncoupled to coupled state.
Collaborative creative coordination		Greater reliance on predictive mechanisms Multiple, informative phase shifts. As a function of temporal and structural hierarchies, one stream may influence another to a greater or lesser extent.

Figure 1: Comparison of spontaneous, emergent coordination & collaborative creative coordination.

An example of this form of change in coordination is described by Noy and colleagues' related work (Noy et al., 2011) using a joint improvisation task (to be detailed further in later sections). The authors observed that movement “*amplitude and frequency showed continuous or abrupt changes... Some rounds showed stops of varying duration with interspersed staccato motion*” (p. 20947). Dynamic changes in the degree of coupling between coordinating agents will vary as a function of several factors that also shape collaborative creativity. These may be related to the nature of the task (e.g. who is following whom), those involved in the interaction (group make-up, e.g. experts vs. novices), the group/team environment as well as social, cognitive, and motivation aspects (Paulus & Dzindolet, 2008). While these are important processes, when the interaction and creative processes are unfolding in real-time, sensorimotor-based coordination dynamics are likely to dominate (Walton et al., 2018). This is to say, as the multi-modal and mutual information exchange occurs, coordination through certain informational channels may be the key factor that governs how a creative process unfolds. Perhaps more boldly, we posit here that all

other factors can be reduced to the nature of the exchange of information between interacting agents (Fairhurst, 2020; Gallotti et al., 2017). As interacting agents respond and adapt to one another, one can describe this “give and take” by measuring the directionality of information flow and the level of mutual adaptation (Fairhurst, 2020).

One key way in which the direction and degree of information flow varies will depend on the division of labor: who initiates changes in tempo, rhythm, dynamics or mood, for example. Previous studies looking at leader-follower dynamics have shown the importance of directionality of the information (Goebl & Palmer, 2009; Konvalinka et al., 2010); that is who is following whom or, in informational terms, which signal is predictive of the other. The guiding principle that informs several of the computational approaches for identifying and quantifying the division of labor rests on the information flow with the leader sending out a signal for the follower to follow. Lagged cross correlations assume that two time-series will be offset as a function of the leader-follower relationship (Konvalinka et al., 2010, 2014). More recently, transfer entropy has been used to investigate the causal information flow between two systems in terms of leader-follower dynamics (Takamizawa & Kawasaki, 2019).

Pertinent to several real-world contexts of collaborative creativity, the nature of the sensory channels through which cues to coordination are available will change the information flow between interacting agents. For example, when people play music with others, they may watch the way others move, but are primarily aligning their actions with auditory cues (Alderisio et al., 2017; Wang et al., 2020). When considering the nature of the signal and the effect this has on coordination, one should consider not only the modality, but the spatial and temporal features of the stimulus, the form of the external signal produced through that modality, the compatibility of

those features with the synchronized motor behavior and more specifically the task as well as potential cross-modal integration (Schirmer et al., 2021).

2.3 Prediction and Improvisation in music and movement

Previous work using improvisational tasks has looked both at the hallmarks of improvisation in a music production task (Keller et al., 2011) and how these may be perceived by listeners and observers (Engel & Keller, 2011; Setzler & Goldstone, 2020). This suggests that the properties we hope to capture and quantify as changes in information flow may in fact serve as a form of communication, signaling a degree of accommodation between interacting agents (Burgoon et al., 2014; Young, 2003). Additionally, music may in fact have evolved to provide a number of important adaptive values with synchrony enhancing communication between individuals and fostering social cohesion (Duranton & Gaunet, 2016).

Jazz improvisation is a complementary joint action that, like verbal exchanges, requires turn taking in which the actions of each player are related to, but different from, those of the other (Phillips-Silver & Keller, 2012; Walton et al., 2018). It too can be the case that improvisation of movements or in music is much like a dialogue in which ideas are bounced off of each other during the creative process. In such cases, “Effective coordination during turn-taking therefore requires the participating individuals to predict the spatiotemporal trajectories of each other’s actions via simulation” (Phillips-Silver & Keller, 2012, p. 4). The ability to improvise (or when listening, and making sense of an improvised sequence) relies on the ability to actively listen in order to make sense of the complex and unpredictable nature of unrehearsed exchanges. Humans are able to both track features of the environment and predict future states, especially in the case of music making (Vuust & Witek, 2014). In music, the information processed by these predictive mechanisms are the rhythmic structures of movement and/or sound.

Predictive models allow listeners, players, and dancers to understand and adapt to one another. In the musical domain, it is suggested that this process of mutual understanding operates through two separately evolved systems and neural networks (Kotz et al., 2018; Nozaradan et al., 2011). In both, prediction plays a role, on the one hand tracking the rigid beat component as well as allowing humans to deal with the irregularity of the meter component. Importantly, with the meter providing the ability to flexibly “allow for variation and improvisation”, and thus essential to group music making and dance (Savage et al., 2020), it may represent a form of motor alignment between interactive partners. Interestingly in the case of music making, there is evidence that predictive models can be trained in order to better deal with these more complex scenarios. This suggests again that there may be several levels of predictive models operating (Heggli et al., 2019). Importantly, and as previously explored using the movement improvisation task, the mirror game, others have indeed explored how individuals with either domain specific (theater experience) or domain general (e.g., musicians with joint action experience) vary in their ability to predict, adapt and coordinate with others (Noy et al., 2011). We expect that during both movement and musical improvisation, information flow between the behavioral signals (e.g., movements) provides evidence of the adaptive and dynamic turn-taking inherent to improvisation. Not only this, but if individuals are actively predicting the behavior of another and adapting, then the signals produced by them should not only influence each other, but they should also vary in their degree of predictability (as a function of their experience level). We therefore apply computational methods to examine improvisation-based coordination in which predictive processes may play an increasingly larger role with concomitant increases in scale (number of people coordinating), task complexity increases, and expertise (cf., Wolf et al., 2020)

3. Methods

3.1 Summary of Case Studies

3.1.1 Mirror Game Movement Improvisation (Case Study 1)

The first case study utilizes data collected using a version of the mirror game where dyads improvised their movements by controlling a small handle that they slid along a linear horizontal track (Noy et al., 2011). See Figure 2 and for the full details, see the original paper. There were 12 experts (individuals with at least 10 years of improvisational experience) and eight novices. Participants performed nine trials together where in the *blue* condition the person controlling the blue handle was instructed to take the lead, in the *red* condition the person controlling the red handle was instructed to take the lead, and in the *both* condition blue and red were instructed to jointly improvise. All conditions were indicated to the participants by lights on the mirror game device (i.e., the colored light displayed was supposed to lead) and the order of the conditions was counterbalanced and lasted 60 seconds (except the last *both* condition, which lasted 180 seconds). Participants were explicitly instructed that their goal during each round was to “imitate each other, create synchronized interesting motions, and enjoy playing together” (Noy et al., 2011, p. 20951). The data used for this case study are the 50 Hz velocity traces of each participant's slider movements.

3.1.2 Jazz Pianist Musical Improvisation (Case Study 1)

For this analysis we focus on musical improvisation in jazz musicians using openly available data described in Setzler and Goldstone (2020) and made available on OSF <https://osf.io/wxf4s/>. In their study, there were 28 professional pianists with an average of 22 years

of piano playing experience and 15 years improvisational experience on average. Their task was to perform a 4-7 minute compelling musical improvisation on a MIDI piano with no additional musical constraints. Participants had no visual information about each other, but they could hear the performance of the other musician (live or recorded) through headphones. There were two conditions: *coupled* in which duos improvised simultaneously and thus were able to mutually influence each other and the *one-way* condition in which an individual was improvising along with a recording of a prior improvisation (See Figure 2). Participants completed multiple trials from the conditions resulting in 50 coupled duets and 86 one-way performances. The data used for this study were the note onset density time series sampled with a 2 second sliding window and 0.2 second hop interval as described in (Setzler & Goldstone, 2020). Onset density has been thought to indicate the level of overall rhythmic activity (Farbood, 2012).

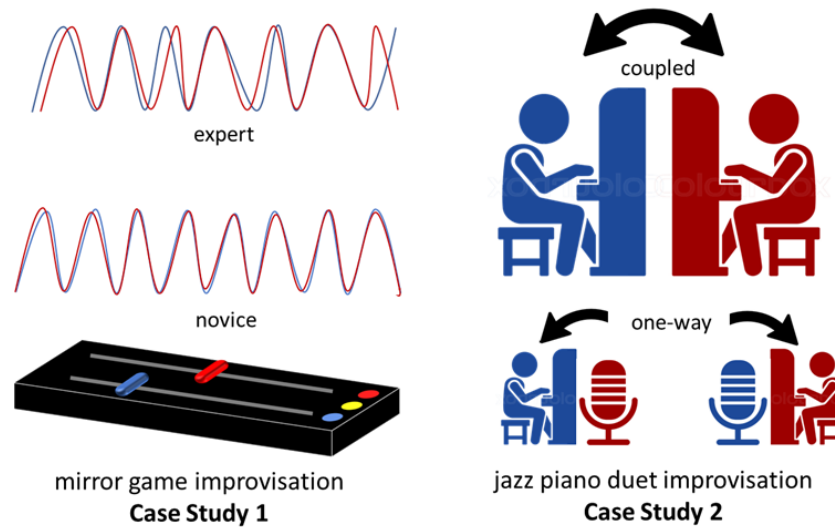


Figure 2. Dyadic Improvisation and Dynamic Information Exchange. Case Study 1 (left) represents a movement improvisation exercise in which two players play a mirror game were instructed to synchronize while creatively moving together and in which movement patterns were shown to vary differentially as a function of expertise and who was leading (red follows blue or blue follows red). Case Study 2 (right) represents a jazz improvisation task in which directionality of the information exchange was modified so as to test coupled bidirectional and one-way contexts (either a duo improvising together in real-time or individually with pre-recorded track).

3.2 Analytic Strategy

For both of the case studies that follow, we estimate transfer entropy (Behrendt et al., 2019; Borge-Holthoefer et al., 2016) as well as prediction decay (Cenci et al., 2019; Olthof et al., 2020). Combined, we expect these approaches are useful because they capture information exchange between systems and the methods can apply to multiple data modalities and that prior work has shown can scale beyond the dyadic level. With these analyses, our main contribution to understanding coordination dynamics during collaborative creativity is understanding interpersonal information-driven coordination flow in terms of the ability to differentiate unidirectional influence from mutual influence (and if unidirectional, from which direction) as

well as the predictability of signals exhibited during collaborative creativity, that are themselves in many ways the creative product. Code for our analyses is available at: <https://osf.io/fnz6h/>.

3.2.1 Transfer Entropy

In complex systems, transfer entropy has shown utility as a key indication of the directionality of information flow, or in other words, information driven coordination, between components of systems (Bossomaier et al., 2016; Schreiber, 2000) including, for example, the spread of film releases and breakthrough scientific discoveries in social media networks (Borge-Holthoefer et al., 2016), brain connectivity (Vicente et al., 2011), and how people coordinate in rhythmic tasks (Takamizawa & Kawasaki, 2019) and with virtual agents (Kostrubiec et al., 2015). Many even go so far as to liken this to evidence for causal relationships in complex systems (Razak & Jensen, 2014).

Transfer entropy is an information theoretic quantification of the flow of information from one variable to another based on the combination of Shannon's entropy (Shannon, 1948) paired with the Kullback-Liebler distance (Kullback & Leibler, 1951). Its calculation assumes that x and y are discrete random variables that follow probability distributions $p(x)$ and $p(y)$, and joint probability (x,y) , and their dynamics follow Markov processes of order k or l that imply that the probability of observing a given x at time $t + 1$ in state y is conditional on the k previous observations and vice versa for y . Information flow is evidenced from $x \rightarrow y$ as a function of an observed deviation from this Markov property (see Equation 1) or the inverse equation for $y \rightarrow x$.

$$T_{X \rightarrow Y}(k, l) = \sum p(y_{t+1}, y_t^k, x_t^l) \log \left(\frac{p(y_{t+1} | y_t^k, x_t^l)}{p(y_{t+1} | y_t^k)} \right) \quad (1)$$

For the case studies that follow, we conduct transfer entropy analysis using the `transfer_entropy` function from the `RTransferEntropy` package (Behrendt et al., 2019) in R (R Core Team, 2018). In terms of parameter selection, we specify the Markov orders k and $l = 1$. Each time series was discretized using the 5% and 95% quantiles of the empirical distribution. Transfer entropy for each pair of time series is estimated for the $x \rightarrow y$, and $y \rightarrow x$ information flow with 100 Monte Carlo bootstraps. Further, we define the *directionality index* following Borge-Holthoefer et al. (2016) as the difference between the transfer entropy estimates of the two time series.

3.2.2 Estimating prediction decay using Empirical Dynamic Modeling

In order to understand which signals have the highest predictability, we use a method of estimating prediction decay based on work in empirical dynamical modeling for understanding complex systems (C.-W. Chang et al., 2017) and the approach detailed by Olthoff and colleagues (Olthof et al., 2020). The general idea here is that more complex systems become increasingly difficult to predict at time points further ahead into the future (i.e., the prediction horizon). This analysis rests on the Sugihara-May *forecasting skill* algorithm (Sugihara et al., 1994; Sugihara & May, 1990). At a high level, the goal with this algorithm is to take an observed time series from a complex system, properly reconstruct the attractor manifold of that system by determining the appropriate number of time delayed embeddings, then forecast future points of the system using historical and locally weighted neighboring points on the manifold (Sugihara et al., 1994).

By examining the Pearson correlation ρ of the predicted versus actual values at increasing values of T_p (time to prediction), one can assess how predictable a system is across increasing temporal distances into the future. In particular, we use the `simplex` function from the `rEDM` package (Park et al., 2021) to perform the forecasting and calculate ρ for predicted versus observed values for $T_p = 1:200$ for the mirror game data and for $T_p = 1:20$ for the musician improvisation

data. For each time series, we estimate a reasonable embedding dimension and time delay using the CASNET function `est_emLag` (Hasselman & Olthof, 2020) following the work of Olthoff et al. (2020), which is based on identifying the first local minima in the average mutual information. Then, for each time series, we estimate our *prediction decay* as the slope of ρ over the first 200 time lags (i.e., 4 seconds) or 20 time lags for the musician improvisations (i.e., ~ 5.8 seconds).

3.2.3 Mixed-Effects Modeling

The transfer entropy *directionality index* estimates and *prediction decay* values were used as outcome variables in a set of mixed models specified using the `lme4` R package (Bates et al., 2015). In each of the case studies and analyses that follow, we add appropriate details of the random and fixed effects structures of our models. Note that p-values were estimated with t-tests using the Satterthwaite approximations with the `lmerTest` package (Kuznetsova et al., 2017). Table 1 summarizes the dependent variables from each of the case studies.

Table 1. Summary Descriptions of Dependent Variables from Case Studies

Case Study	Dependent Variable	Description
Movement Improvisation in Mirror Game	Directionality index from velocity traces of each participant's slider movements	The difference of the two players' transfer entropy estimates indicates whether there is a unidirectional (non-zero) or bidirectional influence (zero-value) of the players' movements.
Movement Improvisation in Mirror Game	Prediction decay from velocity traces of each participant's slider movements	The slope of ρ - the correlation between the forecasted velocity traces values and observed values for each player - using a prediction horizon of the first 200 time lags (i.e., 4 seconds).
Musical Improvisation with Jazz Piano	Directionality index from onset density estimates of each participant's piano key presses.	The difference of the two players' transfer entropy estimates indicates whether there is a unidirectional (non-zero)

		or bidirectional influence (zero-value) of the player's key presses.
Musical Improvisation with Jazz Piano	Prediction decay from onset density estimates of each participant's piano key presses.	The slope of ρ - the correlation between the forecasted velocity traces values and observed values for each player - using a prediction horizon of the first 20 time lags for the musician improvisations (i.e., ~5.8 seconds).

4. Case studies

4.1 Case Study 1: Movement Improvisation

4.1.1 Transfer Entropy

The directionality estimates from the transfer entropy analyses for novice and experts' mirror games performances are shown below in Figure 3. Generally, both novices and experts appear to display a similar pattern across the conditions. Recall that when the directionality index (DI) is 0, there is a bidirectional influence between the dyad, when $DI > 0$ it suggests that the blue participant is driving the coordination, and when $DI < 0$ the red participant is driving the coordination. Thus, the figures below show that while there is some variability in the DI estimates per condition, the blue and red conditions show the expected pattern where the highest densities are greater than zero or less than zero respectively. And additionally, in the *both* condition, the DI densities are at or very close to zero indicating a general tendency for participants to follow the goals of each condition. Note that this pattern holds for both novices and experts.

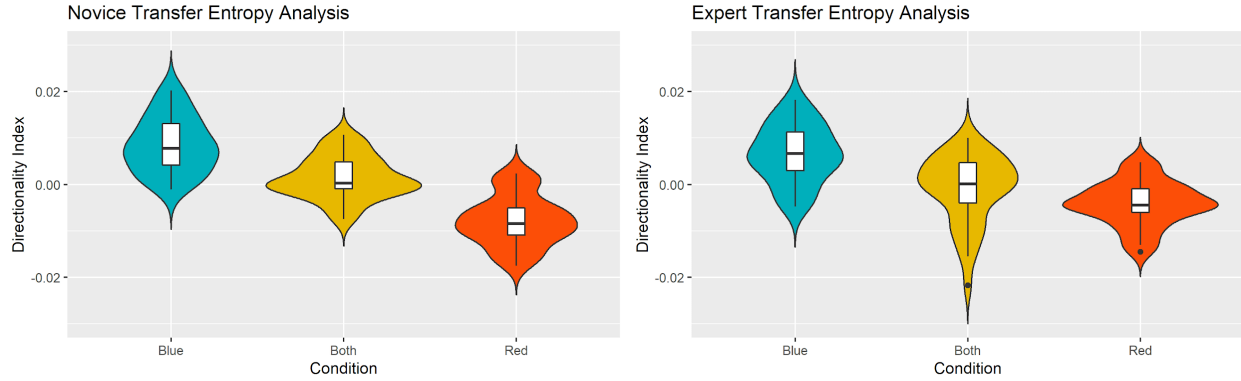


Figure 3. Novice and Expert Transfer Entropy Analyses for Mirror Game.

For our analyses, we ran a mixed model with DI as the outcome variable with condition (blue leads, red leads, or both), and expertise level (novice or expert) as dummy coded fixed effects with random intercepts for trial number nested within game (to account for repeated observations of the same dyad within a given mirror game). Note that for Group, experts are the referent group, and for Condition blue leading is the referent category. We also ran a model that allowed for interactions between the two fixed effects. The BIC and likelihood ratio suggest the model that included the interaction effect was a better fit than the model without the interaction (see Table 2) although the change in marginal R^2 was approximately 3%.

Table 2. Comparison of Models Directionality Index for Mirror Game Data

Model	Df	AIC	BIC	logLik	devianc e	χ^2	χ^2df	p
Fixed Effects Only	6	-1248.5	-1229.7	630.28	-1260.5			
Fixed Effects with Interaction	8	-1253.5	-1228.5	634.78	-1269.5	9.00	2	0.01

Table 3 shows the results of the model including the interactions. Overall, this model was a good fit of the data with the fixed effects accounting for approximately 46% of the variance (marginal R^2). The pattern of results suggests that there was no effect in this sample for expertise, yet there was a reduction in the DI estimates for the both and the red conditions relative to the blue condition (as would be expected from the figures above). Further, the significant interaction effect suggests that there is an additional decrease in the DI estimates for novices when red was leading.

Table 3. Mirror Game Directionality Index Model Output.

	Effect	Estimate	Std. Error	t	p	Bootstrapped 95% CIs	
	Intercept	0.007	0.001	5.812	<.001	0.004	- 0.009
	Group (Novice)	0.002	0.001	1.173	0.242	-0.001	- 0.005
	Condition (Both)	-0.007	0.001	-5.002	<.001	-0.010	- -0.005
	Condition (Red)	-0.012	0.002	-6.696	<.001	-0.014	- -0.008
Group (Novice) *	Condition (Both)	0.0004	0.002	0.200	0.842	-0.004	- -0.005
Group (Novice) *	Condition (Red)	-0.006	0.002	-2.412	0.017	-0.010	- -0.001

4.1.2 Prediction Decay

For the prediction decay analyses of the mirror game movement improvisational data, Figure 4 shows a violin plot of the prediction decay values for each condition as well as across novices and experts. Recall that prediction decay captures the rate at which the correlation between the forecasted values and observed values begin to drop at increasing time steps into the future.

For novices, we see more variability in the range of estimates for prediction decay when compared to experts, with some more negative values suggesting stronger prediction decay for novices.

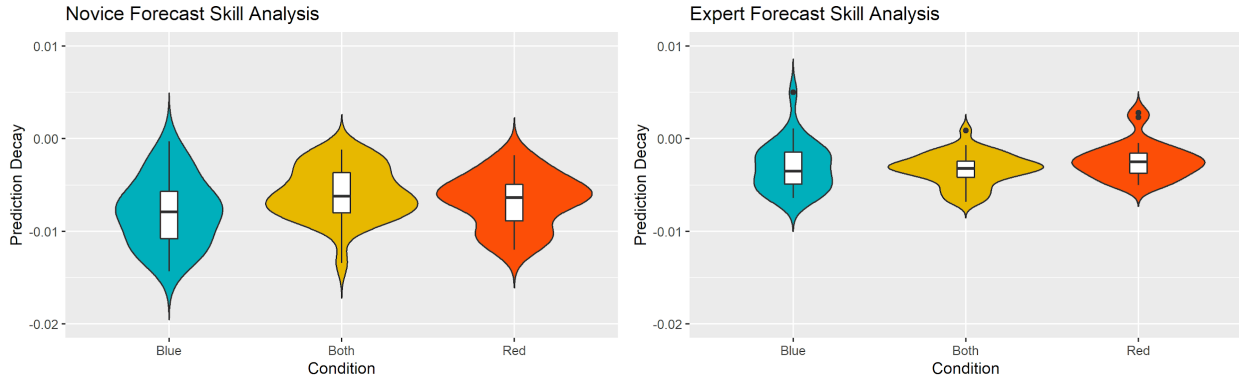


Figure 4. Violin plots of Prediction Decay for Novices and Experts in the Mirror Game.

To analyze these values further, we ran two separate mixed models with prediction decay for blue players and red players separately, again with condition (blue leads, red leads, or both), and expertise level (novice or expert) as dummy coded fixed effects with random intercepts for trial number nested within game (to account for repeated observations of the same dyad within a given mirror game). Here for Group, experts are the referent group, and for Condition blue leading is the referent category. And, like with the prior analyses, models with and without interactions between the main variables were tested to evaluate which model fit better (see Table 4). Whereas for the model with Blue Prediction Decay as the outcome variable, the model with the interaction effects was a better fit (marginal $R^2 = 0.37$), the model without the interaction effect was a better fit for Red Prediction Decay (marginal $R^2 = 0.28$).

Table 4. Comparison of Model Fit for Directionality Index from Mirror Game Data.

Blue Model	Df	AIC	BIC	logLik	deviance	χ^2	$\chi^2 df$	p
Fixed Effects Only	6	-1526.8	-1508.0	769.39	-1538.8			
Fixed Effects with Interaction	8	-1529.8	-1504.7	772.91	-1545.8	7.047	2	0.0295
Red Model								
Fixed Effects Only	6	-1537.3	-1518.4	774.62	-1549.2			
Fixed Effects with Interaction	8	-1538.0	-1512.9	777.01	-1554.0	4.776	2	0.0918

The results from the Blue Prediction Decay Model are shown in Table 5 and the Red Prediction Decay Model are shown in Table 6. Both models show an effect for Group (Novice) indicating that overall, the movement signals generated by novices become less predictable more quickly at further time points in the future. The condition generally did not have an effect on the Prediction Decay estimates. However, there was a significant interaction effect for the model of the players controlling the blue slider for the novices and both leading conditions such that during the joint improvisations, novices' prediction decay was less negative than the other conditions. In other words, blue novices' movements during the both condition were more predictable at increasing time delays than when the blue person was leading.

Table 5. Mirror Game Blue Prediction Decay Model Output.

	Effect	Estimate	Std. Error	t	<i>p</i>	Bootstrapped 95% CIs	
	Intercept	-0.003	0.0005	-5.981	<.001	-0.004	- -0.002
	Group (Novice)	-0.005	0.001	-6.992	<.001	-0.006	- -0.004
	Condition (Both)	-0.0003	0.0007	-0.428	0.670	-0.002	- -0.001
	Condition (Red)	-0.0006	0.0007	0.852	0.396	-0.0008	- 0.002
Group (Novice) *	Condition (Both)	0.002	0.0009	2.501	0.014	0.0005	- 0.004
Group (Novice) *	Condition (Red)	0.0006	0.001	0.564	0.574	-0.001	- 0.002

Table 6. Mirror Game Red Prediction Decay Model Output.

	Effect	Estimate	Std. Error	t	<i>p</i>	Bootstrapped 95% CIs	
	Intercept	-0.004	0.0004	-8.574	<.001	-0.004	- -0.002
	Group (Novice)	-0.003	0.0003	-8.360	<.001	-0.004	- -0.003
	Condition (Both)	0.0007	0.0005	1.451	0.150	-0.0002	- 0.002
	Condition (Red)	0.0004	0.0005	0.669	0.505	-0.0007	- 0.001

4.1.3 Case Study 1: Movement Improvisation Summary

Taken together, these analyses demonstrate that, during this observation of experts and novices playing the handle-controlled version of the mirror game, transfer entropy analysis can detect instances of unidirectional and bidirectional influence between improvisers. The degree to which improvisers influenced each other seemed largely independent of their improvisational experience level. Further, we showed that movement improvisation signals generated by experts are generally more predictable than those of novices and the particular condition (who was leading) did not display much effect on these estimates.

4.2 Case Study 2: Musical Improvisation

4.2.1 Transfer Entropy

The directionality estimates from the transfer entropy analyses for coupled and one-way music improvisations are shown below in Figure 5. Generally, both conditions appeared to exhibit some degree of bidirectional influence, despite that not being a physical possibility for the one-way condition. The higher density of DI values slightly lower than 0 suggests that, at least in some cases, the pre-recorded signal was driving the player.

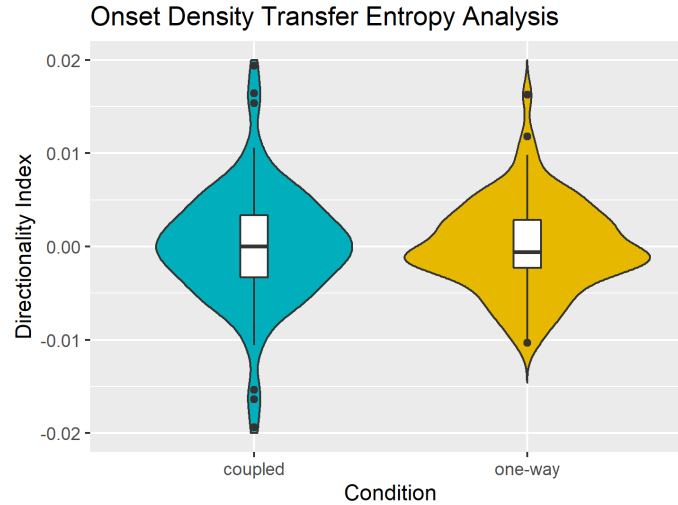


Figure 5. Transfer Entropy Analyses for Musician Improvisation Onset Density.

For our analyses, we ran a mixed model with DI as the outcome variable and condition (coupled or one-way) as a dummy coded fixed effect with random intercepts for the yoked dyad id and the yoked piece id to account for the nesting of players and pieces used across multiple trials (Setzler & Goldstone, 2020). Note that for condition, coupled was the referent group. Table 7 shows the results of the model. Overall, this model was a poor fit of the data with the fixed effects accounting for less than 1% of the variance (marginal R^2). The pattern of results suggest that there was no systematic effect in this sample for condition using DI as a measure of the information driven coordination.

Table 7. Music Improv Onset Density Directionality Index Model Output.

Effect	Estimate	Std. Error	t	p	Bootstrapped 95% CIs
Intercept	< -0.001	0.0006	< 0.00	1.00	-0.001 - 0.001
Condition (One-way)	< 0.001	0.0009	0.014	0.99	-0.002 - 0.002

4.2.2 Prediction Decay

For the prediction decay analyses of the musician onset density improvisational data, Figure 6 shows a violin plot of the prediction decay values for each condition. The distributions of prediction decay values for both conditions are relatively similar with the one-way appearing to have a slightly lower median and slightly larger interquartile range. Recall that prediction decay captures the rate at which the correlation between the forecasted values and observed values begins to drop at increasing time steps into the future.

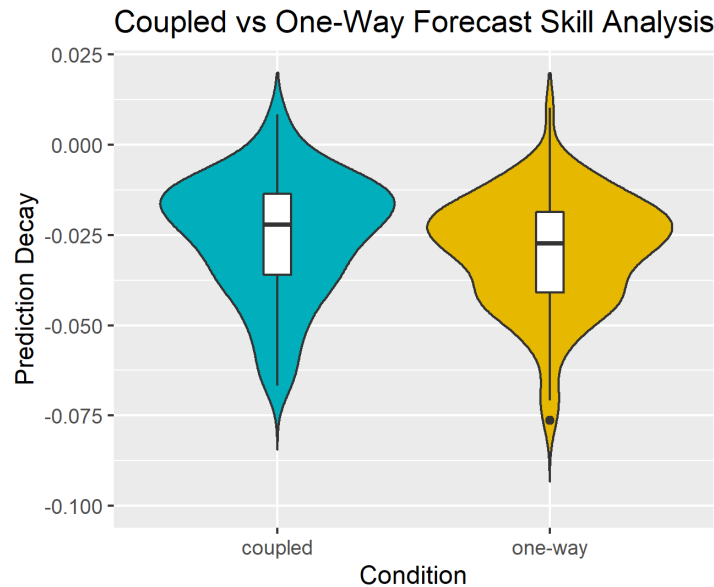


Figure 6. Prediction Decay for Musician Improvisation Onset Density.

To analyze these values further, we ran a mixed model with prediction decay as the outcome and condition (coupled or one-way) as a dummy coded fixed effect with random intercepts for the yoked dyad id and the yoked piece id. Here for condition, coupled was the referent category. The results from the model are shown in Table 8. We did not observe that condition had a systematic effect on the Prediction Decay estimates. Overall, this model was a poor fit of the data with the fixed effects accounting for approximately 2% of the variance (marginal R^2) and when including the random effects about 8% (conditional R^2). The plotted results

and estimates from the model suggest that there was only a slight reduction in predictability as a function of whether participants were coupled or not, although overall, the significant intercept suggests that that was a decrease in predictability at increasing time lags.

Table 8. Music Improvisation Onset Density Prediction Decay Model Output.

Effect	Estimate	Std. Error	t	<i>p</i>	Bootstrapped 95% CIs	
Intercept	-0.025	0.002	-14.18	<.001	-0.029	- -0.022
Condition (One-Way)	-0.004	0.002	-1.78	0.077	-0.009	- 0.0004

4.2.3 Case Study 2: Music Improvisation Summary

Taken together, these analyses demonstrate that, during this observation of experienced improvisational musicians, the directionality index from the transfer entropy analysis suggested that there was unidirectional and bidirectional influence between the coupled and one-way conditions. This was the case at least for the onset density data that was analyzed. Further, we did not observe a systematic difference in the prediction decay rate for those musicians who improvised together versus those who improvised along to a recording.

5. Discussion

In this chapter, we set out to investigate collaborative creativity from a model-free coordination dynamics perspective, with a focus on two types of improvisational creativity. The two case studies were chosen because the mirror game and jazz improvisation typify dynamic collaborative creativity in which information exchange is essential. Not only this, but these are

relatively complex tasks that require coordination and may rely on predictive processes. Here we will summarize results across the two studies and in so doing discuss the commonalities across these two forms of creative coordination, as well as reasons for distinctions identified across the two cases. Specifically, we will revisit the concepts of directionality and predictability introduced earlier, as a function of the individual setups in the two experiments. We will then discuss the distinct modes of expressivity and subsequent differences in the output of the collaborative performance. While the mirror game involves movement along a single dimension, in performing a musical piece, coordination will occur both in the movements we make and the sounds these actions produce. As such, while both examples of collaborative creativity and the improvisers' experiences are multimodal, the specific informational channels that constrain and drive the collaborative processes are worth considering further.

In terms of our results, building on the work of the original authors (Noy et al., 2011), we observed in the mirror game that experts and novices exhibited unidirectional and bidirectional influence on each other's movements and this appeared independent of their improvisational experience level. Further, we showed that movement improvisation signals generated by experts were generally more predictable than those of novices. In terms of the jazz music improvisation task (Setzler & Goldstone, 2020), our results were somewhat unexpected. There was evidence of bidirectional influence between the onset densities of coupled *and* one-way improvisational dyads and the predictability of the signal did not vary systematically across these conditions.

Before we unpack these findings further, let us first turn to what is different in terms of coordination and prediction in the two cases. In the mirror game (Case Study 1), interacting agents rely primarily on shared visual information (the hand and slider of the players) while in the musical context (Case Study 2), players had to depend solely on the auditory channel to share and

understand each other. Therefore, the number of modalities in which to observe coordination as well as the informational channels to convey that information were different and this could affect the ability for individuals to not only track that information, but to build their predictions upon. In addition, the task for the jazz improvisation is relatively more difficult as players must not only balance between coordinating with the other but also account for the musical dimension. In the mirror game, by contrast, this is a case where the creative act itself is to lead, follow, or move in unison with the other, making tracking and prediction relatively more straightforward.

One possible explanation for the findings with the jazz improvisation data (Setzler & Goldstone, 2020) is that performing music with recordings is actually quite common in music production (e.g., playing with a backing track, recording to previously recorded tracks). Using other computational methods, Setzler and Goldstone (2020) observed that there was greater temporal coordination (in terms of lagged cross-correlations) of the onset densities as well as higher harmonic coordination in the dyads that were able to mutually adapt to each other. Our observations with transfer entropy and prediction decay could be an artifact of the inherent predictability, based on musical norms, that is still evident in an improvisational setting and therefore results in ‘apparent’ information exchange between a live player and a pre-recorded player. These norms could include structural hierarchies (i.e., melody leads the accompaniment) typical of most Western music which would dictate a certain temporal relationship between parts (Uhlig et al., 2013). Relatedly, participants could have even realized, at least implicitly, in the one-way condition that the other person is not quite adapting to them, in which case they could be engaging in mental simulation/prediction to a greater extent than those that are mutually adaptive (going in and out of following and leading during the improvisation). By doing so, there could be some increased anticipatory elements in the player that do coincide with what the recorded signal

actually did end up performing. And thus, the transfer entropy analysis would pick up on these cases where the player is slightly ahead or anticipating the recorded signal and vice versa. Future work could evaluate these possibilities more systematically and even compare other so-called ‘dynamic causal’ methods (Clark et al., 2015; Razak & Jensen, 2014) to better understand the observed information flow to pre-recorded signals that was evident for some of the jazz improvisation trials.

Given the results we have advanced here, we come away with many more questions for understanding the role and interrelatedness of coordination dynamics, prediction, and collaborative creativity. The first: how can we better understand the local and global time scale interaction patterns (Fine et al., 2015; Gorman et al., 2017)? While the methods we have used here rely on windowing (thus capturing local interactions), the overall analysis primarily gives an averaged depiction of the global dynamics. We expect that future work will tackle the distinctions and relationships between local and global dynamics. An important aspect of this, focusing on local time course interaction, is the ability to identify and zoom in on key fluctuations over the time course of the improvisation; that is, *informative transitions*. Importantly, despite a focus on “optimal coordination”, lower points of coordination may in fact represent a period of exploration, of novelty, an effort to be creative, or perhaps simply to have fun at the cost of performance (and this in itself might be informative). As an example of a more dynamical approach to variation across time, the recent “spotlight” proposal by Rahman and Gray seems worthy of mention as it highlights the need to investigate “plateaus, dips and leaps”, that convey both improvements and potentially informative decreases in skilled performance (Rahman & Gray, 2020). These changes may demonstrate local variations in information flow (one person takes the lead, in a form of turn-taking). These phase shifts could therefore include a recovery phase following a perturbation

(Dahan et al., 2016), periods of creative “discovery and invention” (Gray & Lindstedt, 2017) as described above, or generally distinct phases of the collaboration (Wiltshire et al., 2018), that include both examples of coupling and decoupling (Dahan et al., 2016; Dumas & Fairhurst, 2019). Indeed, Noy and colleagues (Noy et al., 2011) have suggested that the key difference between experts and novices is that as a function of expertise, dyads may differentially prioritize the two instructed tasks, to synchronize while creating interesting movement patterns. Therefore, across a protracted period of interaction, experts may show multiple different phases of coordination, some in which synchronization is prioritized interspersed with other phases in which the cost of creativity will be lower levels of synchrony.

Improvisation is quite interesting because during well-rehearsed music, for example, musicians are not always predicting each other or actively listening, but improvisation requires this to a greater extent. Coupled agents are required to predict changes and react to perturbations (or unexpected events). However, another open question might be to dig deeper into how humans make sense of, coordinate, and predict the actions of others as a function of the number of information channels and modalities that are involved in most multisensory collaborative exchanges. This challenging concept of signal complexity is of course further compounded by increasing group size (e.g., larger musical groups). It could also be that there are other context or task dependent constraints that govern the importance of certain modalities for information exchange (Hoehl et al., 2020; Keller et al., 2014). For example, coordination in the bodily sway of musicians can reflect the expressivity created by musicians (A. Chang et al., 2019; Demos et al., 2018), which could be a key aspect of the interpersonal coordination above and beyond what a musical score might dictate. Auditory cues are paramount to musical performances, but predictive processes in music improvisation could also be underscored by visual cues such as general body

movement, breath, and sway (Sofianidis et al., 2015; Wing et al., 2014; Yamamoto & Miyake, 2003). In the mirror game, the slider is more closely related to the bodily expression (less rigid requirements of musical structures), so this might occur more locally in movements only of the wrist or in the face to face exchange. While not explicitly studied here, another potentially worthwhile comparison may be that of dance and music making, where to varying extent the reliance on a mix of sensory modalities (e.g., visual, auditory, or even haptic channels) will dictate the nature of the information exchange (Chauvigné et al., 2019).

How and when leadership emerges during collaborative creativity such as improvisations is another open and interesting question. There are, of course, different types of leadership, where for example, in the mirror game, there is explicit instruction for one participant or the other to take the leadership role. The relationship between a top-down instruction to take the leadership and what actually occurs during an interaction are not necessarily one-to-one. And, as there are more individuals involved, who exactly is taking the lead may vary over the time course of the collaboration.

A final open question for us is: What is the functional relevance of collaborative creativity for learning? To better contextualize this question, recall that we (and others) presume that coordination underpins the ability to work with and create with others, and social learning is often key to this process. As a social process, mirroring and more general social coordination are critical for infant development and relationship formation (Feldman, 2007, 2017). It is suggested that this form of interactional improvisation is an extension of these behaviors and is inherent throughout the developmental process. We posit that it provides a safe opportunity for learning about the social world (Savage et al., 2020). It may even be the case that these low level synchronization patterns in movements and physiology (for example) can support higher level, and more complementary,

interaction patterns (Fusaroli et al., 2014; Dumas & Fairhurst, 2019). Future work could investigate the degree to which these levels of coordination as well as the specific types of interaction patterns are required for engaging in musical improvisation and other types of skilled performance such as intentional herding (Nalepka et al., 2017, 2019) and skill-based games (Gray & Lindstedt, 2017).

To conclude, in this work, we sought to investigate the coordination dynamics of improvisation as a special case of collaborative creativity in both a movement-based mirroring game and jazz improvisation. We expect that these efforts and our discussion of them will contribute to future work attempting to understand the intersection of coordination, prediction, and collaborative creativity, more generally.

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