CAPTURING HIGH-LEVEL INTENTION SIGNALLING IN JOINT IMPROVISATION: A COMPLEX SYSTEMS APPROACH

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1 MOTIVATION

Joint action, or the "coordination of bodies and minds", can be described as any activity that involves at least two individuals coordinating their actions to achieve a joint outcome (Knoblich, Butterfill, & Sebanz, 2011). It is a fundamental part of human life and appears in situations ranging from highly creative and expertise-dependent tasks, to comparatively simple day-to-day activities. Successful coordination and cooperation in joint action scenarios largely rests on continuously monitoring the success of the joint action, predicting partners' actions and, in turn, making one's own actions easier to predict (Vesper, Butterfill, Knoblich, & Sebanz, 2010). Ideally, the need for such prediction is minimized through 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 action-based communication to signal their intentions to coactors (Sebanz & Knoblich, 2021). Making one's actions more predictable by reducing its variability (Lelonkiewicz & Gambi, 2020) and exaggerating certain parameters of an action (Pezzulo, Donnarumma, & Dindo, 2013) are at least some of the ways in which humans use action-based intention signalling to 'smoothen' their coordination. Yet further research is needed to establish exactly how joint action partners settle upon a course of action when faced with asymmetrical knowledge, perception and/or abilities (Sebanz & Knoblich, 2021).

With this research, we aim to use techniques originating in complex systems science to quantify the elusive phenomenon of intention signalling in an improvised joint action setting with particularly limited modes of communication. We hereby aim to find out how humans, under these rather extreme conditions, succeed in propagating their goals to coactors and settling on a joint course of action. As the basis of our analyses, we make extensive use of data collected and generously made available by Goupil, Wolf, Saint-Germier, Aucouturier, and Canonne (2021). Briefly summarised, 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 communicate to each other in a straightforward fashion, since each musician in a trio played in a separate booth. 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 affect the quality of an improvisation, presumably through stronger inter-musician coordination.

In this research, we build on the assumption that successful coordination in joint action is strongly related to recurrent, tight interactional patterns Fusaroli and Tylén (2016). As our methods with which to quantitatively capture coordination within these groups of improvising musicians, we introduce novel implementations of Transfer Entropy (Transfer Entropy) (Schreiber, 2000) and Empirical Dynamic Modelling (EDM) (Sugihara et al., 2020) over a set of acoustic features, and empirically test the capacity these modelling techniques have in capturing inter-musician coordination when deployed on the acoustic features. Following a baseline test of validity, the remainder of the research will use Transfer Entropy to examine how improvisers' intentions relate to magnitude and directionality of information flow, while EDM is used to investigate how intentions affect the predictability of the trio and its constituent musicians. We hypothesize 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 other group members. Furthermore, we hypothesize that predictability at the system level increases as collective intentions become more shared. We additionally expect musicians to increase the predictability of their playing upon being prompted with a collective intention, as a means of action-based intention signalling. Lastly, we will examine possible connections between information flow and group-level predictability on the hand, and Enjoyment Ratings by listeners on the other. Here, we expect greater information flow, stronger bidirectionality of information flow and greater group-level predictability to all positively affect listener appreciation of performances.

We hope that our research will shed light on the issue of how high-level intentions are communicated and propagated in joint action scenarios and how this information exchange impacts the success of a joint action, in particular where modes of communication are very limited. Unlike much of the existing work (Noy, Dekel, & Alon, 2011; Setzler & Goldstone, 2020; Valdesolo, Ouyang, & DeSteno, 2010), this research will investigate joint action in a non-dyadic scenario, and in a realistic, non-trivial task where shared high-level goals likely factor in achieving a desirable outcome. Investigation of whether the sharedness and collectiveness of high-level goals is reflected in information flow and system predictability can 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 behaviour more effectively (Lelonkiewicz & Gambi, 2020; Vesper, Van Der Wel, Knoblich, & Sebanz, 2011). We also aim to establish how the results we obtain with Transfer Entropy and EDM tie back to subjective experience by testing for effects of information flow and system predictability on listeners' Enjoyment Ratings of the performance. 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 behaviour provide any indication of the quality of a joint improvisation.

An overview of the hypotheses and their constituent tests is provided below:

Hypothesis I It is possible to distinguish between coordinating and non-coordinating musicians by applying Transfer Entropy (Transfer Entropy) and Empirical Dynamic Modelling (EDM) to acoustic feature time-series.

- RQ1a *Transfer Entropy on RMS amplitude time-series.*
- RQ1b *Transfer Entropy on tonal centroid time-series.*
- RQ1c *Transfer Entropy on spectral flatness time-series.*
- RQ1d *EDM on RMS amplitude time-series.*
- RQ1e *EDM on tonal centroid time-series.*
- RQ1f *EDM on spectral flatness time-series.*

Hypothesis II Amount of information flow, directionality of information flow and group-level predictability are indicative of subjective quality of improvisations.

RQ2a *Does the amount of information flow predict musicians' enjoyment of improvisations?*

RQ2b *Does directionality of information flow predict musicians' enjoyment of improvisations?*

RQ2c *Does group-level predictability predict musicians' enjoyment of improvisations?*

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Hypothesis III Sharedness and collectiveness of intentions predict coordination during musical improvisations.

RQ3a *Is greater sharedness and collectiveness of intentions reflected in greater information flow?*

RQ3b *Is greater sharedness and collectiveness of intentions reflected in greater group-level predictability?*

Hypothesis IV How do individually held or partially shared intentions propagate through a group of improvisers?

RQ4a *Do improvisers' intentions predict directionality of information flow?*

RQ4b *Do improvisers transfer more information to partners when their actions are more predictable?*

RQ4c *Do improvisers signal their intentions by increasing the predictability of their actions?*

2 BACKGROUND

2.1 *Joint Action and Joint Improvisation*

A large chunk of the literature on joint action has focused on cooperation towards shared goals on the basis of motor synchronization (Friston, Mattout, & Kilner, 2011; Kawasaki, Kitajo, & Yamaguchi, 2018; Wolpert, Doya, & Kawato, 2003), with researchers investigating how dyads achieve simple interpersonal motor coordination, such as synchronously walking side-by-side (Almurad, Roume, & Delignières, 2017). 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 (Sartori & Betti, 2015). Complicating matters further, real-life joint action often occurs in the absence of pre-established plans; in such situations, humans have to use signalling strategies to communicate plans on the fly (Candidi, Curioni, Donnarumma, Sacheli, & Pezzulo, 2015) and appear to be more actively mentalizing, i.e. interpreting partners' behaviour as underlying mental states (Chauvigné, Belyk, & Brown, 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, Paternotte, & Canonne, 2021). The spontaneous development of complementary strategies and the signalling of higher-level intentions can go a long way towards achieving a desirable performance in joint improvisation scenarios (Sartori, Betti, & Castiello, 2013).

2.2 *Joint Action Scenarios as Complex Systems*

In recent years, parallels have been drawn between complex systems and joint action (Trendafilov, Polani, & Ferscha, 2021). Complex systems can be described as collections of relatively simple entities that give rise to global behaviour of far greater complexity than the behaviour of any single entity in the system (Prokopenko, Boschetti, & Ryan, 2009). In order for entities to be part of the same system, there must be some level of information transfer between entities, which is also known as coupling (Paluš, 2019). Transfer Entropy (Transfer Entropy) and Empirical Dynamic Modelling (EDM) techniques have traditionally been used in the study of complex systems; more recently, Transfer Entropy as a metric has seen limited and modestly successful use in capturing coordination in simple forms of joint action. For example, Trendafilov, Schmitz, Hwang, Effenberg, and Polani (2020) found that in a simple rhythmic joint action task, tight bidirectional coupling slightly improved task performance and was positively correlated with subjective measures of coordination. A recent study by Wiltshire and Fairhurst (2022) also showed promising results in the use of both Transfer Entropy 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 and creatively demanding form of improvised joint action. Further application of predictive techniques from EDM in joint action research has not been observed. As in complex systems, coupling between two entities in a joint action scenario can be unidirectional, with adaptation only occurring in one direction, or bidirectional, in which case both subsystems (i.e. individuals) share in the adapting. 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 forms of non-verbal communication, such as head movements, to maintain temporal coordination on small timescales as well as expressively signal intentions that are most apparent on longer timescales Hilt et al. (2019). 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, Carter, Wanderley, & Palmer, 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). However, teasing apart low-level coupling and coordination that occurs around a rhythmic pulse from coupling of higher-level plans poses a serious challenge, not in the least due to the inherently rhythmic nature of most forms of music. As such, not much is clear about the inner workings of how these higher-level goals and intentions are propagated, and what the role of (bidirectional) coupling is in this form of goal propagation. In the case of Collective Free Improvisation (CFI), performers refuse to establish plans on the content of a performance beforehand, and performances are generally devoid of clear temporal structure such as a regular pulse (Canonne, 2018). 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 signalling of high-level goals, and which is particularly suitable for investigating the role of high-level goals in joint improvisation (Canonne & Garnier, 2012).

3 MATERIALS AND METHODS

3.1 *Data*

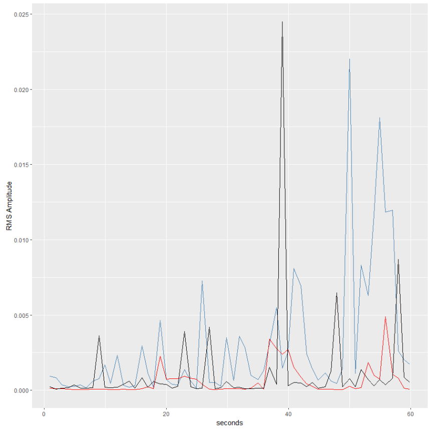
The dataset we use was collected as part of a study by Goupil, Wolf, Saint-Germier, Aucouturier, and Canonne (2020), which aimed to investigate the effects of shared information, collective intentions and shared intentions on the presence of signalling strategies. 'Signalling strategies' refers to any means in which musicians signal their intentions to their fellow musicians, thereby propagating their individual intention to make it a shared intention. To this end, the researchers invited 21 musicians (19 m/2 f, mean age = 39.8, SD = 9.1 years) to record improvised musical group performances. All were professional musicians who were actively involved in Collective Free Improvisation (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. 15 of the 21 musicians played in two different trios. Across two experiments, each of the trios recorded 16 performances, adding up to a total of 192 recordings. Musicians played and were recorded in separate booths, and were therefore unable to communicate with each other through any non-musical modality.

The first experiment consisted of 4 trials per trio, in which the musicians received the instruction to perform for approximately 3-4 minutes, 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 s to 391 s (mean = 203 s, SD = 53 s). The second experiment featured another 12 trials per trio. 1-3 musicians in each trial received a prompt over their headphones that instructed them to either work towards a suitable ending for their own part (ME-goal) or a suitable ending for the group (WE-goal). For each trial in this experiment, the musicians were asked to rate on a 7-point Likert scale their enjoyment of the improvisation. Because of this additional information on intentions and the enjoyment ratings, we will limit ourselves to data from the second experiment for all research questions that relate 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 parts are not used in this research.

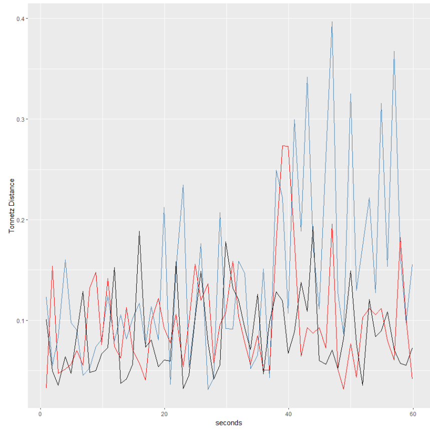
3.2 *Feature Extraction*

To facilitate the application of statistical techniques on the recordings, we extracted a number of acoustic features for each individual musician in each recording. The acoustic features we extracted for our analyses were root mean square (RMS) amplitude, tonnetz distance and spectral flatness[1]. Amplitude describes the volume of an audio signal. Spectral flatness is an indicator of how 'pitch-like' versus 'noise-like' the timbre of a sound is, with higher values for more noise-like sounds. Similarly to (Harte, Sandler, & Gasser, 2006), we compute Tonnetz distance by taking the Euclidean distance between the Tonnetz projection of a given window and of the window before it; doing so quantifies the extent of harmonic change in a musician's playing at a given time point. Time series representations of these features are extracted using the Librosa library (McFee et al., 2015) in Python. The time series for each feature are sampled using a 0.16 s non-overlapping sliding window. This particular window size was chosen because it corresponds to the average human auditory reaction time (Jain, Bansal, Kumar, & Singh, 2015), which we can assume to be the shortest possible timescale at which one can adapt to a partner's action in

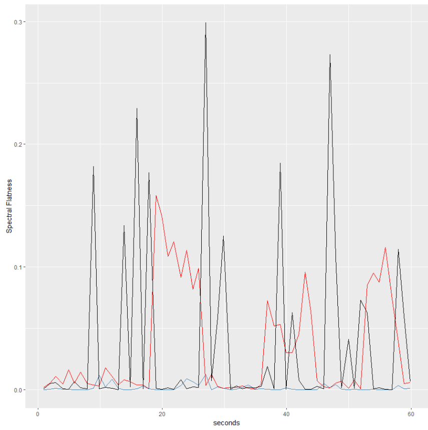
[1] The choice of features was informed by what can be reliably extracted from polyphonic audio signals. This is why, unlike similar research conducted with MIDI data (Wiltshire & Fairhurst, 2022), we do not include onset density as a feature.



(a) RMS Amplitude



(b) Tonnetz Distance



(c) Spectral Flatness

Figure 1: These plots show the time series representation of the first 60 seconds of trio 1-trial 1 on each of the acoustic features. In each plot, the three lines represent the three musicians in the trio.

a joint action scenario.[2] We expect that all of the included features encode valuable information on some aspect of coordination between musicians, and that bundling the features may give us a more reliable measure of coordination within a trio than considering one single acoustic feature. To get a sense of the variability in the features, we have plotted what the time series representations of these features look like in an example case (Figure 1).

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

3.3 *Transfer Entropy*

Transfer Entropy is a non-parametric statistical method that quantifies the amount of information flow $TE_{x \rightarrow y}$ from one stochastic process x to another process y (Schreiber, 2000). It is based on Mutual Information (MI), but differs importantly in the sense that Transfer Entropy eliminates shared history and common external influences, making it less susceptible than MI to spurious implication of dependence between two systems (Kaiser & Schreiber, 2002). Furthermore, unlike MI, Transfer Entropy reports a directional flow of information, making it a suitable measure for investigating causality within a system. Transfer Entropy bears 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, Transfer Entropy and G-Causality have been shown to be entirely equivalent when dealing with Gaussian variables (Barnett, Barrett, & Seth, 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 non-linear and/or non-Gaussian processes (Bossomaier, Barnett, Harré, & Lizier, 2016). Lindner, Auret, Bauer, and Groenewald (2019) further suggests that at least on simulated data, Transfer Entropy achieved slightly better accuracy than G-Causality in identifying true causality within complex systems. The information that Transfer Entropy 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 Transfer Entropy to quantify information flow in this research.

One limitation of Transfer Entropy 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 a hyperparameter that is referred to as the Markov order. Concretely, given two time series X and Y and a Markov order n, the values X_t and Y_t are assumed to be influenced by X_{t-n} and Y_{t-n}. To mitigate this, whenever we calculate Transfer Entropy, we use Markov orders of 1 (0.16 s) up to 20 (3.19 s), thereby effectively calculating 20 different Transfer Entropy values. The Transfer Entropy value $TE_{x \rightarrow y}$ for a pair is then the average of these 20 values (and the Transfer Entropy value of a trio is the average over all of its pairs' values).

Furthermore, Transfer Entropy strictly requires discrete data. To get our continuous time series data in a usable format, it was binned in four quartiles. All Transfer Entropy calculations in this research were performed using the calcte() function from the RTransferEntropy package in R (Behrendt, Dimpfl, Peter, & Zimmermann, 2019).

3.4 *Empirical Dynamic Modelling*

To quantify the predictability of the system (i.e. group) and of individual musicians within the system, we will look to techniques from Empirical Dynamic Modelling (EDM). EDM is a class of non-parametric 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. neighbouring points on the manifold) in the history of the time series, weighting each point by how recently it occurred and then taking the average of the values that followed these points. The accuracy of these predictions is measured by taking the Pearson correlation coefficient ρ of predicted versus actual values. Thanks to this empirical approach of looking for nearest neighbours on the manifold, EDM can uncover both linear as well as nonlinear dynamics, whereas mechanistic models often fail in the latter case. We cannot simply assume the dynamics within musical trios to be linear, mechanistic functions; the robustness of EDM (as well as Transfer Entropy) in the face of nonlinearity is what motivates its use in this study.

The specific EDM technique we use is the Simplex projection forecasting algorithm, which can perform both uni- and multivariate time series forecasting based on a weighted average of nearest neighbors in the time series phase space (Sugihara & May, 1990). To determine the predictability of a performance, we will compute values of ρ for up to 20 time lags into the future, consistent with our application of Transfer Entropy that relies on a Markov order of 20. The predictability of a given time series (musician) or system (trial) is then computed as the average of its ρ coefficients over these 20 lags, averaged over all time points that were predicted.

In all of our applications of Transfer Entropy and EDM, we only consider 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.

3.5 ***Hypothesis I***: *It is possible to distinguish between coordinating and non-coordinating musicians by applying Transfer Entropy (Transfer Entropy) and Empirical Dynamic Modelling (EDM) to acoustic feature time-series.*

As a prerequisite for any further analysis using Transfer Entropy or EDM, we must first test whether these methods capture any coordination within groups at all, and if so, which acoustic feature(s) allow them to do so. Testing the technique-feature combinations against the null requires surrogate data, which we will obtain via a participant shuffling (Moulder, Boker, Ramseyer, & Tschacher, 2018) approach: we will compute Transfer Entropy values for all 576 possible 'real' pairs of musicians (same group, same trial) and for an equal number of 'random' pairs (same group, different trial) on each acoustic feature. The participant shuffling approach was chosen because it leads to a more conservative assessment of which features are informative than do other approaches such as permutation testing. For our application of the simplex algorithm, we will use 192 real and 192 random trios rather than pairs. If an acoustic feature is successful in capturing inter-musician coordination, then that feature should yield significantly higher Transfer Entropy 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 Transfer Entropy and time lag-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 Transfer Entropy and ρ values for real trios than for random trios, we can safely assume that the acoustic feature reliably encodes coordination in a performance. As such, only acoustic features that reached significance on this test for both Transfer Entropy and EDM went on to be used in the remainder of this research.

Detailed descriptions of the variables introduced in this part are provided below.

- **Group-Level Transfer Entropy**: Average of all pairwise Transfer Entropy values in a trial, summing over the acoustic measures used.
- **Group-Level Predictability**: Group-Level Predictability is our measure of the predictability of a given performance and was computed as follows:
    1. Use EDM to make predictions for each number of time lags between 1 and 20, at every time step in the performance.
    2. Calculate ρ for each number of time lags between 1 and 20. First have musician 1 serve as the 'to-be-predicted' time series, then musician 2, and finally musician 3.
    3. Average ρ over the 20 time lags for each musician and over the states.

4. Finally, average ρ over the 3 musicians. This is the group-level predictability.

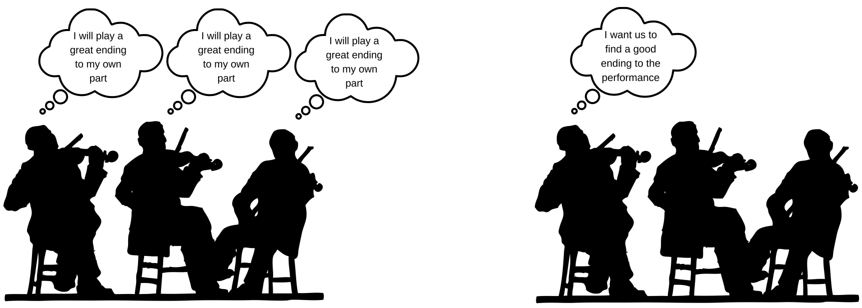
3.6 ***Hypothesis II****: Amount of information flow, directionality of information flow and group-level predictability are indicative of subjective quality of improvisations.*

We proceed to put our Transfer Entropy and EDM methods to a test that is somewhat less trivial than telling real pairs / trios apart from random ones. Here, we seek to establish a link between the supposed coordination captured by Transfer Entropy and EDM and the subjective quality of joint improvisations. Subjective quality of joint action is conceptualised in the musicians' ratings of their own improvisations. We also introduce a measure for the unidirectionality of information flow within a trio and, likewise, investigate how this relates to the quality of the improvisation.

Tests in this part will be conducted using linear mixed effects models with the trio ID as a random effect. Our measures for amount of information flow, directionality of information flow and group-level predictability will serve as the independent variables. The enjoyment rating variable had one missing value, so 143 of the 144 trials from Experiment 2 will be used. Linear mixed effect models come with several assumptions (including linearity of the relationship and homoscedasticity of residuals), which were tested using the check_model function from the performance package in R (**?**). A log or square root transformation would be applied to the dependent variable if assumptions were violated. The same approach was taken for all subsequent mixed models in this research.

Descriptions of the variables newly introduced in this part are provided below.

- **Trio**: The trio ID, used as a random effect in the mixed models.
- **Enjoyment Rating**: The musicians' average enjoyment rating for a given trial, on a 7-point Likert scale. This will serve as the dependent variable in all tests.
- **Group-Level Unidirectionality Index**: First, the Unidirectionality Index for a pair is computed by calculating the Transfer Entropy values of a pair both ways, then dividing the larger value by the smaller one. The Group-Level, then, is the average Unidirectionality Index over the three unique pairs within the trio. A higher value indicates more unidirectional information flow, whereas a value closer to 1 indicates a stronger presence of bidirectional information flow.



(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 2

3.7 ***Hypothesis III***: *Sharedness and collectiveness of intentions predicts coordination during musical improvisations.*

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. As an example, if 3 group members have the intention to find a good ending to their own individual parts, this is a shared intention but not a collective intention; conversely, if a group member has the intention to find a good ending to the group's performance as a whole, then this is a collective intention but not necessarily a shared intention (it is only so if other group members have the same intention). Figure 2 provides some examples to further elucidate these concepts. Sharedness of intentions is captured in the Prompt Number variable, while collectiveness is captured in Prompt Type.

The below variables were introduced to put our hypothesis on shared and collective intentions to the test.

- **Post-Prompt Transfer Entropy**: Dependent variable. The average pairwise Transfer Entropy value for the trial, only considering the part of the improvisation after the prompt.
- **Post-Prompt Rho**: Dependent variable. Average ρ for the trial, only considering the part of the improvisation after the prompt. 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).

3.8 ***Hypothesis IV***: *Improvisers use predictability of actions as a smoothing mechanism by which to propagate their intentions.*

In this part, we aim to get a better understanding not just of how intentions affect a trial-wide measure of information flow, but also how these intentions are propagated. We first test whether improvisers indeed transfer more information to partners when prompted with a collective intention (WE-goal) than with a non-collective 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. We go on to investigate whether the improvisers propagate goals by means of the coordination smoothing mechanism of making their actions more predictable. We do 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 limit ourselves to 83 trials from Experiment 2 that continued for at least 10 seconds after the prompt occurred (meaning all three musicians in the trial continued playing for at least 10 seconds), to prevent the situation that we might just catch the final sustained note of an improvisation and nothing else. Lastly, we investigate whether greater predictability in one's playing corresponds with stronger information flow towards partners.

As before, variables newly introduced in this part are described below.

- **Post-Prompt Directionality Ratio**: For a pair of musicians x and y, Post-Prompt Directionality Ratio is computed by dividing the post-prompt $x \to y$ Transfer Entropy by the post-prompt $y \to x$ Transfer Entropy. A value above 1 here indicates that musician x transferred more information to musician y than vice versa. Used as dependent variable to test whether information transfer to and from partners is affected by the type of prompt one receives.
- **Change in Individual Predictability**: Computed by dividing post-prompt ρ by pre-prompt ρ for an individual musician. A higher value thus indicates that a musician increased the predictability of their playing following the prompt. ρ is computed for one musician at a time, only using the time series of the musician themselves as the state space history. Used as a dependent variable to test whether musicians use predictability

- **Individual Prompt Type**: Denotes the prompt an individual musician received. 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.
- **Pairwise Transfer Entropy**: Directional Transfer Entropy values for each pair of musicians. Used as dependent variable to test the effect of individual predictability on information transfer to fellow musicians.
- **Individual Predictability**: Average ρ for an individual musician, for the full duration of their playing in the trial. Used as independent variable to investigate its effect on pairwise transfer entropy.

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