Capturing Coordination and Intentionality in Joint Musical Improvisation

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Our research was submitted as a bachelor thesis in the Cognitive Science & Artificial Intelligence program at Tilburg University. The data we used was originally collected for the study “Emergent Shared Intentions Support Coordination During Collective Musical Improvisations” by Goupil, Wolf, Saint-Germier, Aucouturier, and Canonne (2021).

Code for our analyses can be found at: osf.io/y84rd

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Abstract

Humans collaborate with each other on a wide variety of tasks that are often largely improvised and unscripted. In this study, we investigated the dynamics of coordination in a joint musical improvisation task, what the effect of intentions is on coordination, and how musicians propagate these intentions. To quantify coordination within musical trios, we derived per-musician time series of acoustic features to which we applied effective transfer entropy (ETE) and empirical dynamic modeling (EDM), two methods derived from complex systems science. Using ETE allowed us to investigate coordination as directional information flow between musicians, whereas through EDM we conceptualized coordination as the predictability of a complex system. We found that both techniques, when applied to root-mean-square (RMS) amplitude time series, could be used to distinguish coordinating from noncoordinating musicians. Various other feature–technique combinations, such as fractal dimension–ETE and Tonnetz distance–EDM, were also viable. Our results further suggest that coordination improves as an intention gets more shared, that is, as more musicians in the joint improvisation have the same intention. Lastly, we found evidence suggesting that musicians increase the predictability of their playing when seeking to end a performance, though our results did not provide an indication that this was done with the intention of improving coordination with partners.

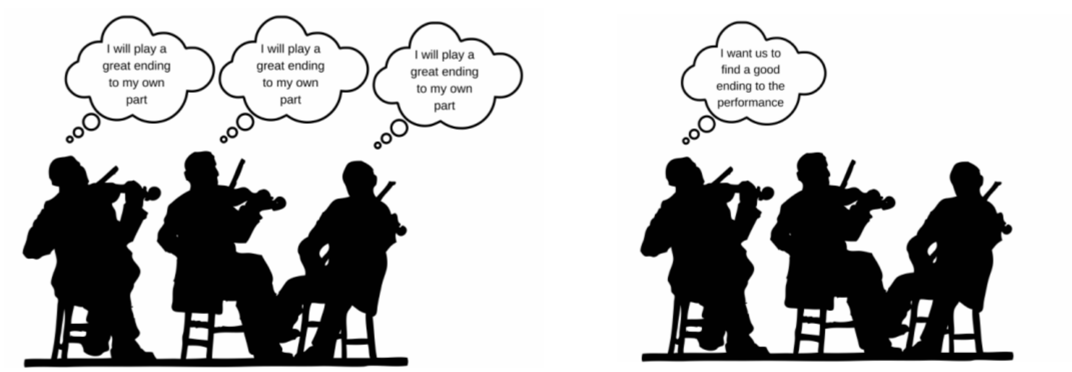
Keywords: Joint improvisation; Musical performance; Joint action; Dynamical systems

Supplemental materials: https://doi.org/10.1037/pmu0000299.supp

Introduction

Joint action has been described as any activity that involves at least two individuals coordinating their actions in space and time to achieve a joint outcome (Knoblich et al., 2011). It is a fundamental part of human life and appears in situations ranging from highly creative and expertise-dependent tasks to simple day-to-day activities. Successful coordination and cooperation in joint action scenarios largely rest on continuously monitoring the success of the joint action, predicting partners' actions, and, in turn, making one's own actions easier to predict (Vesper et al., 2010). Ideally, the need for such prediction is minimized through the use of conventional modes of communication, such as speech and gesture. Perhaps more interesting, though, are cases where such modes are not available or practical; here, actors must instead resort to using observable, task-related actions to signal intentions to coactors (Sebanz & Knoblich, 2021). An everyday example of a task-related action being used to communicate an intention is when a passenger occupying a window seat on a bus demonstratively prepares to get off the bus; the action contributes to the task of disembarking and is modulated in such a way that it also effectively signals an intention to the person in the aisle seat. Exaggerating certain parameters of an action or reducing the variability of one's actions, thereby making one's actions more predictable appear to be some of the ways in which humans use action-based intention signaling to "smoothen" their coordination (Lelonkiewicz & Gambi, 2020; Pezzulo et al., 2013). Yet further research is needed to investigate the effect of these coordination smoothers on task performance and to establish exactly how joint action partners settle upon a course of action when faced with between-agent asymmetries in knowledge and perception (Sebanz & Knoblich, 2021).

In this research, we use techniques derived from complex systems science in an attempt to quantify the elusive phenomenon of intention signaling in an improvised musical joint action setting with particularly limited modes of communication. We hereby aim to investigate whether, and if so, how humans succeed in propagating their goals to coactors and settling on a joint course of action under these conditions. As the basis of our analyses, we make extensive use of data collected and generously made available by Goupil et al. (2021). Briefly summarized, their research involved trios of musicians participating in collective free improvisation (CFI) performances. CFI is a musical paradigm that is characterized by its performances being entirely improvisational in nature. Musicians' intentions were manipulated experimentally via auditory prompts delivered by the researchers, which musicians could not straightforwardly communicate to each other, as the musicians making up a trio played in separate booths. The research made an important distinction between shared intentions (intentions that are present in several group members) and collective intentions (intentions that relate to group-level performance, but are not necessarily shared) and found evidence that both greater sharedness and greater collectiveness of intentions positively affected the quality of improvisations, presumably through stronger intermusician coordination. Figure 1 shows an example of a shared and a collective intention.



(a) This intention is shared, as it is present in several improvisers. It is not collective, because it does not relate to coordinating with fellow improvisers.

(b) This intention is collective, because it relates to coordinating with fellow agents. It is not shared, because it is not present in several improvisers.

Figure 1: A Shared Intention and a Collective Intention

Note. Intentions can also be both collective and shared, or neither of the two.

Building on their findings, in our research, we aim to shed light on the issue of how high-level intentions are communicated and propagated in joint improvisation scenarios and how this information exchange impacts the success of a joint improvisation, particularly where modes of communication are very limited. Unlike much of the existing work (Noy et al., 2011; Setzler & Goldstone, 2020; Valdesolo et al., 2010), this research will investigate joint improvisation in a scenario larger than a dyad, and in a realistic, nontrivial task where shared high-level goals appear vital to achieving a desirable outcome.

Coordination can be conceptualized as mutual *information flow* between entities in a system (Curioni et al., 2019; Kelso, 2009). Another way in which we conceptualize coordination is the *predictability* of the musicians' collective playing. Glowinski et al. (2013) provide compelling evidence that system predictability is indeed a reliable indicator of coordination in a musical task. Investigation of whether the sharedness and collectiveness of highly general goals are reflected in information flow and system predictability can thus provide valuable insight into how these goals affect group-level coordination. By also considering the effect of collective intentions on predictability at the individual level, and in turn the effect of individual predictability on information flow, we set out to quantitatively test the notion that improvisers signal their intentions by making their actions more predictable (Glover & Dixon, 2017; Goupil et al., 2021) and that doing so allows partners to adapt to their behavior more effectively (Vesper et al., 2011). We also aim to establish how the results we obtain with effective transfer entropy (ETE) and empirical dynamic modeling (EDM) tie back to subjective experience by testing for the effects of information flow and system predictability on the subjective quality of the joint action. In this way, we seek to find out whether the amount of information flow, the extent to which this information flow is bidirectional, and the predictability of the system's behavior provide any direct indication of the quality of a joint improvisation.

Related Work

Joint Action and Joint Improvisation

Much of the literature on joint action has focused on cooperation toward shared goals on the basis of motor synchronization (Friston et al., 2011; Kawasaki et al., 2018; Wolpert et al., 2003), with researchers investigating how dyads achieve simple interpersonal motor coordination, such as synchronously walking side by side (Almurad et al., 2017) or rocking in chairs (Richardson et al., 2012). However, not only synchronization, but also action complementarity and the alignment of higher-level goals and intentions are crucial to many forms of joint action (Fusaroli et al., 2014; Sartori & Betti, 2015). Complicating matters further, real-life joint action often occurs in the absence of preestablished plans; in such situations, humans have to use signaling strategies to communicate plans on the fly (Candidi et al., 2015) and appear to be more actively mentalizing, that is, interpreting partners' behavior in terms of underlying mental states (Chauvigné et al., 2018). This subset of joint action that (a) occurs only through a highly general shared intention and (b) is devoid of plans that specify immediate means to this end is what we refer to as *joint improvisation* (Saint-Germier et al., 2021). The spontaneous development of complementary strategies and the signaling of higher-level intentions can go a long way toward achieving a desirable performance in joint improvisation scenarios (Sartori et al., 2013).

Joint Action Scenarios as Complex Systems

Complex systems are collections of relatively simple entities that, through both their interconnectivity and their openness to external influence (what Borgo, 2022 describes as "openness from closure"), give rise to global behavior of far greater complexity than the behavior of any single entity in the system (e.g., Favela, 2020; Prokopenko et al., 2009). In order for entities to be part of the same system, there must be some level of information transfer, also known as coupling, between entities (Paluš, 2019). Coupling between two entities in a complex system can be *unidirectional*, with adaptation only occurring in one direction, or *bidirectional*, in which case both entities are mutually adaptive. Nonlinearity is inherent to complex systems due to the existence of feedback loops and interactions among entities, which generate emergent properties that cannot be deduced solely from any individual entity's properties (Plsek & Greenhalgh, 2001).

Analysis of joint action scenarios as complex systems is an increasingly common practice (Trendafilov et al., 2021; Wiltshire et al., 2019). One key driver of this approach was David Borgo's landmark book *Sync or Swarm*, which developed complex systems thinking into analysis of joint musical improvisation, through methods such as fractal analysis of raw audio data (Borgo, 2022). Other work has, for example, applied Granger causality in combination with low-level audio features (Pachet et al., 2017) and cross wavelet spectral analysis of improvising musicians' head movements (Walton et al., 2015). We consider the complex systems approach suitable for studying joint musical improvisation, as it combines both theory and methods for understanding the emergent and time-varying dynamics of this form of joint action.

Transfer entropy (TE) and EDM are yet more examples of complex systems methods that have found their way into joint action research. For example, Trendafilov et al. (2020) found that in a simple rhythmic joint action task, tight bidirectional coupling as captured by TE was positively correlated with both task performance and with subjective measures of coordination. A recent study by Wiltshire and Fairhurst (2022) also showed promising results in the use of both TE and EDM methods as indicators of coupling strength in a simple form of improvised joint action, yet these same methods did not effectively capture coupling in a more complex, musical form of improvised joint action. Further application of predictive techniques from EDM in joint action research has, to the best of our knowledge, not yet been conducted.

As in other examples of complex systems, coupling in joint action scenarios may be unidirectional or bidirectional. It has been shown that professional musicians bidirectionally coordinate, using the auditory feedback produced by their own and partners' actions to anticipate and adapt to their partners (Schultz & Palmer, 2019; Van Der Steen & Keller, 2013). They may also use gestural movements, such as head movements, that help maintain temporal coordination on shorter timescales (on the order of milliseconds) and signal expressive, higher-order intentions that are most apparent on longer timescales, on the order of seconds and beyond (Hilt et al., 2019; Walton et al., 2015). Research in which coupling between musicians was experimentally manipulated has thus far indicated that such bidirectional coupling gives rise to stronger coordination, which is reflected both in statistical analyses (Demos et al., 2017; Setzler & Goldstone, 2020) as well as in quality judgments by musicians and listeners (Setzler & Goldstone, 2020). The phenomenon of bidirectional coupling resulting in optimal coordination is supported mathematically by the dynamical systems framework (Strogatz, 2000). Research by Wiltshire et al. (2019) suggested that coupling at short timescales is an effective predictor of performance in a complex, collaborative problem-solving task. In the musical domain, however, it has proven difficult to uncover such a link between low-level coupling and higher-level group phenomena such as shared intentions (Pachet et al., 2017).

In the case of CFI, performers refuse to establish plans on the content of a performance beforehand. While CFI can vary in the extent to which the performers abide by clear temporal and harmonic structure, most often performances are devoid of a regular pulse and of traditional, tonal harmony (Canonne & Garnier, 2015), as is the case for the performances in this research (for an audio/video example, see: https://osf.io/ 2j4yw). CFI thus constitutes a particularly pure and flexible form of joint improvisation, where the quality of a performance likely depends strongly on on-the-fly signaling of high-level (i.e., more general) intentions, and so it is particularly suitable for investigating the role of high-level goals in joint improvisation (Canonne & Garnier, 2012).

Hypotheses

Our research rests on the assumption that successful coordination in joint action is strongly related to recurrent, tight interactional patterns (Fusaroli & Tylén, 2016). As our methods with which to quantitatively capture coordination within these groups of improvising musicians, we applied ETE (Schreiber, 2000) and EDM (Sugihara et al., 2020) to a set of acoustic features and empirically tested the capacity these modeling techniques have in capturing intermusician coordination when deployed on the acoustic features. We expected that all of the included features encode information on some aspect of coordination between musicians.

Following these baseline tests of the techniques and acoustic features, we examined how the results obtained via ETE and EDM relate to the subjective quality of improvisations, as indicated by the musicians taking part in them. Here, we expected greater information flow, stronger bidirectionality of information flow, and greater group-level predictability to all positively affect listener appreciation of performances. We hypothesized that the presence of collective intentions increases the amount of information flow in the system (i.e., group), particularly through increased information flow from group members holding these intentions to partners. In a similar vein, we hypothesized that predictability at the system level increases as intentions become more shared and that this effect is strongest for collective intentions. Lastly, we expected musicians to increase the predictability of their playing upon being prompted with a collective intention, and we predicted that this coordination smoothing device would indeed yield greater information flow to partners.

An overview of the hypotheses is provided below:

Hypothesis 1: It is possible to distinguish between coordinating and noncoordinating musicians by applying effective transfer entropy (ETE) and empirical dynamic modeling (EDM) to acoustic feature time series.

Hypothesis 2: Amount of information flow, bidirectionality of information flow and group-level predictability are positive indicators of subjective quality of improvisations.

Hypothesis 3: Sharedness and collectiveness of intentions positively impact coordination during musical improvisations in terms of information flow and greater group-level predictability.

Hypothesis 4: Improvisers successfully propagate intentions by increasing the information transfer and the predictability of their actions to facilitate adaptation.

Materials and Methods

Data

The data we used were collected as part of a study by Goupil et al. (2020), which investigated the effects of shared information, collective intentions, and shared intentions on the presence of *signaling strategies* and coordination in a joint improvisation task. *Signaling* *strategies* refers to any means by which musicians signal their intentions to their fellow musicians, thereby propagating their individual intention to make it a shared intention.

Goupil et al. (2020) invited 21 musicians (19 male/two female, M_{age} = 39.8, *SD* = 9.1 years) to Aeronef Studio, Paris, France, to record improvised musical group performances. Ethical approval was obtained by the original authors. All participants in the recording were professional musicians who were actively involved in CFI at the time of the research. Participants were grouped in 12 unique trios, which were assembled in such a way that prior familiarity between the musicians was minimized. Fifteen of the 21 musicians played in two different trios. A broad range of instruments was used in the improvisations, including brass instruments, drums, prepared piano, and electronics. Wind instruments were especially common, being used by 12 of the 21 musicians. All instruments allowed for the manipulation of timbre, while only a subset of the instruments was capable of melodic playing and was used in such a way. A full list of the instruments per trio is included in the online supplemental materials of this study. Across two experiments, each of the trios recorded 16 performances, adding up to a total of 192 improvisations. Musicians played and were recorded in separate booths[1] and were therefore unable to communicate with each other through any nonmusical modality.

The first experiment consisted of four trials per trio, in which the musicians received the instruction to perform for approximately 3–4 min, but were free to seek an ending to the performance whenever they saw fit. The duration of the 48 improvisations in this first experiment varied widely, ranging from 93 to 391 s (*M* = 203 s, *SD* = 53 s). The second experiment featured another 12 trials per trio. Moreover, 1–3 musicians in each trial received a

[1] This procedure is also what allowed for clean audio separation of the individual musicians' playing.

prompt over their headphones that instructed them to either work toward a suitable ending for their own part (ME-goal) or a suitable ending for the group (WE-goal). Right after each trial in this experiment, the musicians were asked to rate on a 7-point Likert scale their enjoyment of the improvisation (M = 4.97, SD = 1.22). Because of the additional information on intentions and the enjoyment ratings, we limited ourselves to data from the second experiment for all research questions that related to intentions or subjective quality of improvisations. The third and fourth experiments in the original research respectively involved listener ratings of endings of a subset of 24 trials and listener ratings of extracts from individual musicians' performances. These data were not used in this research.

Feature Extraction

To facilitate the application of statistical techniques on the recordings, we extracted six acoustic features for each individual musician in each recording: root-mean-square (RMS) amplitude, spectral flatness, Tonnetz distance, (Higuchi) fractal dimension, spectral centroid, and zero-crossing rate (ZCR).[2]

RMS amplitude describes loudness of the audio signal. RMS amplitude is based on the magnitude of a signal as a measure of signal strength, regardless of whether the amplitude is positive or negative, which makes it a useful indicator of loudness as compared to raw amplitude values.

Spectral flatness (the ratio of the geometric mean to the arithmetic mean of the signal's power spectrum) is an indicator of how "pitch-like" versus "noise-like" the timbre of a sound is,

[2] We initially conducted our research using only the first three features. Fractal dimension, spectral centroid and zero-crossing rate were added later as a follow-on exploratory question during the peer review process.

with more noise-like sounds resulting in higher values. An advantage to including spectral flatness in our research is its utility in analyzing music that is largely defined by its timbral qualities over harmonic and rhythmic properties (Dean & Bailes, 2010).

Following Harte et al. (2006), we compute *Tonnetz distance* by taking the Euclidean distance between the Tonnetz projection of a given window and of the window before it. In the Tonnetz space, close harmonic relationships, such as the perfect fifth, have small Euclidian distances, even if the difference in pitch is large. As such, a measure of Tonnetz distance quantifies the extent of harmonic change in a musician's playing from one time point to the next.

Higuchi fractal dimension (Higuchi, 1988) is a measure of how many simple dynamical subsystems would be needed to achieve the complexity of the initial time series. It is a time series-specific version of the box-counting dimension algorithm and measures how many subsystems would be needed to produce the complexity of the signal in a given window. Among other applications, it has been used on electroencephalogram data for the assessment of medical interventions (Anier et al., 2004) and early detection of Alzheimer's disease (Al-Nuaimi et al., 2017). In the musical domain, Borgo (2022) used a fractal dimension measure to analyze solo improvisations and qualitatively found it to be a good indicator of the perceived musical complexity over the course of an improvisation.

Spectral centroid is a weighted mean of the frequencies present in a signal. The weights are determined by the magnitudes of the frequencies. In audio applications, it has been found to be a reliable indicator of the perceived brightness of a sound (Schubert & Wolfe, 2006). Interestingly, in Goupil et al. (2021), spectral centroid in combination with Pearson's correlation was not found to be a reliable indicator of coordination within trios.

Finally, *ZCR* is a measure of the number of times the signal amplitude crosses the zero line in a given window, divided by the number of samples in that window. It is often used for audio classification tasks, for example, distinguishing between different musical instruments (Gajhede et al., 2016; Gouyon et al., 2000) or voiced/ unvoiced phonemes (Jalil et al., 2013).

Taken together, the features encode information on loudness (RMS amplitude), timbre (spectral flatness, spectral centroid, ZCR), and harmony (Tonnetz distance), with fractal dimension serving as a more general measure of signal complexity. Time series representations of these features were extracted in Python using the Librosa library (McFee et al., 2015), with the exception of the fractal dimension, which was computed using the AntroPy library (Vallat, 2022). The time series of each feature were sampled for each individual musician using a 0.16 s nonoverlapping sliding window. This particular window size was chosen because it corresponds to the average human auditory reaction time (Jain et al., 2015), which we can assume to be the shortest timescale at which one can adapt to a partner's action in a joint action scenario.[3] To give a sense of the variability in the features, Figure 2 shows what the time series representations of these features look like in an example case. The Pearson correlation coefficients for each combination of features can be found in Table 1. All combinations showed statistically significant correlations, with particularly strong correlations among the timbral features (spectral flatness, spectral centroid, ZCR). RMS amplitude and Tonnetz distance show relatively weak correlations with each other and with the other features.

[3] It should be noted that, for technical reasons related to the Librosa library, the actual window size was closer to 0.1596.

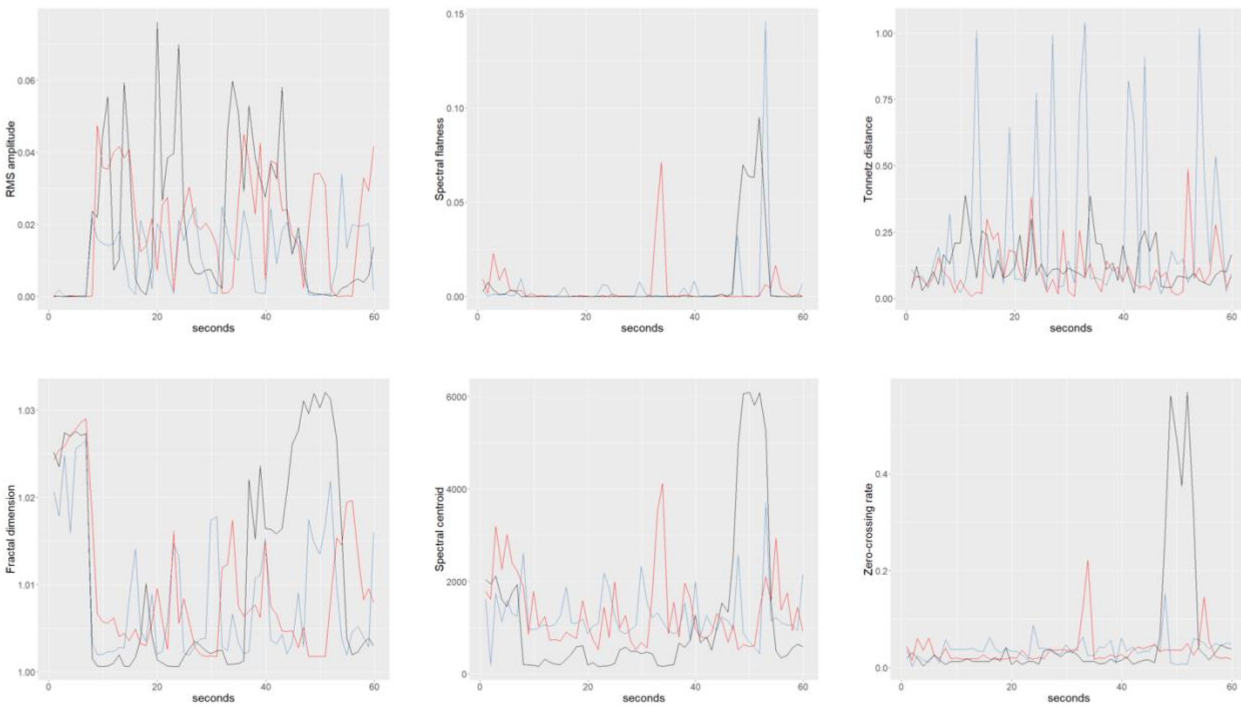


Figure 2: These plots show the time series representations of the first 60 seconds of trio 12-trial 1 on each of the acoustic features.

Note. This trial was chosen because it featured active playing from all musicians, as well as a variety of instruments and playing styles: strongly melodic flute playing by one performer (the blue line), amelodic drumming by another (black) and a mix of percussive and melodic saxophone playing by the remaining performer (red).

Table 1

Matrix Showing Correlations of Window-Averaged Feature Values

	RMS amp.	**Spec. flat.**	**Tonn. Dist.**	**Frac. dim.**	**Spec. cen.**	**ZCR**
RMS amp.						
Spec. flat.	-0.10***					
Tonn. dist.	0.20***	-0.04***				
Frac. dim.	-0.34***	0.37***	-0.20***	-0.20***		
Spec. cen.	-0.16***	0.67***	-0.02***	-0.64***	-0.64***	

ZCR	-0.04***	0.65***	0.03***	0.31***	-0.20***	

Note. RMS = root-mean-square; ZCR = zero-crossing rate.
*** $p < .001$.

(Effective) Transfer Entropy

Shannon TE is a nonparametric statistical method that quantifies the amount of information flow $TE_{X \to Y}$ from one stochastic process *X* to another process *Y* (Schreiber, 2000). If *X* has a causal influence on *Y*, then predicting future value(s) of *Y* based only on past values of *Y* should be less accurate than predicting *Y* conditioned on both its past and the past of *X*. A TE of 0 indicates no dependence, while a TE of 1 means *Y* is fully dependent on *X*. Unlike mutual information (MI), a similar measure of mutual dependence between two variables, TE reports a directional flow of information, and so TE can be calculated separately from *X* to *Y* and from *Y* to *X*. This makes it a suitable measure for investigating causality within a system.

TE bears yet greater resemblance to Wiener–Granger Causality (or G-Causality), a statistical measure of causality based on vector autoregression (VAR) model predictions (Granger, 1969). In fact, TE and G-Causality have been shown to be entirely equivalent when dealing with Gaussian variables (Barnett et al., 2009). G-Causality, however, is subject to the assumptions of its underlying VAR model, which can result in poor performance in the case of highly nonlinear and/or non-Gaussian processes (Bossomaier et al., 2016). Lindner et al. (2019) further suggest that at least on simulated data, TE achieved slightly better accuracy than G-Causality in identifying true causality within complex systems. The information that TE provides on directionality—crucial to addressing several of the research questions—and its greater flexibility over the parametric G-Causality test is what motivates the use of TE to quantify information flow in this research.

Given two time series *X* and *Y* and Markov orders *k* and *l*, TE is calculated as follows:

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

It should also be noted that (E)TE strictly requires discrete data. To convert our continuous time series data into a usable format, we discretized it into four quartiles.

TE has a known tendency to be biased in the case of small sample sizes, where spuriously high transfer entropy values may be recorded. To mitigate this issue, we calculate ETE as opposed to “raw” TE. ETE is essentially a bias-corrected TE estimate, where TE calculations from randomly shuffled data are used to estimate the bias induced by small sample effects (Marschinski & Kantz, 2002). We used 20 shuffles to obtain our bias estimate for each ETE calculation. The formula for ETE, given below, shows that the bias estimator is subtracted from the “raw” TE estimate to obtain the ETE estimate.

$$ETE_{X\to Y}(k,l) = TE_{X\to Y}(k,l) - TE_{X_{shuffled}\to Y}(k,l)$$

One limitation of (E)TE is that it assumes that “current” values of the time series *X* and *Y* are influenced by values that are a fixed number of time lags in the past. This fixed number of time lags is determined by the Markov order hyperparameter. Concretely, given two time series *X* and *Y* and a Markov order k (for interpretability’s sake, we always kept *k* and *l* identical), the values at time points X_t and Y_t are assumed to be influenced by X_{t-k} and X_{t-k}. To avoid making such an assumption, we always calculated ETE for all Markov orders between 1 (0.16 s) and 20 (3.19 s) throughout this research, which allowed us to capture coordination at very short as well as relatively longer time scales. The ETE value $ETE_{X \rightarrow Y}$ for a pair, then, is the average of its ETE values over the 20 Markov orders, and the ETE value of a trio is the average over all of its pairs' ETE values. All ETE calculations in this research were performed using the calc_ete() function from the RTransferEntropy package in R (Behrendt et al., 2019).

Empirical Dynamic Modelling

To quantify the predictability of a system (i.e., group) and of individual musicians within a system, we utilized techniques from EDM. EDM is a class of nonparametric techniques for predicting future instances of a time series by reconstructing the attractor manifold of the time series, possibly in combination with other time series that belong to the same dynamical system (Ye et al., 2015). Predictions are made by searching for similar patterns (i.e., neighboring points on the manifold) in the history of the time series, weighting each pattern by how recently it occurred and then taking the average of the values that followed these patterns. The accuracy of these predictions is measured by taking the Pearson correlation coefficient ρ of predicted versus actual values. A correlation of 1 here would imply that the model makes perfect predictions. By identifying nearest neighbors on the manifold, EDM can uncover both linear as well as nonlinear dynamics, whereas mechanistic models often fail in the latter case (Perretti et al., 2013). Precisely because behavior in improvised, creative joint action is difficult to explain solely through low-level mechanisms such as mimicry and rhythmic entrainment, we cannot simply assume the dynamics within these musical trios to be successfully modeled in a linear fashion (Zhai et al., 2016). This robustness of EDM (as well as ETE) in the face of nonlinearity is what motivated its use in this study.

The specific EDM technique we used is the Simplex projection forecasting algorithm, which can perform both univariate and multivariate time series forecasting based on a weighted average of nearest neighbors in the time series phase space (Sugihara & May, 1990). Consistent with our application of ETE that included Markov orders between 1 and 20, we computed values of ρ for up to 20 time points into the future (the "prediction horizon"). The predictability of a given time series (musician) or system (trial) was then computed as the average of its ρ coefficients over these 20 prediction horizons.

In all of our applications of ETE and EDM, we only considered the part of the improvisation up to the moment at which at least one musician has stopped playing. The reason for excluding the part of the improvisation after which at least one musician has finished playing is that these parts are not representative of the improvisation as a whole and may thus affect the results to varying degrees depending on how "drawn out" the ending is.

Analysis Plan

All code and data for our analyses are available at: https://osf.io/ 7f3sy (Vaarten & Wiltshire, 2023). As a prerequisite for any further analysis using ETE and EDM, we must first test whether these methods capture any coordination within groups at all (Hypothesis 1), and if so, which acoustic feature(s) best allow(s) them to do so. Testing the technique–feature combinations against the null requires surrogate data, which we obtained via a participant shuffling approach: we computed ETE and ρ values for all 192 possible "real" trios of musicians (same group, same trial) and for an equal number of "random" trios (same group, different trials) on each acoustic feature. The participant shuffling approach was chosen because, compared to more destructive approaches such as permutation testing (Moulder et al., 2018), it leads to a more conservative assessment of which features are informative. If an acoustic feature is successful in capturing intermusician coordination, then that feature should yield significantly higher ETE and ρ values for real pairs and trios than for random pairs and trios. Qualitative observation using quantile–quantile plots indicated strongly skewed distributions for both ETE and prediction horizon-averaged ρ values. As such, "real" and "random" results were compared using two-samples Wilcoxon tests rather than *t*-tests. If an acoustic feature gives rise to significantly higher ETE and ρ values for real trios than for random trios, then we can safely assume that the acoustic feature reliably encodes coordination in a performance. For subsequent research questions, we went on to only include acoustic features that could convincingly distinguish real trios from random trios in combination with both ETE and EDM.

For this part (Hypothesis 1) of the analyses, the key variables are as follows. *Group-level ETE*: This represents the amount of information flow within an improvisation. Calculated by averaging all six pairwise ETE values in the improvisation. *Group-level predictability*: Our measure of the predictability of a given performance, computed as follows: (a) use the Simplex algorithm to make predictions for each prediction horizon between 1 and 20, at every time step in the performance; (b) calculate ρ for each prediction horizon between 1 and 20. First have musician one serve as the "to-be-predicted" time series, then musician two, and finally musician three; (c) average ρ over the 20 prediction horizons for each musician and over the states; and (d) average ρ over the three musicians. This is the group-level predictability for a trial.

For Hypothesis 2, we investigated a possible link between the supposed coordination captured by ETE and EDM and the subjective quality of joint improvisations. Each performance from Experiment 2 was rated by the three musicians taking part in it, and we took the average of their ratings to be the subjective quality of an improvisation. We also introduced a measure for the unidirectionality of information flow within a trio and, likewise, investigated how this relates to the quality of the improvisation. Tests in this part were conducted using linear mixed-effects models with random intercepts for the Trio ID. Our measures for the amount of information flow, directionality of information flow, and group-level predictability served as the independent variables (IV), while the subjective quality of improvisations was the dependent variable (DV) in all models. The subjective quality of improvisation variable had one missing value, so 143 of the 144 trials from Experiment 2 were used. Model selection was done via a stepwise comparison of Bayesian information criterion (BIC) values for different combinations of IVs, using the compare_performance function from the *performance* package in R (Lüdecke et al., 2021). The various assumptions of linear mixed effect models, such as linearity of the relationship and homoscedasticity of residuals, were tested on the selected model using the check_model function, also part of the aforementioned *performance* package. A log or square root transformation was applied to the DV if this ensured that assumptions were not violated. This procedure was applied to all mixed models in this research.

Specifically, the variables used in this part of the analyses are provided below, with descriptions for newly introduced variables (see prior descriptions for already introduced variables). *Trio ID*: An identifier that indicates which of the 12 trios recorded the improvisation was included as a random effect in the mixed models. *Subjective quality of improvisation*: The musicians' average enjoyment rating for a given trial, on a 7-point Likert scale, which served as the DV in these models. *Unidirectionality index*: The unidirectionality index for a pair was computed by calculating the ETE values of a pair both ways, then dividing the larger value by the smaller one.[4] The unidirectionality index for a trial, then, is the average unidirectionality index over the three unique pairs within the trio. A value close to 1 implies a strong presence of

[4] To avoid dividing by 0, a smoothing factor equal to the smallest nonzero pairwise ETE value (0.000001) was added to all pairwise ETE values. Moreover, pairwise unidirectionality indices were capped at 10, to compensate for the occurrence of extreme outliers.

bidirectional information flow, whereas a higher value indicates more unidirectional information flow. *Group-level ETE* and *group-level predictability* were also used.

Shared intentions, as defined in Goupil et al. (2021), are intentions that are the same across several group members; collective intentions are intentions that relate to group-level coordination, but are not necessarily shared. Sharedness of intentions is captured in the prompt number variable, while collectiveness is captured in prompt type (defined below). This hypothesis (Hypothesis 3) was put to the test with two linear mixed-effects models: one with postprompt ETE as the DV and one with postprompt ρ. Prompt type and prompt number were the IVs in both models, and random intercepts for Trio ID were included.

The following variables were used to evaluate our hypothesis on shared and collective intentions. *Postprompt ETE*: The average pairwise ETE value for the trial, only considering the part of the improvisation after the prompt, which was the DV in the first part of this analysis. *Postprompt predictability*: Average ρ for the trial, only considering the part of the improvisation after the prompt, which is the DV used in the second analysis for this part. The attractor manifold is constructed from the time series up to the prompt. *Prompt type*: What kind of prompt the musicians in the trio received (ME-goal or WE-goal). *Prompt number*: How many musicians in the trio were prompted (1–3). *Trio ID* (see above).

To investigate this hypothesis (Hypothesis 4), we first tested whether improvisers indeed transferred more information to partners when prompted with a collective intention (WE-goal) than with a noncollective intention (ME-goal) or with no intention (NO-goal). This would signify that the musician with a collective intention succeeds in getting the other musicians to adapt to her playing. This test is referred to as Hypothesis 4a in in Table 5. Moving on, we investigated whether the improvisers propagated goals by means of the coordination smoothing mechanism of making their actions more predictable (Hypothesis 4b). We did this by testing whether musicians increase the predictability of their individual playing after being prompted with a WE-goal. For these first two tests, we limited ourselves to 83 trials from Experiment 2 where group performance continued for at least 10 s after the prompt occurred (meaning all three musicians in the trial continued playing for at least 10 s), to prevent computing our measures based just on, say, the final sustained note of an improvisation. Lastly, we investigated whether greater predictability in one's playing corresponds with stronger information flow toward partners (Hypothesis 4c).

As before, variables used in this part are listed below, with detailed descriptions for newly introduced variables. *Postprompt directionality ratio*: For a pair of musicians *X* and *Y*, postprompt directionality ratio was computed by dividing postprompt $\mathrm{ETE}_{X\to Y}$ by postprompt $\mathrm{ETE}_{Y\to X}$. A value above one here indicates that musician *X* transferred more information to musician *Y* than vice versa. This was used as the DV in our test of whether information transfer to and from partners is affected by the type of intention present in the improviser and in the partner. *Postprompt individual predictability*: Postprompt ρ for an individual musician. A higher value indicates that a musician played more predictably after the prompt. ρ was computed for one musician at a time, only using the time series of the musician themselves as the state space history. This was used as DV to test whether musicians use increased predictability as a "coordination smoothing" device. *Individual prompt type*: Denotes the prompt an individual musician received. Recall that this is not necessarily the same as the group-level prompt: If a musician remained unprompted while its two partners were prompted with a WE-goal, the individual prompt type for this musician is thus NO-goal. *ETE to partners*: The average ETE from the musician in question to their two partners. *Individual predictability*: ρ for an individual musician, for the full duration of their playing in the trial, which was used as IV to investigate its effect on pairwise ETE.

Results

In evaluating the first hypothesis, Wilcoxon rank-sum tests revealed significant differences between real-trio and random-trio ETE values for time series of the acoustic features RMS amplitude (M_{real}=0.0022, SD_{real}=0.0017; M_{random}=0.0008, SD_{random}= 0.0008; p < .001), ZCR (M_{real} = 0.0018, SD_{real} = 0.0014; M_{random} = 0.0012, SD_{random} = 0.0020; p < .001), fractal dimension (M_{real}=0.0014, SD_{real}=0.0011; M_{random}=0.0008, SD_{random}= 0.0014; p < .001), and spectral centroid (M_{real} = 0.0018, SD_{real} = 0.0014; M_{random} = 0.0012, SD_{random} = 0.0020; p < .001). For Tonnetz distance (M_{real} = 0.0019, SD_{real} = 0.0012; M_{random} = 0.0019, SD_{random} = 0.0023; p = .53) and spectral flatness (M_{real} = 0.001, SD_{real} = 0.0009; M_{random} = 0.0008, SD_{random} = 0.0008; p =.07), real-trio ETE did not differ from random-trio ETE. Comparisons between real and random trios for all features are shown in Figure 3.

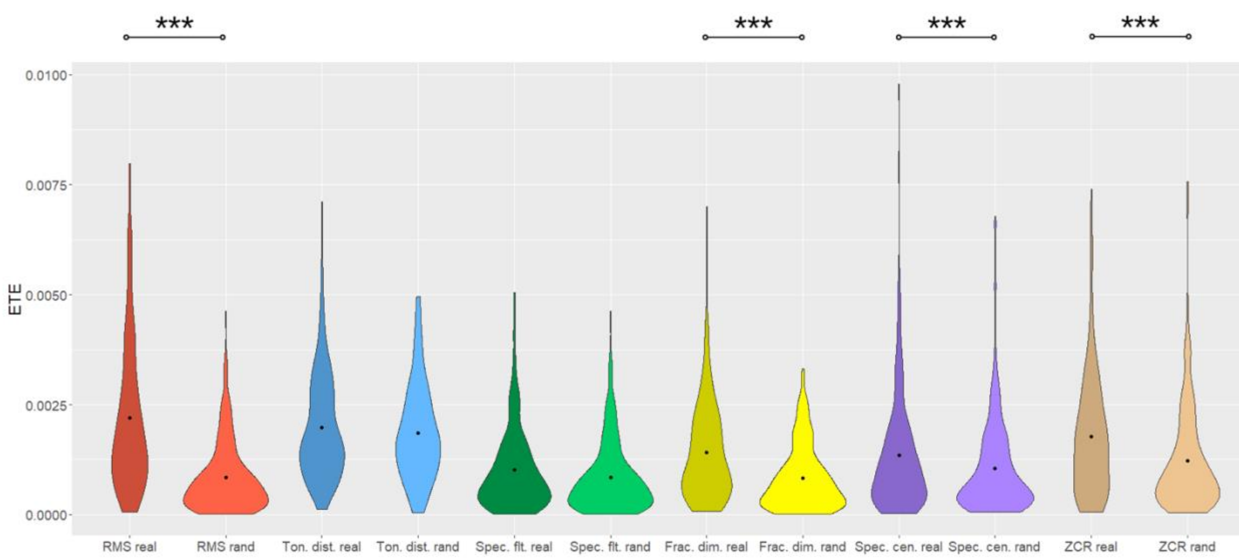


Figure 3: The RMS amplitude, fractal dimension, spectral centroid, and zero-crossing rate time series for real trios resulted in ETE values that were significantly higher for real trios than for random trios. RMS amplitude looks to be the feature that most reliably captures coordination.

Note. RMS amplitude looks to be the feature that most reliably captures coordination. RMS = root-mean-square; ETE = effective transfer entropy. See the online article for the color version of this figure.
*** $p < .001$.

When applying EDM to real trios versus random trios and extracting the ρ coefficients, significant differences were found for RMS amplitude ($M_{\text{real}} = 0.184$, $SD_{\text{real}} = 0.128$; $M_{\text{random}} = 0.099$, $SD_{\text{random}} = 0.078$; $p < .001$), Tonnetz distance ($M_{\text{real}} = 0.045$, $SD_{\text{real}} = 0.030$; $M_{\text{random}} = 0.024$, $SD_{\text{random}} = 0.020$; $p < .001$), and spectral flatness ($M_{\text{real}} = 0.082$, $SD_{\text{real}} = 0.076$; $M_{\text{random}} = 0.052$, $SD_{\text{random}} = 0.050$; $p < .001$), but not for ZCR ($M_{\text{real}} = 0.106$, $SD_{\text{real}} = 0.080$; $M_{\text{random}} = 0.101$, $SD_{\text{random}} = 0.077$; $p = .61$), fractal dimension ($M_{\text{real}} = 0.158$, $SD_{\text{real}} = 0.102$; $M_{\text{random}} = 0.150$, $SD_{\text{random}} = 0.085$; $p = .51$), and spectral centroid ($M_{\text{real}} = 0.122$, $SD_{\text{real}} = 0.090$; $M_{\text{random}} = 0.118$, $SD_{\text{random}} = 0.088$; $p = .73$). Comparisons between real and random trios for all features are shown in Figure 4. Additionally, correlations between ETE and ρ coefficients for the various features can be found in Table S2 in the online supplemental materials.

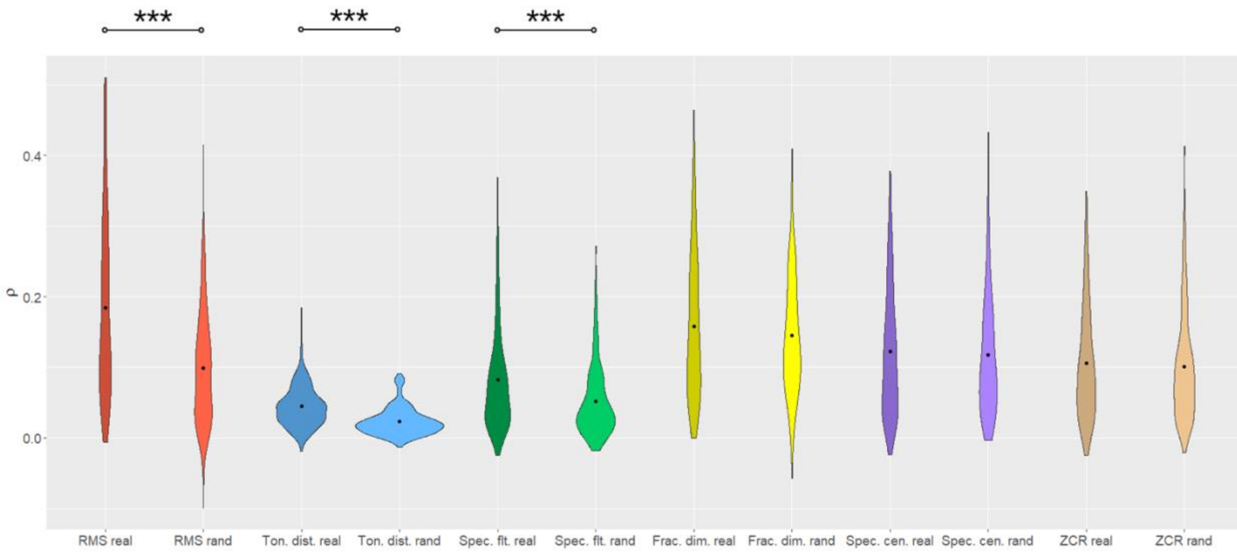


Figure 4: RMS amplitude, Tonnetz distance, and spectral flatness yielded significantly higher ρ values for real trios than for random trios.

Note. Again, RMS amplitude was the feature that most reliably differentiated real and random trios. RMS = root-mean-square. See the online article for the color version of this figure.
*** $p < .001$.

RMS amplitude is thus the only feature that allowed both ETE and EDM to distinguish real trios from random trios to a statistically significant degree. Moreover, the violin plots in Figures 3 and 4 show larger differences between real and random trios for RMS amplitude than for any of the other features, and the correlations in Table 1 suggest a high level of redundancy among many of the features. With these findings in mind, and in the interest of streamlining our statistical analysis, we continued our research using RMS amplitude as our acoustic feature of choice.

In testing Hypothesis 2, results from our linear mixed-effects models with subjective quality of improvisation as the DV showed that group-level ETE and group-level predictability appeared to have weak positive effects on subjective quality of improvisation, but none of the

IVs reached significance. Overall, the model was a poor fit of the data with a conditional R^2 of .241 and a marginal R^2 of .015, meaning the fixed effects only explained about 1.5% of the observed variance in the data. Stepwise removal of IVs did not noticeably improve model fit. The results from the mixed model are summarized in Table 2.

Table 2

Mixed-Effects Model for Hypothesis 2

DV	**BIC**	***R²*** **(cond.)**	***R²*** **(marg.)**	
Subj. quality	352.467	0.241	0.015	
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	4.768	0.233	20.482	<.001
ETE	44.190	39.18	1.128	.261
Predictability	0.709	0.605	1.172	.243
Unidirectionality	0.017	0.032	0.515	.607

Note. DV = dependent variable; BIC = Bayesian information criterion; ETE = effective transfer entropy.

To test Hypothesis 3, postprompt ETE values were square root transformed, as this ensured that the assumption of normally distributed residuals was met for the mixed model. The full model, with postprompt ETE as the DV and all IVs included, was a mediocre fit of the data with a marginal R^2 of .092. Iterative model selection based on BIC yielded a linear model with prompt type as the only predictor, which was not significant. The mixed models with postprompt ETE as DV are summarized in Table 3.

Table 3

Mixed-Effects Models for Hypothesis 3, With Postprompt ETE as the DV

DV	**BIC**	**R^2 (cond.)**	**R^2 (marg.)**	
Postprompt ETE	-1140.806	0.197	0.092	
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	0.064	0.012	5.163	<.001
Pr. Num.	0.006	0.006	1.051	.297
Predictability	-0.023	0.016	-1.434	.156
Unidirectionality	0.005	0.008	0.654	.515

DV	**BIC**	**R^2 (cond.)**	**R^2 (marg.)**	
Postprompt ETE	-1143.485	0.141	0.036	
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	0.076	0.006	12.952	<.001
Pr. Type (WE)	-0.012	0.007	-1.833	.070

Note. ETE = effective transfer entropy; DV = dependent variable; BIC = Bayesian information criterion. The prompt type ‘WE’ indicates musicians were prompted with a collective intention (as opposed to an individual intention, i.e. a ME-prompt).

Next, we ran a mixed model with postprompt predictability as the DV and the same IVs as the previous model. The full model displayed a marginal R^2 of .131, better than the full model with ETE as the DV. Again, a BIC-based stepwise procedure was applied for model selection, and this resulted in a model with prompt number as the only IV. Prompt number was highly significant as a positive predictor of postprompt predictability, suggesting that as more musicians in a trio shared an intention, be it a collective or noncollective one, coordination within the trio improved. Results from the mixed models with group-level predictability are shown in Table 4, and results for both aspects of this hypothesis are shown in Figure 5.

Table 4

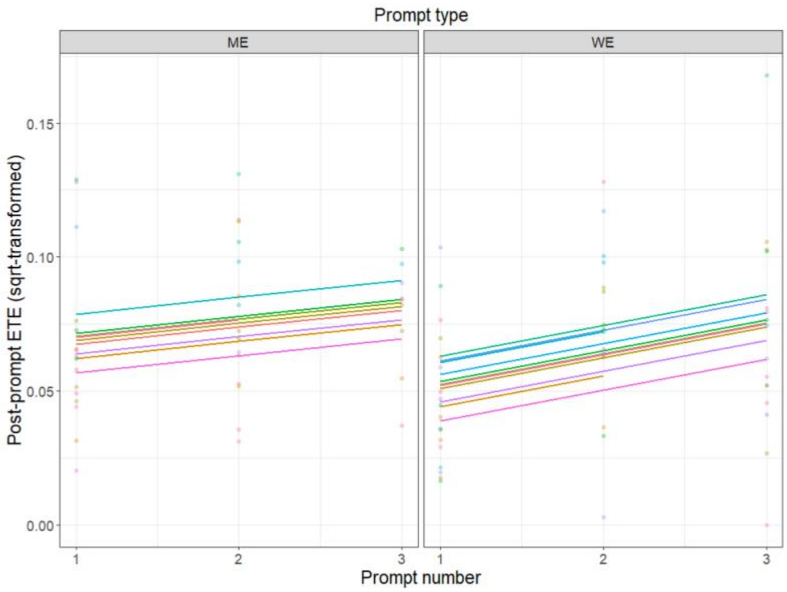
Mixed-effects models for hypothesis 3, with postprompt predictability (i.e., ρ) as the DV.

DV	**BIC**	**R^2 (cond.)**	**R^2 (marg.)**	
Postprompt pred.	-35.070	0.181	0.131	
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	0.090	0.071	1.271	.207
Pr. Num.	0.400	0.035	1.127	.263
Predictability	-0.186	0.137	-1.356	.179
Unidirectionality	0.066	0.046	1.427	.158

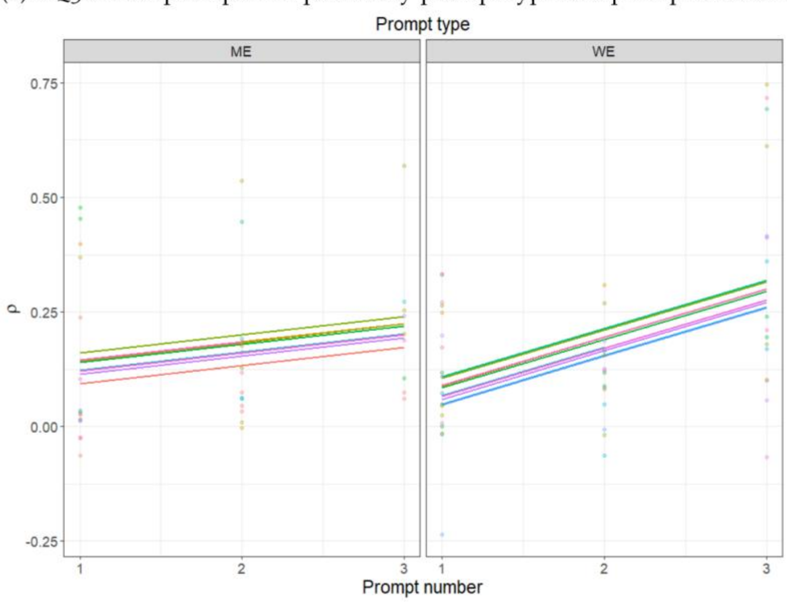
DV	**BIC**	**R^2 (cond.)**	**R^2 (marg.)**
Postprompt pred.	-42.016	0.158	0.114

Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	-0.057	0.006	-0.831	.408
Pr. Type (WE)	0.078	0.023	3.469	<.001

Note. DV = dependent variable; BIC = Bayesian information criterion.



(a) RQ3a: Post-prompt ETE plotted by prompt type and prompt number.



(b) RQ3b: Post-prompt predictability plotted by prompt type and prompt number.

Figure 5: These plots show the effect of prompt type and prompt number on postprompt ETE and postprompt ρ.

Note. The different colors of the lines indicate random intercepts for the various trios. A significant positive effect was found for prompt number on postprompt ρ.

To investigate our last hypothesis, we created a linear model with postprompt directionality ratio as the DV and from-prompt and to-prompt as the IVs. The reference level was NO-goal for both of the IVs. To counteract nonnormality of residuals, we applied a log transformation to postprompt directionality ratio. While collective intentions weakly predicted information transfer in our model, this relationship did not approach significance and neither did any of the other relationships. This remained so when removing the to-prompt IV. The results of the model are shown in Table 5.

Table 5

Linear Model for Hypothesis 4a, With Postprompt Directionality Ratio as DV

DV	**F**	**DF**	R^2 **(mult.)**	R^2 **(adj.)**
Postprompt dir. ratio (log)	0.303	4, 244	0.005	-0.011
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	-0.580	0.343	-1.692	.091
From-prompt (ME)	0.241	0.441	0.546	.586
From-prompt (WE)	0.354	0.410	0.764	.388
To-prompt (ME)	-0.007	0.440	-0.015	.988
To-prompt (WE)	-0.264	0.406	-0.650	.516

Note. DV = dependent variable.

Next, we ran a linear model with postprompt individual predictability as the DV and from-prompt as the IV. Here, we observed that having an intention to end the piece increased the predictability of individual musicians' playing. This was the case for both individual (ME-goal) and collective intentions (WE-goal), with a more pronounced effect in the case of collective intentions. However, a Wilcoxon test did not reveal a difference between the ME-goal and WE-goal condition (M_{WE} = 0.202, SD_{WE} = 0.199, M_{ME} = 0.195, SD_{ME} = 0.192, p = .69); notably, individual predictability varied greatly in all conditions. The results of the model are summarized in Table 6, with Figure 6 showing a comparison of the different conditions.

Table 6

Linear Model for Hypothesis 4b, With Postprompt Individual Predictability as the DV

DV	**F**	**DF**	R^2 **(mult.)**	R^2 **(adj.)**
Postprompt ind. pred.	4.024	2, 246	0.032	0.024
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	0.128	0.019	6.599	<.001
From-prompt (ME)	0.065	0.030	0.546	.032
From-prompt (WE)	0.071	0.027	2.625	.009

Note. DV = dependent variable.

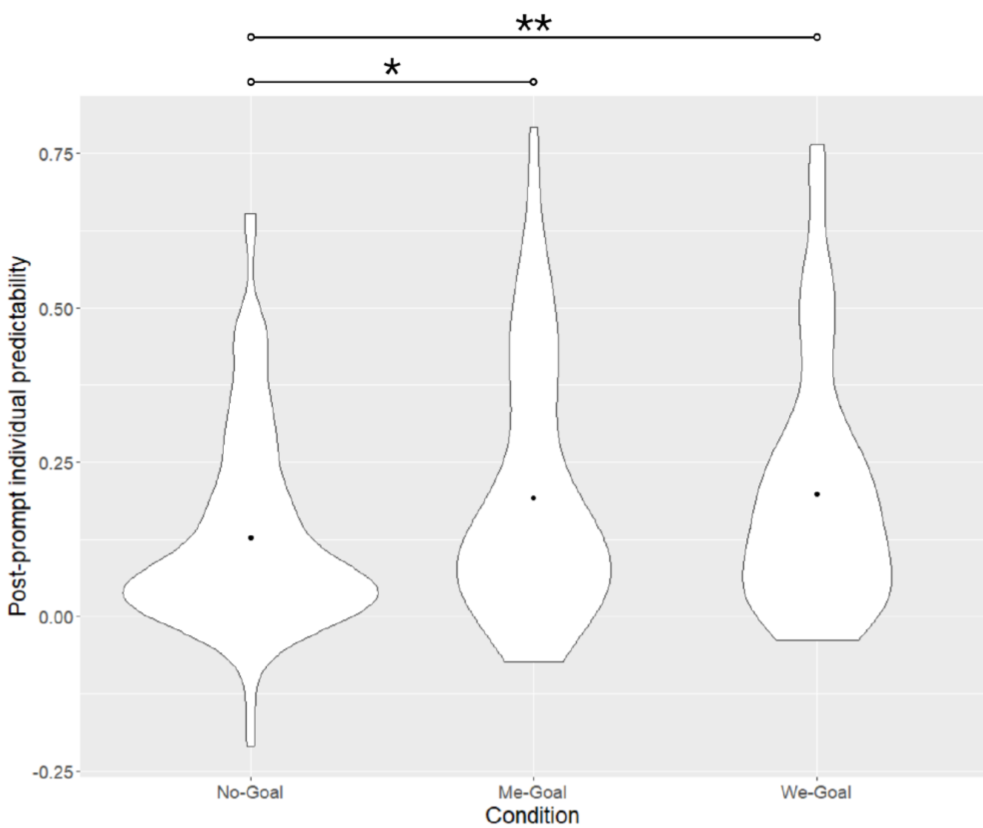


Figure 6: Postprompt predictability of individual musicians' playing, grouped by the type of prompt the musician received

Note. Overall, musicians who were prompted and thus had an intention to end the piece played more predictably than unprompted musicians.
*p < 05. **p <01.

Finally, we ran a linear model with ETE to partners as the DV and individual predictability as the IV. Contrary to our hypothesis, no relationship was observed, indicating that greater predictability in one's playing did not in fact result in greater information transfer to partners as quantified by ETE (see Table 7).

Table 7

Linear Model for Hypothesis 4c, With ETE to Partners as the DV

DV	**F**	**DF**	**R^2 (mult.)**	**R^2 (adj.)**
ETE to partners	0.548	1, 550	0.001	-0.001
Effect	**Estimate**	**Std. Error**	***t***	***p***
Intercept	0.005	0.000	17.81	<.001
Ind. predictability	-0.001	0.001	-0.74	0.459

Note. ETE = effective transfer entropy; DV = dependent variable.

Discussion

In line with our first hypothesis, application of ETE and EDM to acoustic features resulted in higher ETE and ρ values for real trios than for random trios. This was most apparent for RMS amplitude, the most low-level acoustic feature, where the analysis yielded significantly higher ETE and ρ values for real trios than random trios. ETE also yielded significant differences in combination with fractal dimension, ZCR, and spectral centroid, as did EDM in with spectral flatness and Tonnetz distance. An explanation for why RMS amplitude led to somewhat more convincing results than the other features is that the more high-level features may only encode useful information for a subset of instruments and performances, whereas our data contained a broad range of different instruments and playing styles. For example, spectral flatness is likely to be most appropriate when dealing with instruments that allow for the manipulation of timbre and when the performer playing the instrument makes use of the instrument's capacity for timbre variation. Similarly, a tonality-based measure like Tonnetz distance is most likely only suited to pitched instruments, which exclude many percussion instruments and even excludes pitched instruments when these are used to play a continuous drone or percussive pattern. A note for future research is to consider choosing the included acoustic features on a case-by-case basis, taking the innate properties of the instruments and the method of playing into consideration. Another approach that may prove fruitful is the inclusion of cross-feature comparisons, as done on a large scale in a study of (partially) improvised jazz music by Pachet et al. (2017). It would also be interesting to discover whether our finding of ETE and EDM pairing better with different sets of acoustic features is consistent across different data sets.

Regarding our second hypothesis investigating the relationship between the coordination measures and ratings of enjoyment, we ran models with musicians' enjoyment ratings of improvisations as the DV and the results obtained with ETE and EDM as IVs. We expected the relationship with the DV to be positive for ETE and ρ and negative for unidirectionality. We observed very weak positive relationships for ETE and ρ, but these did not reach significance. No relationship was found for unidirectionality, and the model as a whole poorly explained the variance. From this, we can conclude that neither ETE, nor ρ, nor unidirectionality was reliable predictors for the perceived quality of a joint (musical) improvisation. This could be explained by the fact that our analysis was strictly a global one: obtaining performance-wide ETE, ρ, and unidirectionality values meant averaging properties that might vary over the course of a performance, thereby sacrificing information available at the local level. Gray and Lindstedt (2017) suggest that periods of lower coordination ("dips") might in fact represent creative exploration, where a trade-off is made between optimal coordination and an effort to be more creative. Similarly, Borgo (2022) argued that "if too many references to traditional musical idioms creep into a performance or an underlying harmonic character or tempo lingers for too long, many [contemporary musical] improvisers will immediately begin to search for more uncharted and uncertain musical terrain" (p. 127). Given that subjective quality ratings were provided by the musicians themselves, it could very well be that periods of "messy" exploration did not affect their appreciation of the performance negatively. It would be interesting to examine in future research whether the strength of coordination—both globally and locally—impacts appreciation of a musical performance differently for passive listeners than it does for musicians who actively took part in the performance. In general, future research would benefit from zooming in on the significance of local fluctuations in coordination in creative joint action. The approach taken by Jakubowski et al. (2020), where participants rated the synchrony of musical excerpts continuously throughout the piece, is of particular interest and could be extended to include qualities beyond synchrony. As for quantitative local measures of coordination, one could look to local TE, a measure of TE computed at each time point rather than over the entire history. To the best of our knowledge, this method has not seen any use in human joint action research as of yet, but Tomaru et al. (2016) describe an interesting application for analyzing swarm behavior in soldier crabs.

For our third hypothesis, we posited that shared and collective intentions would positively affect coordination as quantified by ETE and EDM. For ETE, no significant effects were found. When applying EDM, sharedness of intentions was a significant positive predictor of group-level predictability. This result is in line with our hypothesis and with the findings by Goupil et al. (2021), which revealed strong effects of shared intentions on perceived coordination in joint improvisation. However, no significant main effect for prompt type was observed, nor did the positive interaction effect of prompt type and prompt number reach significance. The results thus suggest that what matters most for coordination is that an intention is shared by several group members, even if this intention does not involve actively coordinating with other group members. This is in accordance with the view, put forth by Bratman (2009), that the kind of shared intentions that facilitate successful joint action can emerge from multiple noncollective, individually held intentions. However, we should be careful to draw such a conclusion based solely on the specific scenario and the two intentions investigated here, and more research in different task settings and coordination in other modalities would be needed to corroborate this view.

As our fourth and final hypothesis, we expected that improvisers would propagate intentions through increased predictability of their actions. Our model with individual postprompt predictability as the DV and individual prompt type as the IV showed that musicians' playing became more predictable as soon as they had an intention to end the performance. This was the case regardless of whether the intention was collective or not; although the effect was more pronounced for collective intentions, no significant difference was found when comparing the WE-goal to the ME-goal condition. Our interpretation of this is that musicians, for artistic reasons, play more predictably in the final phase of a performance, perhaps not considering the ending of a performance to be an appropriate moment for unexpected creative exploration. Our results do not, however, suggest that improvisers increased the predictability of their actions specifically to signal intentions to partners and improve coordination. Lastly, we did not observe any relationship between the predictability of an individual's playing and the amount of information they transferred, and no significant relationships were observed between the type of intention an improviser held and the amount of information the improviser transferred to partners. Perhaps this is an indication that our methods were not fine-grained enough to identify more nuanced and shorter periods of coordination between the musicians. Again, we stress the importance of investigating local coordination dynamics in future research to address this limitation.

Conclusion

Our research showed that ETE and EDM hold promise as methods with which to quantify coordination in joint improvisation tasks, with both of these methods allowing us to distinguish coordination from noncoordination even in a highly unstructured, nonpulsed musical improvisation. For the specific musical improvisation task researched here, RMS amplitude was the acoustic feature that most reliably encoded intermusician coordination. The success of the other features was more limited and dependent on whether they were used in combination with ETE or EDM. Our results indicate that as (highly general) intentions in joint improvisation become more shared, this positively contributes to coordination, regardless of whether the intention is collective or not. We also found evidence that musicians increased the predictability of their playing as they intended to end a performance, yet we could not establish whether this was done as a means of smoothing coordination with partners. Future research could benefit from more closely examining local changes in coordination dynamics and what they mean for the quality of a joint improvisation, perhaps through a local-level variant of the methodology we have developed here. Another interesting venue for future work would be to apply our design to other forms of joint action and joint improvisation, to investigate the extent to which our observed effects of shared and collective intentions hold up in different task settings.

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