USING COMMUNICATION TO MODULATE NEURAL SYNCHRONIZATION IN TEAMS

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USING COMMUNICATION TO MODULATE NEURAL SYNCHRONIZATION IN TEAMS

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LIST OF SYMBOLS AND ABBREVIATIONS

A	Experimenter condition
B	Team member condition
C3	Central center-left electrode
C4	Central center-right electrode
CNS	Central nervous system
Cz	Central midline sagittal electrode
d	Cohen’s d
EEG	Electroencephalogram
η^2	Eta-squared
F	F-test statistic
F3	Frontal center-left electrode
F4	Frontal center-right electrode
F7	Frontal left electrode
F8	Frontal right electrode
Fz	Frontal midline sagittal electrode
Hz	Hertz
i	Index of summation
IEC	Inter-event code
M	Mean
N	Length of time series
NEO	Non-combatant evacuation operation
NS	Neurodynamic symbol

O1	Occipital left electrode
O2	Occipital right electrode
p	Probability value
P3	Parietal center-left electrode
P4	Parietal center-right electrode
P7	Parietal left electrode
P8	Parietal right electrode
PDF	Probability density function
p_i	Relative frequency of distribution i
POz	Parietal-occipital midline sagittal electrode
Pz	Parietal midline sagittal electrode
SD	Standard deviation
t	Student's t-test
T3	Temporal left electrode
T4	Temporal right electrode

SUMMARY

Trainers often assess team processes in conjunction with team performance outcomes to identify which behaviors contributed to the success or failure of the team during training. A current topic in team research is developing covert measures, which are easier to analyze in real-time, to identify team processes as they occur during training; however, little is known about how exactly overt and covert measures of team process relate to one another. In my thesis, I investigated the relationship between overt and covert measures of team process by manipulating the interaction partner (participant or experimenter) team members worked with and the type of task (decision-making or action-based) teams performed to assess their effects on team neural synchronization (measured as neurodynamic entropy) and communication (measured as both flow and content). The results indicated that the type of task affected how the teams dynamically structured their communication but had no effect on the neural synchronization of the team when averaged across the task session. The interaction partner also had no effect on team neural synchronization when averaged. However, there were significant relationships over time between neural synchronization and the communication flow and content due to both the type of task and the interaction partner. Specifically, significant relationships across time were observed when participants were interacting with the other participant, during the second task trial, and across different areas of the cortex in the beta frequency depending on the type of task being performed. The findings from the time series analysis extend my previous work on task constraints and communication dynamics by illustrating that the interaction partner and the team's task constraints also structure the relationship between

team communication and neural synchronization across time, suggesting that these need to be taken into account when developing covert measures of team process.

CHAPTER 1. INTRODUCTION

Trainers often assess team processes in conjunction with team performance outcomes to identify which behaviors contributed to the success or failure of the team during training. This approach to team assessment is based on the Input-Process-Output (IPO) theory, where input (e.g., the knowledge of the team members) is processed by team members through coordination to produce some team outcome, or output (Hackman, 1987). Overt behaviors (e.g., team communication) are among the more common team process measures due to the low cost and ease of data acquisition. However, despite the ease of communication data acquisition, the process of analyzing communication data for semantics is time consuming. To partially overcome this limitation, trainers have brought in experts to rate overt team behaviors, either during or after the training session, but many of these tools have not been fully validated or tested for reliability (Li, Marshall, Sykes, et al., 2018). A current topic in team research is developing covert measures, which are easier to analyze in real-time, to identify team processes as they occur during training (e.g., Stevens, Galloway, Gorman, Willemsen-Dunlap, & Halpin, 2016a); however, little is known about how exactly overt and covert measures of team process relate to one another. In my thesis, I address the following research question: How do overt and covert measures of team processes relate to or influence one another?

According to a dynamical systems theory of team coordination (Gorman, Dunbar, Grimm, & Gipson, 2017; Gorman, 2014), different types of team processes, whether overt or covert, are all part of the same system—the team. As a dynamical system, teams coordinate simultaneously across multiple components (e.g., team members) and levels of analysis (e.g., physiological, cognitive, and motor). If a change occurs in one part of the system (e.g., a component or level), this change is reflected across other parts of the system because variability in one part becomes constrained by, or nested within, variability in another part. More specifically, processes on multiple levels of analysis are simultaneously impacted by the same team dynamics, producing temporally cross-correlated dependencies between levels as people interact (Gorman, Martin, Dunbar, et al., 2016). This effect is called a "cross-level" effect (Gorman et al., 2016), and is thought to occur unconsciously and without intention as people interact. The purpose of my thesis is to establish whether cross-level effects exist between the communication (overt) and neurophysiological (covert) levels of analysis by constraining the coordination of the team.

Empirical grounding for this research can be found in studies performed on individuals and teams where cross-level effects occur through the coupling of motor, perceptual, and neural processes during task performance. In individual speech, for example, the speed of speech syllables, the movement of the mouth, and the electrical activity in the auditory cortex all modulate at a frequency between 3-8 Hz (Chandrasekaran, Trubanova, Stillittano, Caplier, & Ghazanfar, 2009; Ghazanfar & Schroeder, 2006; Luo, Liu, & Poeppel, 2010; Schroeder, Lakatos, Kajikawa, Partan, & Puce, 2008). This entrainment across levels of analysis (mouth movements, speech, and auditory neural activity) suggests that these processes (motor, perceptual, neural) are coupled during the production of speech. Entrainment also occurs in interpersonal communication, where neural synchronization (i.e., temporal coupling due to interacting in a shared medium; Strogatz, 2003) occurs incidentally between people during conversation. More specifically, the neural activity of the speaker is spatially and temporally correlated with the listener's neural activity (Stephens, Silbert, & Hasson; 2010). This neural coupling often occurs at a delay, but it can also be predictive, where the listener's neural activity anticipates the speaker's neural activity (Kuhlen, Allefeld, & Haynes, 2012; Stephens et al., 2010). According to Stephens and colleagues (2010), this coupling may serve as a method for how brains coordinate, or convey information successfully between individuals; however, it is currently unknown how this coupling is controlled through conversation. Prior research has focused on neural-communication coupling between a speaker and a listener. This thesis will expand on this research by experimentally inducing cross-level effects during actual, back-and-forth conversation.

In this thesis, cross-level effects were experimentally induced in two ways: Type of task and the interaction partner. According to the theory of interactive team cognition, team processes should be inextricably tied to the type of task, or task context (Cooke, Gorman, Myers, & Duran, 2013). Subsequently, if the communication and neural levels of analysis in teams are coupled, then changes in the communication level will be concomitant with changes in the neural level. In previous research, I found that the type of team task determines the communication patterns that emerge over time (Dunbar & Gorman, 2014). In this study, dyads performed one of two task types: either the Non-combatant Evacuation Operation planning task (NEO; Warner, Wroblewski, & Shuck, 2003) or the Minecraft visual-spatial coordination task (Dunbar & Gorman, 2014). Dyads that performed the NEO task dynamically structured their communication around interpretations (i.e., communication based on planning and cognitive processes; Butner, Pasupathi, & Vallejos, 2008), whereas dyads that performed the Minecraft task dynamically structured their communication around concrete facts (i.e., communication based on perceptual information directly available in the environment; Butner et al., 2008). Because their effects on communication are known and they differently emphasize interpretive, planning-based vs. factual, action-based communications, I used these two task types to manipulate cross-level effects in the current study.

According to predictions from the dynamical systems theory of team coordination (Gorman et al., 2017; Gorman, 2014), the neural synchronization that occurs within these two tasks is likely coupled with cognitive-behavioral (here, communication) differences between the tasks. Although the effects of these two specific tasks on the patterns of neural synchronization in teams is unknown, research on related tasks might inform us where possible indicators of neural synchronization might occur for the tasks used in the current study. Relevant for the NEO task, neural synchronization has been observed in submarine crews engaged in planning using electroencephalogram (EEG) in the 10-12 Hz frequency range using a measure of engagement (Berka, Levendowski, Lumicao, et al., 2007) at the dipole of Fz/POz (Gorman et al., 2016; Stevens & Galloway, 2015, 2017). Higher-level social coordination processes, such as when people are engaged in planning, have been linked to increased coupling in the mu medial and phi complex rhythms in the alpha band (8-12 Hz) in the FCz and CP4 electrodes of EEG (Tognoli & Kelso, 2013). Abstract communication, such as interpretation-based communication, has also been tied to the FC1 and FC2 electrodes in the alpha band (Moreno, de Vega, & Leon, 2013). This pattern of results suggests that for the NEO task, the Fz, POz, CP4, FCz, FC1, and FC2 electrodes in the alpha frequency range are possible locations to investigate for indicators of team neural synchronization.

Relevant to the Minecraft task, a similar type of task is the map task where people communicate about the shapes and locations of objects on maps. For teams performing the map task, neural synchronization occurs in the 16-17 Hz frequency range of EEG at the sensor sites Fz, C3, and C4 (Stevens & Galloway, 2014; Stevens & Galloway, 2015). Action-based communication, which is captured in the fact-based communication of the Minecraft task, has been tied to mu and low beta rhythms in the beta band (13-30 Hz) in the C3, Cz, and C4 electrodes of an EEG (Moreno et al., 2013). These correspond to similar areas associated with motor simulation processes when people observe another person perform an action (Muthukumaraswamy, Johnson, & McNair, 2004). This pattern of results suggests that for the Minecraft task, the Fz, C3, C4, and Cz electrodes in the beta frequency range are possible locations to investigate for indicators of team neural synchronization.

The overall pattern of the neural activation results suggests that there may be different indicators of neural synchronization due to the type of task the team is performing. Table 1 summarizes the pattern of research findings on neural synchronization. Based on these findings, in this thesis, I developed the hypothesis that experimentally manipulating the type of team task modulates both communication behavior and neural synchronization, which may be indicated along different EEG frequency bands at pre-specified sensor sites such as the Fz, POz, P4, Cz, C3, and C4 electrodes depending on whether the task is more planning-based (NEO) vs. action-based (Minecraft). Because the spatial resolution of EEG is low, I also looked broadly at the frontal, central, and parietal areas for neural synchronization differences between the two tasks.

Table 1 – Summary of Findings on Neural Synchronization.

Study	Alpha (8-12 Hz)	Beta (13-30 Hz)
Tognoli & Kelso (2013)	**Social coordination:** FCz, CP4	
Stevens & Galloway (2015, 2017) Gorman et al. (2016)	**Submarine crews:** Fz/POz dipole	
Stevens & Galloway (2014, 2015)		**Map task:** Fz, C3, C4
Moreno, de Vega, & Leon (2013)	**Abstract:** FC1, FC2 **Action:** Cz, C3, C4	**Action:** Cz, C3, C4

I also experimentally induced cross-level effects by manipulating who the team member was performing the task with. The reasoning behind this manipulation is based on basic research on interpersonal cognitive and motor processes, such as postural synchronization (Shockley, Santana, & Fowler, 2003) or visual coupling (Richardson, Dale, & Kirkham, 2007) during conversation. In these studies, the researchers provide a control condition to help eliminate the possibility that the observed synchronization is spurious. The control condition consists of the participant working on the task with an experimenter, whereas the experimental condition consists of the participant performing the task with the other participant. In the participant condition, participants couple with one another through verbal communication and synchronization occurs due to the verbal coupling between the participants. However, in the experimenter condition, synchronization is expected to occur only spuriously between the participants because the participants are verbally communicating with the experimenters and are thus coupled to the experimenters, rather than to the other participant. During both the control and experimental task sessions, the researcher measures the same physiological or motor measure and compares the synchronization between participants. If synchronization is significantly higher in the participant condition, this suggests that the observed synchronization is not spurious. Thus, the experimenter condition allows the researcher to control (in the analysis) for spontaneous synchronization that occurs that is not due to the shared interaction medium. In my thesis, I similarly manipulated the interaction partner to provide a control condition to account for spontaneous neural synchronization.

1.1 Current Study

In the current study, participants performed one of two tasks as a dyad, the NEO task or the Minecraft task (between-subjects manipulation). These tasks were performed twice: once with their teammate and once with an experimenter (within-subjects manipulation). During task performance, I measured the EEG of the participants and the communication of both participants and experimenters. Measuring the EEG of the teams using dry EEG headsets allowed me to determine if the same manipulations affected team neural dynamics as they do communication and other physiological dynamics without interfering as much with the team’s task performance. This could also possibly allow me to extend the dynamical systems theory of team coordination into neural coordination between team members. My manipulations were used to test four hypotheses:

Hypothesis 1: Dynamic structuring of communication patterns depends on the type of team task being performed.

Hypothesis 1 is a manipulation check to ensure that my task type manipulation impacts communication as expected based on prior research. Specifically, in the NEO task, communication patterns should be dynamically structured around interpretation-based communication, and in the Minecraft task, communication patterns should be dynamically structured around fact-based communication.

Hypothesis 2: Neural synchronization with a teammate occurs when talking to a teammate but not when talking to an experimenter.

According to Hypothesis 2, synchronization between team members should only occur when the team members are communicating, or coupled, with one another. When team members are communicating with the experimenter, the team members are not coupled with one another; rather, they are coupled with the experimenters, and thus synchronization between team members should not occur. The purpose of testing this hypothesis, therefore, is to provide a control condition against which the state of spontaneous synchronization between people during conversation can be compared.

Hypothesis 3: The neurophysiological synchronization between teammates depends on type of team task.

According to Hypothesis 3, by manipulating the communication behavior of team members, Task Type should also modulate neural synchronization if the communication and neural processes are coupled. Specifically, based on prior research, indicators of neural synchronization should be found in the alpha band (8-12 Hz) in the Fz, POz, and P4 electrodes for the NEO task, whereas indicators for neural synchronization in the Minecraft task should be found in in the beta band (13-30 Hz) in the Fz, Cz, C3, and C4 electrodes. I also looked more broadly across the frontal, central, and parietal cortical areas for task type differences.

Hypothesis 4: Communication and neural activity should be related, such that changes in communication patterns should be reflected in the neural activity of teams (and vice versa).

According to Hypothesis 4, if teams coordinate across multiple levels of analysis simultaneously, these levels of analysis should be related to one another across the entire task session. Specifically, events that occur in the neural activity (e.g., periods with high, low, or fluctuating neural synchronization) should be temporally reflected in and/or anticipated by the communication content and flow across multiple points in time. The alternative prediction to this hypothesis is that temporal coupling between the neural and communication levels of analysis occurs only immediately (e.g., in the same second). To test this hypothesis, I investigated the neural and communication time series together for temporal correlations between the levels of analysis.

CHAPTER 2. METHOD

2.1 Participants

Forty-six participants (23 dyads) were recruited from the Georgia Institute of Technology psychology participant pool and were compensated with course credit for completing the study. Ten dyads' data were discarded due to equipment failures and one dyads' data was discarded due to a participant dropping out of the study session early. This data loss left 24 participants (6 dyads per between-subjects condition) remaining for the analyses in this study, which was the original sample size I planned for based on an a priori power analysis. One team that remained did not have recorded communication data for the experimenter condition, but all neural data for this team was intact. Average participant age was M = 19.70 (SD = 1.77). The sample was predominantly male, with 28.26% of the participants being female, and the remaining 71.74% were male. Of the dyads that remained in the analysis, eight dyads were mixed gender and four dyads were all male. No participants reported knowing each other prior to the experiment; any recent caffeine, nicotine, or alcohol consumption; alcohol and drug abuse or dependence; CNS active medications; or any systemic disorders with CNS involvement, psychiatric disorders, or neurological disorders. No participants tested as colorblind during the session.

2.2 Experimental Design

Participants performed as dyads in one of two task conditions corresponding to a between-subjects variable, Task Type, with two levels, NEO and Minecraft. Interaction served as a within-subjects variable with two levels, where A refers to performing the task with an experimenter and B refers to performing the task with their team member. Participants performed their task twice, either in the AB or BA order, which served to counterbalance the order of trials across teams, and neural synchronization between participants was recorded at each level of Interaction. Finally, a between-subjects variable, Trial Order, indexed the order in which dyads performed the A and B Interaction conditions. This variable was used to check for differential transfer effects.

2.3 Apparatus

Participants were seated in separate rooms with the doors closed for the duration of participation, ensuring that participants were unable to see each other and coordinated only through verbal communication. Two experimenters were located in different rooms, adjacent to the participants. Each participant and the experimenters used a computer with dual monitors to complete the task. Participants and experimenters communicated with one another via microphone using TeamSpeak (TeamSpeak, 2017) by holding down the shift key in a push-to-talk format.

For EEG data collection, I used dry electrode 20-channel EEG headsets from Cognionics. A software package that comes with the Cognionics system, Cognionics Data Acquisition (Cognionics, 2018), acquired all neural data from the EEG channels of the two participants. A Cognionics remote trigger was used to synchronize the EEG data at every trial. To coordinate the communication activity with the neural activity, the experimenters stated "We are marking the EEG recording now" into their microphone whenever they pressed the Cognionics remote trigger. The experimenter pressed the trigger when they said the word “now.” The neural activity of the experimenters was not measured because it was not pertinent to the hypotheses outlined in this study.

2.4 Measures

2.4.1 Communication Measures

2.4.1.1 Communication Content

Each dyad’s audio recordings were manually transcribed and split into verb phrases. Two research assistants blind to the purposes of the study coded the verb phrases independently into facts, interpretations, and conversation regulation (Butner et al., 2008; Pasupathi & Hoyt, 2009; Pasupathi & Wainryb, 2010). Using the coding scheme, Facts are verb phrases relating to something present in the world and to the five senses (e.g., “I see your red blocks”); Interpretations are verb phrases relating to “mental processes” and refer to inferences, emotions, or evaluations (e.g., “I think an airplane would be faster than a helicopter”); and Conversation regulations are verb phrases relating to backchanneling or establishing understanding (e.g., “I agree”). Agreement between coders was acceptable, $\kappa = .78$ for Minecraft, $\kappa = .84$ for NEO. A more detailed description of the coding rules can be found in Appendix A.

For each team’s transcript, I calculated inter-event codes (IECs) as the number of other codes between each code being analyzed (e.g., if interpretations are being analyzed, then the number of facts and conversation regulation between interpretation coded communication comprise the IECs). These IECs were used for dynamical structuring analysis using the Multiscale Probability Density Function (PDF; Brown & Liebovitch, 2010), which measures the amount of dynamic organization ("self-organized criticality"; Bak, 1996) of each code. The more dynamic organization a code has, the greater its role in team dynamics (Dunbar & Gorman, 2014).

IECs were grouped into different scale sizes (e.g., for scale sizes of three, we would have the bins 0-2, 3-5, etc.), and the frequency of IECs at each scale size was obtained, forming a histogram. I then calculated the probability density, which determines the proportion of data that lies in the bins of the histogram at that scale size. This process results in a PDF for that scale size (e.g., for a scale size of three). I calculated a PDF for each iteration of bin size of the histogram, from bin sizes of one to the maximum possible bin size, which is determined by the maximum number of IECs that can be divided into two scale sizes. To obtain the measure of dynamical structuring for each communication code, I calculated the slope of the power law line of log PDF to log scale size for that code. The slope of the line is the scaling exponent or rate parameter (described below) used to quantify dynamic organization of each communication code in the analysis. The result of this analysis is one scaling exponent for each communication code at each level of Interaction (i.e., team member vs. experimenter) for every team.

To ensure that it is proper to use a power law scaling exponent to measure dynamical structuring, I calculated the rate and scaling exponents for exponential (i.e., memoryless Poisson process) and power law (i.e., scale invariant or emergent process), respectively. I determined the goodness of fit of each function using R^2. Equation 1 shows the power law function and Equation 2 shows the exponential function between PDF and scale size. Exponential is used as a point of comparison because it represents the null hypothesis that there is a lack of emergence/dynamic organization in team communication (see Gorman & Crites, 2015 for discussion).

$$\mathrm{PDF} = \mathrm{constant} \times \mathrm{scale\ size}^{\mathrm{scaling\ exponent}} \tag{1}$$

$$\mathrm{PDF} = \mathrm{constant} \times \mathrm{e}^{\mathrm{rate} \times \mathrm{scale\ size}} \tag{2}$$

Assuming a significantly better power law fit, the more negative the scaling exponent, the more emergent, or dynamically organized, the team communication process, reflecting a high degree of self-organized criticality for the code being analyzed. This interpretation is consistent with Brown and Liebovitch (2010), Butner et al. (2008), and Gorman and Crites (2015). Relevant to the current study, I predicted significantly more dynamic organization for interpretation-based communication for the NEO task and significantly more dynamic organization for fact-based communication for Minecraft as a manipulation check on controlling conversation behavior (Hypothesis 1).

2.4.1.2 Communication Flow

After each audio recording was transcribed, I used the program Audacity (Audacity, 2016) to calculate the start and end of each utterance in the audio recordings using the sound finder function, which calculates the timestamps for any noises above a set decibel threshold (in this case, the Audacity default of 20 dB was used). I manually matched the timestamps with the utterances in the transcript. Timestamps that did not match the utterances (e.g., a participant sneezing) were discarded. If there were utterances that did not have any matching timestamps, these were obtained manually by measuring the start and ending points of the speech waveform in Audacity. The timestamps for each utterance were used to create a 1 Hz symbolic time series of who was talking for each second of the transcript. The six possible symbol states for the communication flow time series are shown in Table 2.

Table 2 – Symbolic States for Communication Flow.

Code	Speaker
0	No speakers
1	Participant 1
2	Participant 2
3	Experimenter 1
4	Experimenter 2
5	Multiple speakers

I calculated quantitative estimates of distribution stability, or bits, on the symbolic communication flow time series using Shannon entropy (Shannon & Weaver, 1949). Equation 3 shows the entropy equation, where p_i is the relative frequency of distribution i over a sliding window (e.g., 100 sec). Entropy is first measured over the initial 100 second distribution, then the window is shifted forward one second, creating a new distribution by adding a symbol and removing the first symbol, until the window has been slid over the entire symbol stream. For a symbolic time series of length N, this results in a continuously fluctuating entropy time series of length N-99. I used 100 sec as the window size because prior research has indicated that windows smaller than 100 sec can create artifactual spikes in the entropy time series (Likens, Amazeen, Stevens, Galloway, & Gorman, 2014).

$$Entropy = -\sum_{i=1}^{\#\,Symbol\,States} (p_i \times \log_2 p_i)$$

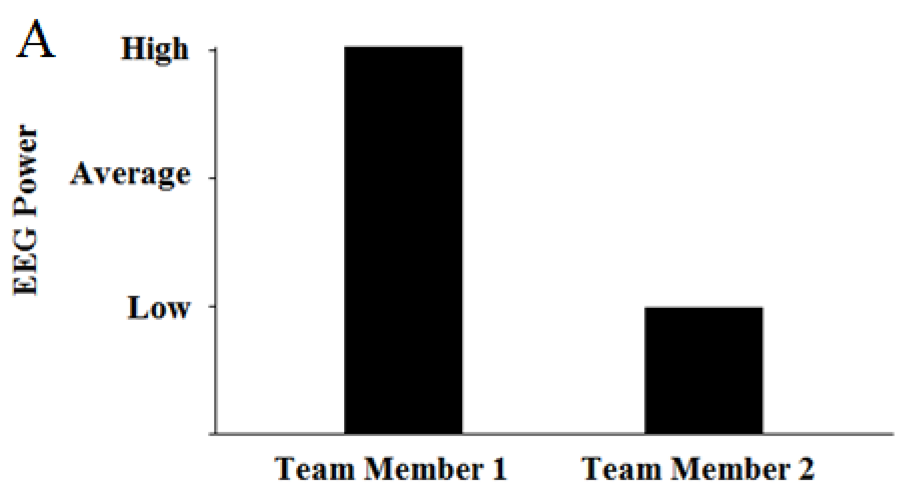
(3)

2.4.2 Neural Measures

The Cognionics Quick-20 Dry EEG headsets included electroencephalography and a full 10-20 EEG array (20 channels plus mastoid reference and ground) which recorded the participants' EEGs continuously throughout the baseline measurement and tasks. The continuous EEG data was subjected to band-pass filtering at 0.1 (high-pass) to 30 (low-pass) Hz and 50 Hz notch filtered to isolate the electrical recording from possible environmental contamination using the open source Matlab Toolbox EEGLab. Following the band-pass and notch filtering, blinks and electromyography artifacts were removed in EEGLab using independent components analysis (ICA; Onton, Westerfield, Townsend, & Makeig, 2006). ICA is used to create components that are maximally independent from one another, minimizing mutual information between the components. I used ICA to remove the components associated with eye blinks and electromyography artifacts from the original EEG channel data, which were usually the first two components in the ICA corresponding to the Fp1 and Fp2 components. Finally, I conducted fast-Fourier transforms using EEGLab to split the neural data into the alpha and beta frequency bands.

Each team's neurodynamics was assessed each second through the relative levels of EEG power (amplitude^2) for each team member. For all EEG channels and frequencies, the distribution of activation was sampled at 500 Hz to capture changes in the distribution (Figure 1a) over time. A set of neurodynamic symbols were created that classifies the activation distribution across a team as a discrete neurodynamic state (NS;

Figure 1b; Stevens & Galloway, 2014; Stevens & Galloway, 2015). A set of nine neurodynamic symbols were created that show the activity levels for both of the team members individually as well as in context of the other team member (Figure 1b; Stevens & Galloway, 2014; Stevens & Galloway, 2015). The activity levels are a split of the upper 33% (high), the middle 33% (medium), and the lower 33% (low) of EEG power levels relative to the average baseline power. The average baseline power was calculated from the 15 minute baseline for each participant, captured prior to the task sessions. For each second, the EEG power levels for each participant during the task session was compared to their individual average baseline EEG power level and subsequently categorized into the high (higher than average baseline), medium (around average baseline), and low (lower than average baseline) categories for each participant. These individual symbolic series were then combined into a team-level symbol series that shows the activity levels for both of the team members individually but also in context of the other team member. An NS symbol stream, sampled at 1 Hz, is the result and provides the input for the neurophysiological synchronization analysis.



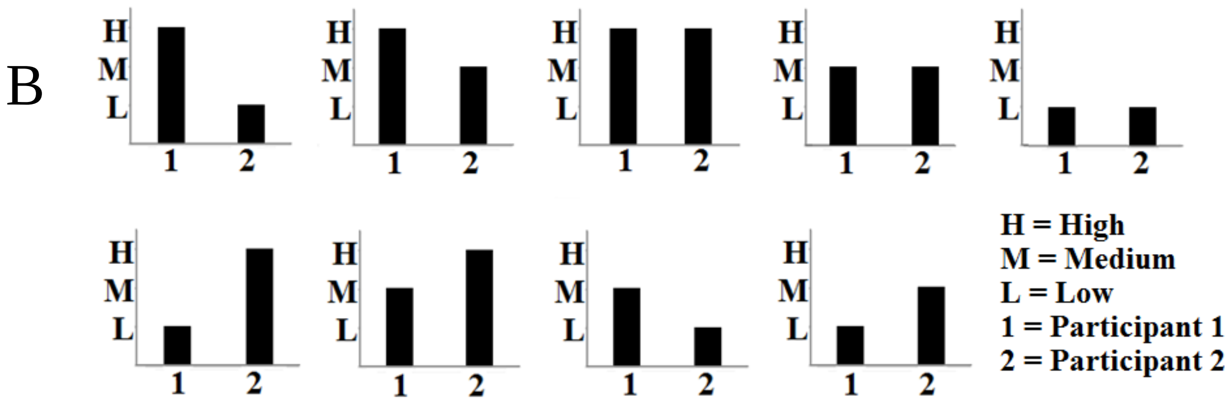


Figure 1 – Example Neurodynamic Symbols (NS). (a) An example NS representing above average EEG power for one team member and below average EEG power for the other team member and (b) the symbol space (NS states) of potential distributions of EEG power at any sensor location for any frequency between two people.

Often, synchronization is characterized as 1:1 phase locking between two signals, perhaps because it is frequently described this way in the psychological literature (e.g., mirroring; Sternad, Turvey, & Schmidt, 1992). However, synchronization is more generally defined as frequency locking between two signals in any proportion (e.g., 2:1; 3:1; Gorman, Amazeen, Crites, & Gipson, 2017). Therefore, in order to quantify neurophysiological synchronization, I calculated synchronization across all amplitude combinations (distributions) shown in Figure 1b. The assumption is that teams synchronize by either both members being low or being high (i.e., mirroring) or by one team member being high and the other low (non-mirroring synchronization), etc., so long as the distribution is relatively fixed over time.

Similar to the communication flow, Shannon entropy was calculated on the neurophysiological data to obtain a quantitative estimate of distribution stability. I selected Shannon entropy because it provides a continuous measure of synchronization beyond 1:1 phase locking by measuring the level of disorder in the signal. Decreased entropy can be operationally defined as higher synchronization because the neurophysiological activity distribution is not changing, whereas higher entropy can be operationally defined as lower synchronization because the neurophysiological activity distribution is changing. Higher synchronization in team neurophysiology would be indicated by lower entropy, which would result from a neurodynamic symbol series that produces lower numbers of symbols over the time window. Higher synchronization in communication flow would also be indicated by lower entropy, which would result from a flow symbol series where the number of symbols expressed over the time window is low. Entropy serves as my measure of synchronization in neural activity to address Hypotheses 2, 3, and 4, and there are two entropy time series for each team, one for Interaction A (team member communication) and one for Interaction B (experimenter communication). For hypothesis 2, synchronization across participants is expected to occur when team members are working on the task together and not when working with an experimenter. For hypothesis 3, synchronization was examined in the context of specific sensor sites particular to the type of task. The NEO task should affect the mu medial and phi complex rhythms in the alpha band (8-12 Hz) in the Fz, POz, and P4 electrodes, and the Minecraft task should affect the mu and low beta rhythms in the beta band (13-30 Hz) in the Fz, C3, CZ, and C4 electrodes. For hypothesis 4, synchronization was examined in conjunction with communication content (graphical interpretations) and flow (graphical interpretations and cross-correlations). I expected to find similar communication content identifying specific types of neural events (e.g., periods with high, low, or fluctuating neural synchronization) and significant cross-correlations between the flow and neural synchronization of the teams.

2.5 Experimental Tasks

Two tasks served as the Task Type conditions for this study: The Non-combatant Evacuation Operation task (NEO; Warner et al., 2003) and the Minecraft task (Dunbar & Gorman, 2014). The NEO task was originally developed by the Navy and was adapted from three participants to two participants for this study. In the NEO task, participants verbally communicate to plan a rescue mission based on a hypothetical military scenario given a limited number of weapons, personnel, and time resources. The team cannot complete the task without verbally communicating because each team member is only given a portion of the information about the resources available for the mission. The team's goal was to develop a 24-hour plan to rescue three Red Cross workers from a church on a fictitious remote island that contains friendly natives and foes. During the task session, the team must plan how they will have the rescuers get to the church, how they will evacuate the Red Cross workers, and how they will return to an Army base or aircraft carrier. To develop their plan, team members must communicate about which personnel they will use throughout the mission, plan the specific route the personnel will take on the island to get to the church, how the personnel will extract the Red Cross workers, how they will safely manage the Red Cross workers injuries, and the route the personnel and Red Cross workers will take to return safely. Participants were expected to type up their planned actions for every hour in a 24-hour period starting at 2:00 AM.

Each participant received a file containing general information about the task that included background information about the island, Red Cross workers, rebel forces, military assets, and maps of the island. Participants also received role specific information containing either weapons expert information or environment/intelligence information that went beyond the general information. The weapons expert information contained information about the various vehicles, weapons, and military personnel that could be used by the participants for their extraction plan. The environmental/intelligence information consisted of weather conditions on the island, information about the water, a more detailed map of the church where the Red Cross workers are located, and information about the island population. For each task iteration, A or B, participants received different information about the island or their resources to minimize a practice or memorization effect. See Figure 2 for examples of information participants receive for the NEO task. The participants typed up their plan during each task session in a shared Google Document that both participants had access to in a web browser.

Transportation & Weapons:

Navy Seahawk (SH-60): A twin-engine helicopter used for anti-submarine warfare, drug interdiction, cargo lifts and special operations in the day or night regardless of the weather conditions.	
Navy Hornet (F-18): A one or two seat super sonic jet used for air-to-air or air-to ground support.	
Zodiac: A 7-man inflatable boat which can travel at speeds up to 15 miles/hour.	

Figure 2 – Example of NEO Task Materials (Warner et al., 2003).

The second Task Type condition was a one-right answer building task involving building a structure in the game Minecraft (Dunbar & Gorman, 2014). The Minecraft game world is constructed of blocks that players can manipulate by destroying or adding blocks of their own. However, for the Minecraft task used in this study, participants were given a specific set of blocks to build in the game world and were restricted in the types of blocks they could place in the game. Each participant was given three individual colors of blocks to use in the game. Participant 1 was restricted to red, green, and blue blocks, whereas Participant 2 was restricted to purple, yellow, and black blocks. In addition, each participant received 36 columns of blocks to build in the game with all six colors of columns of various heights (Figure 3). Each participant's set of columns was unique with no overlapping columns between the two sets. Because the participants were only allowed to use three colors of blocks and each participant was given different sets of columns of containing all six colors of blocks, the task required participants to verbally communicate with each other to complete the task. To complete the task, participants placed columns of blocks in the game world of varying heights and colors based on the maps they were given by the experimenters. Participants and experimenters (depending on the task session) also informed the other participant or experimenter (depending on the task session) of blocks that the participant needed them to place in the world to complete their maps. For each task iteration, A or B, participants received a different set of columns to minimize a practice or memorization effect. The participant's goal was to combine both sets of columns into a 10-by-10 square space and verbally communicate the locations, heights, and colors of blocks to be built with the other participant.

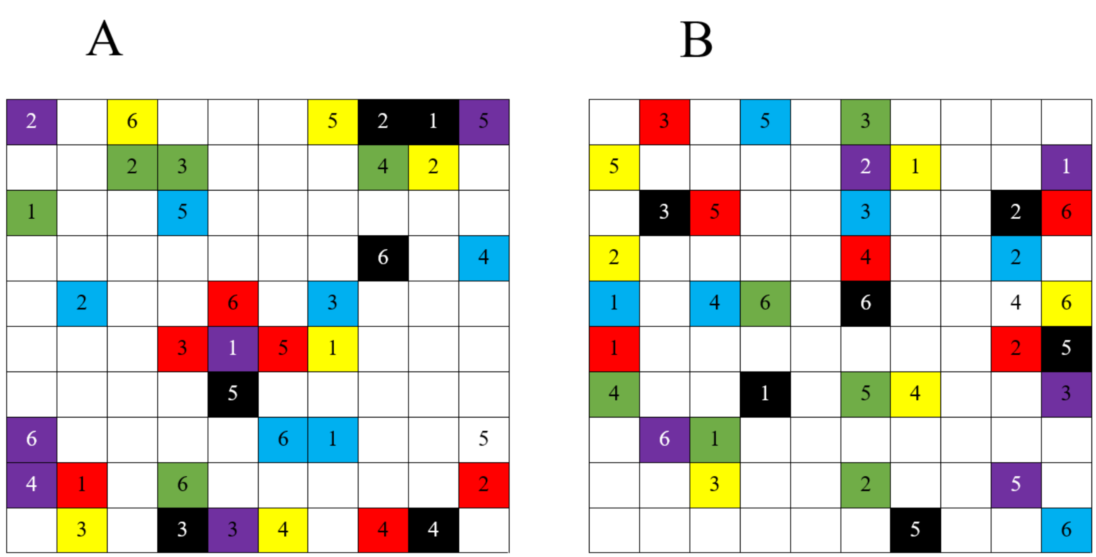


Figure 3 – Example Set of columns for the Minecraft task (Dunbar & Gorman, 2014). A) Participant 1 set of columns. B) Participant 2 set of columns.

2.6 Procedure

Participants were pre-screened in the Sona advertisement to avoid possible complications with the data collected. The pre-screening included: Colorblindness, systemic disorders with CNS involvement, neurological disorders, alcohol and drug abuse or dependence, CNS active medications, or psychiatric disorders. Participants were reminded to avoid caffeine, nicotine, and alcohol consumption 24 hours prior to participation.

Informed consent was obtained before participation. Dyads were randomly assigned to the Task Type and Trial Order conditions before arriving. Following informed consent, participants were tested for colorblindness because the Minecraft task involves differentiating between different colors of blocks and a red-green colorblind individual would be unable to complete the task; however, all participants were given the test to ensure equal treatment. Following the colorblindness test, participants were equipped with the EEG headsets. Prior to the start of the task, a baseline was measured prior to the task for 15 minutes. Participants then had 15 minutes to either read through their materials (NEO) or practice the controls of the game (Minecraft), depending on their task condition. The actual task length lasted 15 minutes for both tasks. Each task was completed two times. In one of the task sessions, both recruited participants performed the task together. For the other task session, the participants performed the task with experimenters. Experimenter task performance was completed in the same manner as described in the section Experimental Tasks. Following the final task session, participants filled out a demographics survey that asked questions about factors that could possibly confound their data (e.g., caffeine, nicotine, or alcohol consumption; neurological or psychiatric disorders) and the experimenter debriefed the participants concerning the purposes of the study. The entire duration of participation lasted 2 hours.

CHAPTER 3. RESULTS

3.1 H1: Effect of Task Type on Communication Structure

In order to test the hypothesis that team communication is dynamically structured around the type of task, I first performed a preliminary analysis comparing the power-law (dynamic/fractal) to exponential (non-dynamic/memoryless) distribution fits for each communication type to determine if the communication was dynamically structured. Paired-samples *t*-tests on the R^2 fit values revealed that both Facts, $t(33) = 5.29$, $p < .001$, $d = .37$, and Interpretations, $t(33) = 4.14$, $p < .001$, $d = .76$, were significantly better fit by a power law. For Conversation Regulation, the power law and exponential fits were not significantly different ($p = .33$). Because I could not assume dynamic structure for Conversation Regulation, I retained exponential slopes (i.e., the null hypothesis) for this code in the following analyses.

To evaluate the effect of Task Type on dynamical communication structuring, I conducted 2 (Task Type) x 2 (Interaction) x 2 (Trial Order) x 2 (Code) mixed ANOVAs for the Fact and Interpretation scaling exponents. This analysis revealed a significant interaction between Task Type and Code, $F(1, 7) = 80.81$, $p < .001$, partial $\eta^2 = .92$. The main effect of Code was also statistically significant, $F(1, 7) = 25.92$, $p = .001$, partial $\eta^2 = .79$, but the main effect of Task Type was not, ($p = .54$). In support of H1, the Minecraft task led to a significantly more negative scaling exponent (i.e., more dynamical structuring) for fact-based communication, $F(1, 7) = 25.43$, $p = .001$, partial $\eta^2 = .78$, and the NEO task led to a significantly more negative scaling exponent for interpretation-based communication, $F(1, 7) = 19.37$, $p = .003$, partial $\eta^2 = 74$ (Bonferroni $\alpha = .025$; Figure 4).

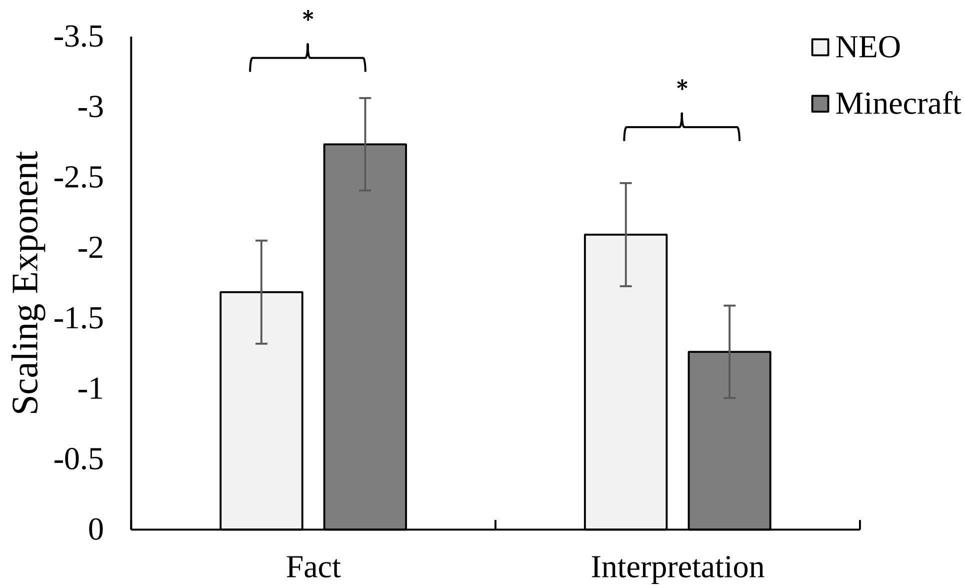


Figure 4 – Scaling Exponents for Task Type by Code. The dynamical communication structuring for facts and interpretations depended on whether teams performed the NEO or the Minecraft task. Error bars are 95% confidence intervals; * $p < .025$.

Conversation Regulation was analyzed as a separate 2 (Task Type) x 2 (Interaction) x 2 (Trial Order) mixed ANOVA with the rate parameter as the dependent variable. Unexpectedly, the main effect of Task Type was significant for Conversation Regulation, such that the rate parameter for the Minecraft task ($M = -.44$, $SD = .14$) was significantly more negative than the NEO task ($M = -.21$, $SD = .08$), $F(1, 7) = 25.50$, $p = .001$, partial $\eta^2 = 79$.

I also conducted a surrogate data analysis (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992), which is a resampling method for testing whether the observed differences are random or due to dynamics. First, I randomly shuffled each team's code sequence, which destroys the temporal ordering (i.e., the dynamics) but retains the marginal properties (e.g., relative frequencies) of codes. I then recalculated power-law slopes using the surrogate data and analyzed them with the same analysis described previously. The Task Type by Code interaction was still significant, $F(1, 7) = 84.75$, $p < .001$, partial $\eta^2 = .92$, indicating that the significant interaction effect in the original power-law data might be due to the aggregate properties (e.g., relative frequencies) of the code sequences.

Finally, to determine if the surrogates were transformed to memoryless processes, I compared power-law to exponential fits for each surrogate series. Paired-samples *t*-tests on R^2 values revealed that the power-law and exponential fits were not significantly different for Facts ($p = .22$), Interpretations ($p = .86$), or Conversation Regulation ($p = .46$). This pattern of results suggests that the resampling method did destroy the dynamics from the original data, but does not support the idea that the surrogates were additionally transformed to memoryless processes.

3.2 H2: Effect of Interaction on Neural Synchronization

To test the effect of the Interaction condition on neural synchronization, I conducted 2 (Task Type) x 2 (Interaction) x 2 (Trial Order) mixed ANOVAs for the electrodes Fz, P4, and POz in the alpha band as well as Fz, Cz, C3, and C4 in the beta band. Because these were planned comparisons, no alpha correction was added. I also conducted exploratory post hoc contrasts with a Bonferroni alpha correction ($\alpha = .008$) in the alpha and beta bands in the frontal, central, and parietal cortical regions. These three regions were selected because they represent the broader regions for the individual electrodes tested in H2 and H3.

Based on my second hypothesis, I predicted that neural synchronization with a team member will only occur when talking to a team member and not when talking to an experimenter. No main effects of Interaction were statistically significant. The results for the planned comparisons are summarized in Table 3 and the exploratory comparisons in Table 4. Controlling for the amount of communication (as both time and number of utterances) as well as the self-reported frequency of hand and head movements when speaking did not alter the pattern of results. Additionally, the pattern of mean differences were not in the hypothesized direction: Means for the Experimenter condition were lower (indicating higher synchronization) than the Participant condition across both task types for all electrodes, regions, and frequencies tested. Both sets of results fail to support hypothesis 2.

Table 3 – Team Member vs. Experimenter Results for Planned Comparisons.

Frequency	Electrode	*F*(1,8)	*p*	partial η^2
Alpha	Fz	.93	.36	.10
Alpha	P4	.93	.36	.10
Alpha	POz	.20	.67	.02
Beta	Fz	.32	.59	.04
Beta	Cz	1.00	.35	.11
Beta	C3	1.94	.20	.20
Beta	C4	1.19	.31	.13

Table 4 – Team Member vs. Experimenter Results for Exploratory Comparisons.

Frequency	Region	*F*(1,8)	*p*	partial η^2
Alpha	Frontal	.71	.42	.08
Alpha	Central	3.02	.12	.27
Alpha	Parietal	3.32	.11	.29
Beta	Frontal	1.47	.26	.16
Beta	Central	2.97	.12	.27
Beta	Parietal	2.77	.13	.26

To ensure that any observed effects were not due to the order of the trials participants engaged in, I conducted similar planned and exploratory comparisons investigating the effect of Trial Order on neural synchronization. The between-subject comparisons of AB and BA, where A refers to the Team Member condition and B refers to the Experimenter condition, were tested. As expected, the pattern of results were null (all $p > .05$), indicating that differential transfer did not occur.

3.3 H3: Effect of Task Type on Neural Synchronization

I used the same mixed ANOVAs from H2 to test H3. Based on my third hypothesis, I predicted that neural synchronization between team members will depend on the type of team task. Specifically, I predicted increased neural synchronization in the alpha band in the Fz, POz, and P4 electrodes for the NEO task and increased neural synchronization in the beta band in the Fz, Cz, C3, and C4 electrodes for the Minecraft task. This hypothesis was only partially supported for the NEO task in the Fz electrode, where the NEO condition's (M = 2.53, SD = .08) neural entropy in the alpha band was significantly lower than in the Minecraft condition (M = 2.99, SD = .08), p = .002. There was a similar result in the Fz electrode in the beta band, but the results were opposite from what was predicted: the NEO condition's (M = 2.70, SD = .09) neural entropy in the beta band was significantly lower than in the Minecraft condition (M = 3.08, SD = .09), p = .02. No other main effects of Task Type were significant. The results for the planned comparisons are summarized in Table 5 and the exploratory comparisons in Table 6. Controlling for the amount of communication (as both time and number of utterances) as well as the self-reported frequency of hand and head movements when speaking did not alter the pattern of results. Additionally, the pattern of mean differences were not in the hypothesized direction for the beta frequency range: Means for the NEO condition were lower (indicating higher synchronization) than the Minecraft condition during both the experimenter and participant sessions for all electrodes, regions, and frequencies tested.

Table 5 – NEO vs. Minecraft Results for Planned Comparisons.

Frequency	Electrode	$F(1,8)$	p	partial η^2
Alpha	Fz	19.39	.002	.71
Alpha	P4	1.58	.24	.17
Alpha	POz	.99	.35	.11
Beta	Fz	8.14	.02	.50
Beta	Cz	1.47	.26	.16
Beta	C3	2.57	.15	.24
Beta	C4	2.32	.17	.22

Table 6 – NEO vs. Minecraft Results for Exploratory Comparisons.

Frequency	Region	$F(1,8)$	p	partial η^2
Alpha	Frontal	1.34	.20	.14
Alpha	Central	1.51	.25	.16
Alpha	Parietal	1.62	.24	.17
Beta	Frontal	.86	.38	.10
Beta	Central	1.23	.30	.13
Beta	Parietal	1.03	.34	.11

To determine if the effect of Task Type was masked by the Interaction condition, I investigated the 2(Task Type) x 2(Interaction) component of the 2x2x2 mixed ANOVA with the same electrodes, frequency bands, and brain regions. No interactions were statistically significant. The results are summarized in Tables 7 and 8. Controlling for the amount of communication (as both time and number of utterances) as well as the self-reported frequency of hand and head movements when speaking did not alter the pattern of results. Overall, these results suggested that the effect of Task Type did not depend on the Interaction condition.

Table 7 – Team Task by Interaction for Planned Comparisons.

Frequency	Electrode	$F(1,8)$	p	partial η^2
Alpha	Fz	.93	.36	.10
Alpha	P4	2.34	.17	.23
Alpha	POz	.78	.41	.09
Beta	Fz	.14	.72	.02
Beta	Cz	.04	.84	.01
Beta	C3	.58	.47	.07
Beta	C4	.91	.37	.10

Table 8 – Team Task by Interaction for Exploratory Comparisons.

Frequency	Region	$F(1,8)$	p	partial η^2
Alpha	Frontal	.74	.41	.09
Alpha	Central	.35	.57	.04
Alpha	Parietal	5.50	.05	.41
Beta	Frontal	.07	.80	.01
Beta	Central	.03	.88	.003
Beta	Parietal	2.28	.17	.22

3.4 H4: Cross-level Effects

The fourth hypothesis was an exploratory hypothesis stating that communication and neural activity should be related, such that changes in communication patterns should be reflected in the neural activity of teams (and vice versa). To investigate this hypothesis, I conducted cross-correlations between the neural entropy time series and the communication flow entropy time series for every team on each electrode, frequency band, and Interaction condition. I also conducted graphical analyses on the raw neural entropy time series for every team on each region (frontal, central, parietal, occipital, and temporal) and frequency band and compared trends in the neural entropy to what was occurring in the transcript (i.e., communication content).

3.4.1 Cross-Correlations

The cross-correlations were calculated using the crosscorr function in Matlab between the neural entropy time series and the communication flow entropy time series. I calculated cross-correlations for each team across 17 electrodes (C3, C4, Cz, F3, F4, F7, F8, Fz, O1, O2, P3, P4, P7, P8, Pz, T3, and T4), two frequency bands (alpha and beta), and both Interaction conditions (experimenter and team member). I examined the graphs of the cross-correlations for significant zero-lag (i.e., significant positive or negative peak around lag 0; see Figure 5), pure lead-lag (i.e., a single significant positive peak and a single significant negative peak in both forward and backwards lag; see Figure 6), or pure lead-lag with seasonality relationships (i.e., multiple significant positive and negative peaks in both forward and backwards lag; see Figure 7). The lag in each graph corresponds to one second in time.

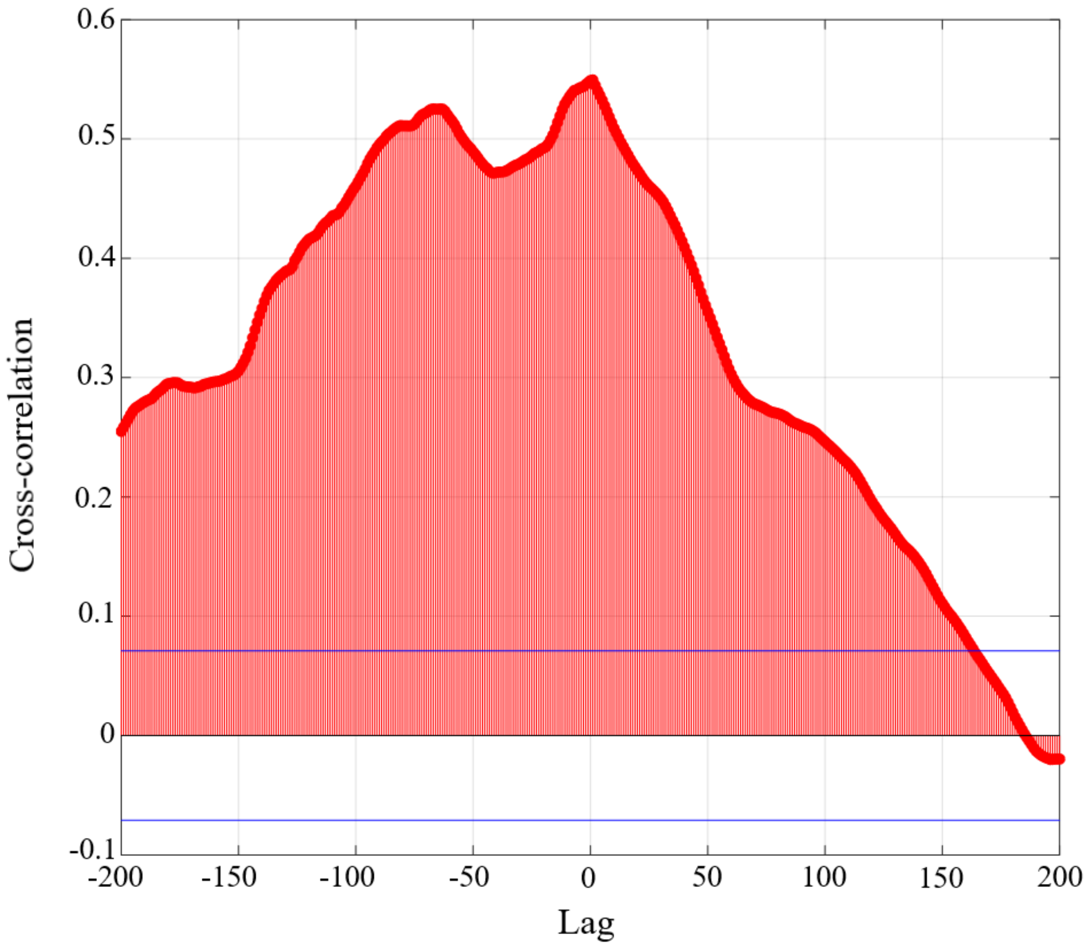


Figure 5 – Example of a Significant Zero-lag Relationship. A significant zero-lag relationship is indicated by a significant positive or negative peak around lag zero. This example comes from Team 5 who performed the Minecraft task. The cross-correlation was calculated between the entropy time series of the alpha frequency in the C4 electrode and the entropy time series of the joint experimenter communication flow. The blue lines indicate the threshold of significance.

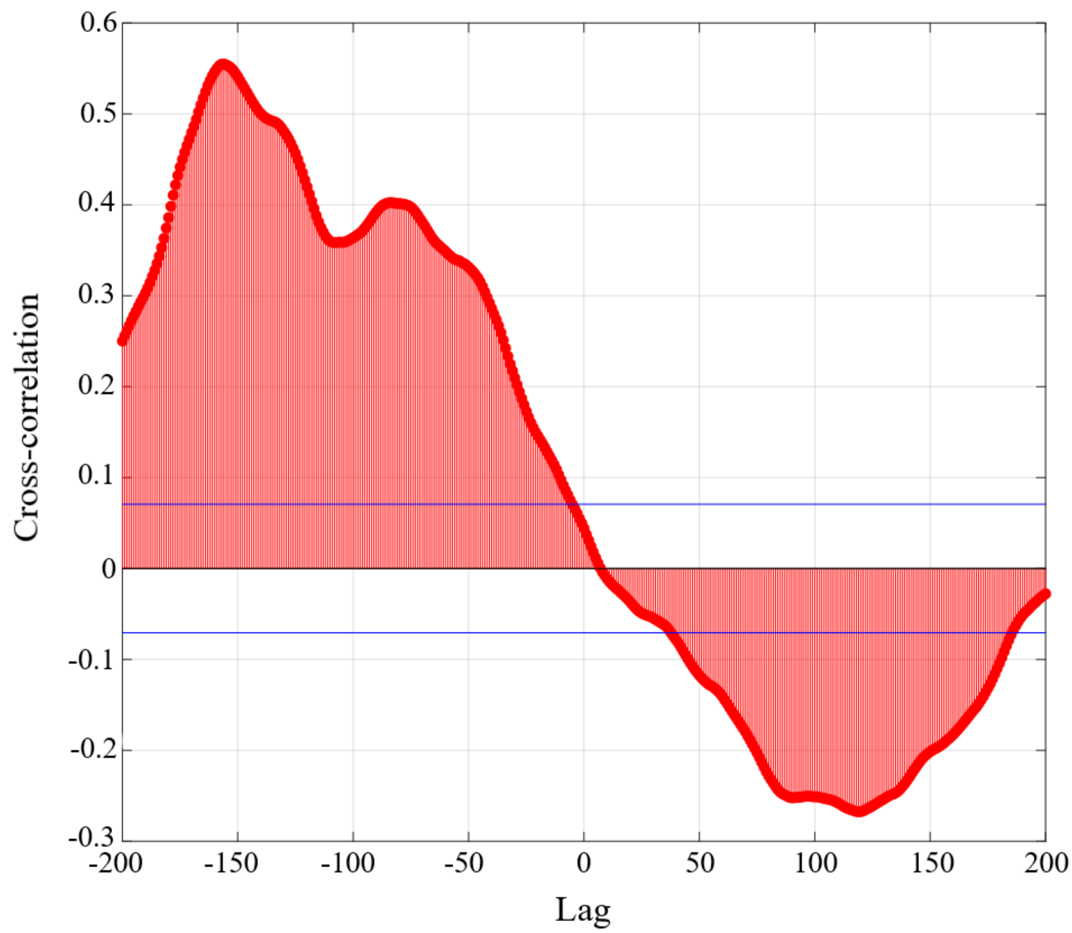


Figure 6 – Example of a Significant Pure Lead-lag Relationship. A significant pure lead-lag relationship is indicated by a single significant positive peak and a single significant negative peak in both forward and backwards lag. This example comes from Team 8 who performed the NEO task. The cross-correlation was calculated between the entropy time series of the beta frequency in the O1 electrode and the entropy time series of the joint experimenter communication flow. The blue lines indicate the threshold of significance.

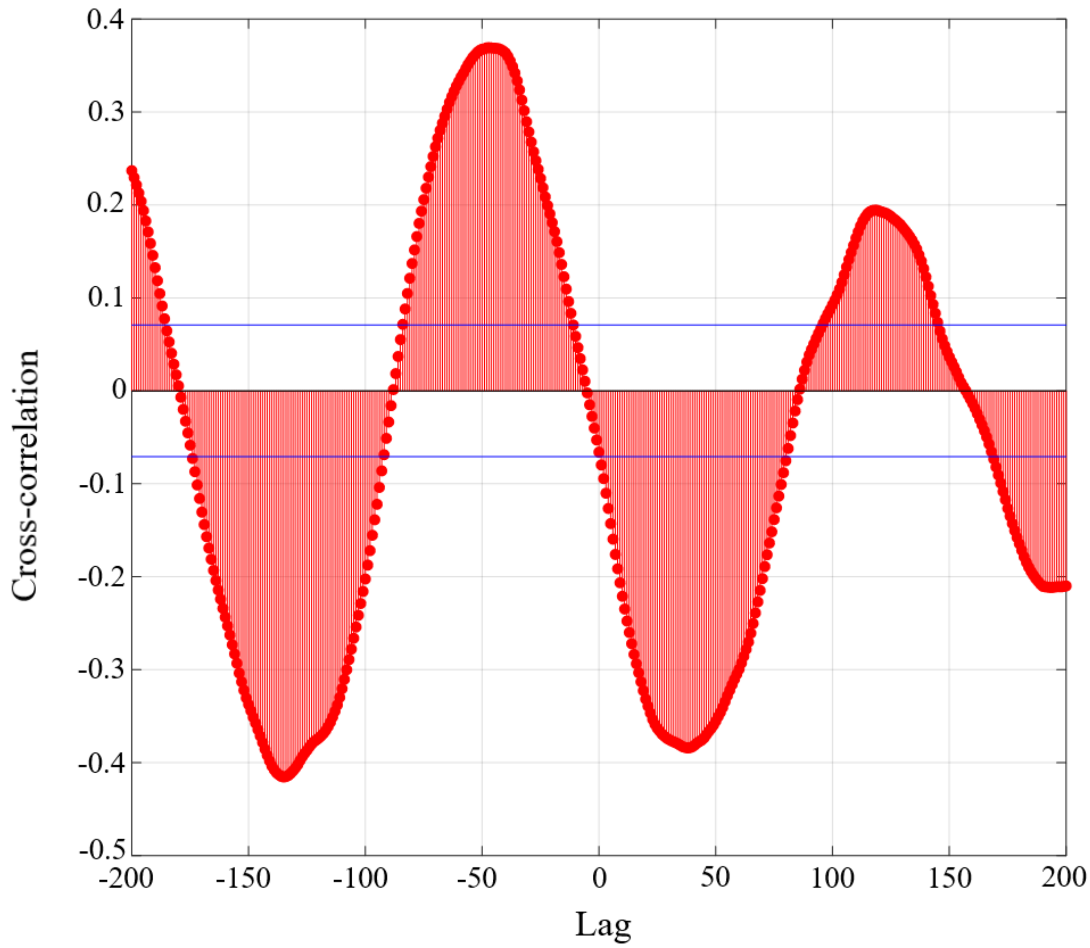


Figure 7 – Example of a Significant Pure Lead-lag with Seasonality Relationship. A significant pure lead-lag with seasonality relationship is indicated by multiple significant positive and negative peaks in both forward and backwards lag. This example comes from Team 23 who performed the NEO task. The cross-correlation was calculated between the entropy time series of the alpha frequency in the F4 electrode and the entropy time series of the participant communication flow. The blue lines indicate the threshold of significance.

3.4.1.1 <u>Experimenter vs. Participant</u>

Overall in the experimenter conditions, collapsing across the electrodes and frequency bands, there were significant zero-lag relationships between the neural entropy and the flow entropy time series. An example of a zero-lag relationship is shown in Figure 5 for team 5. Here, a significant zero-lag relationship indicates that the neural entropy and communication flow entropy changed together at the same time in the experimenter condition.

In the participant condition, again collapsing across the electrodes and frequency bands, the relationship between the neural and flow entropy time series more frequently showed a pure lead-lag with seasonality relationship. An example of this relationship is shown in Figure 7 for team 23. This pattern suggests that neural entropy and communication flow entropy were related to one another across multiple points in time in the participant condition.

Overall, these cross-correlation results suggest that the relationship between team neural physiology and communication flow was affected by the Interaction condition. Specifically, the experimenter condition produced a more superficial relationship in time, whereas the participant condition produced a longer term relationship across time.

3.4.1.2 Minecraft vs. NEO

Overall in the Minecraft condition in the alpha frequency band, the patterns in the cross-correlations indicated a pure lead-lag with seasonality relationship (Fig. 7) in the central, frontal, and occipital regions. This result suggests that in the central, frontal, and occipital regions in the alpha frequency band for the Minecraft task that neural entropy and communication flow entropy were related to one another across multiple points in time. In the parietal and temporal regions, there was a significant zero lag relationship (Fig. 5). This result suggests that in the parietal and temporal regions in the alpha frequency band for the

Minecraft task that neural entropy and communication flow entropy changed together at the same time.

The patterns in the cross-correlations differed in the beta frequency band for the Minecraft task. Seasonality patterns (Fig. 7) were only observed for the frontal region, and a zero-lag pattern (Fig. 5) was observed in the central region. Pure lead-lag relationships (see Fig. 6) were observed in the occipital, parietal, and temporal regions in both directions, which suggests that for some teams, either changes in the communication flow entropy or neural entropy preceded changes in the other variable, depending on the direction of lag.

Overall in the NEO condition in the alpha frequency band, the patterns in the cross-correlations indicated a pure lead-lag with seasonality relationship (Fig. 7) in the central, frontal, parietal, and occipital regions. This result suggests that for these regions in the alpha frequency band in the NEO task that neural entropy and communication flow entropy were related to one another across multiple points in time. In the temporal region, there was a significant zero lag relationship (Fig. 5). This result suggests that in the temporal region in the alpha frequency band for the NEO task that neural entropy and communication flow entropy changed together at the same time.

The patterns in the cross-correlations differed in the beta frequency band for the NEO tasks. Seasonality patterns (Fig. 7) were only observed for the central region and some parietal electrodes (the specific electrodes were inconsistent across teams), a zero-lag pattern (Fig. 5) was observed in the occipital and temporal regions, and pure lead-lag relationships (Fig. 6) were observed in the frontal region and some parietal electrodes in both directions.

Overall, the results for task differences in the cross-correlations suggest that the relationship between neural physiology and communication flow differ across the brain regions and frequency bands depending on the type of task. In the alpha frequency band, the regions that indicated long-term dependencies between neural synchronization and communication flow overlapped substantially between the Minecraft and NEO tasks, including the central, frontal, and occipital regions. The beta frequency band better differentiated the two task types, with the frontal region indicating long-term dependencies for the Minecraft task and the central and some parietal regions for the NEO task.

3.4.1.3 First vs. Second Trial

Overall in the first trial, collapsing across the electrodes and frequency bands, there were significant zero-lag relationships (Fig. 5) between the neural entropy and the flow entropy time series. This pattern indicates that the neural entropy and communication flow entropy changed together at the same time during the first trial.

In the second trial, again collapsing across the electrodes and frequency bands, the relationship between the neural and flow entropy time series more frequently showed a pure lead-lag with seasonality relationship (Fig. 7). This pattern suggests that neural entropy and communication flow entropy were related to one another across multiple points in time in the second trial. Overall, both sets of results suggest that there may have been transfer (order effects) across trials in the relationship between neural entropy and communication flow entropy, such that long-term dependencies between neural synchronization and communication flow developed between the first and second trials.

3.4.2 Graphical Analysis

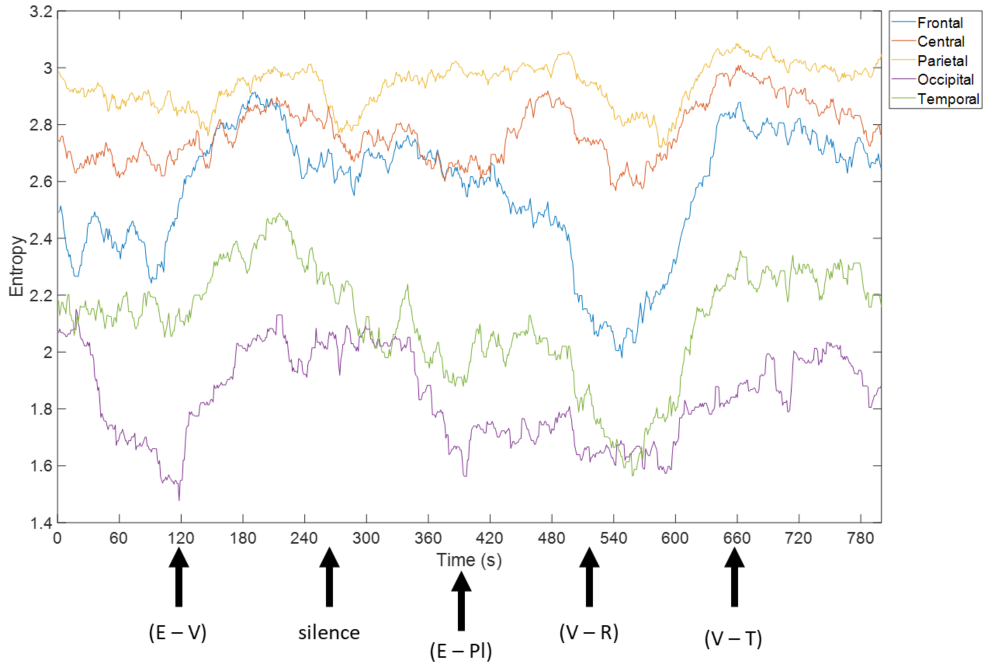
To perform the graphical analysis, I graphed the neural entropy time series of each region (frontal, central, parietal, occipital, and temporal) and both alpha and beta frequency ranges for every team in the participant condition. Graphical analyses were only conducted for the participant condition because it would be difficult to compare the transcripts for both experimenter conditions to a single neural entropy time series. This process resulted in 24 graphs. I approached the graphical analysis bottom-up, identifying changes in neural entropy on the graphs and determining what occurred in the transcript in the minute before and after the changes in neural entropy. I chose one minute before and after because changes in communication occur across a longer timescale than changes in neural activity (Newell, 1994). In the transcripts themselves, I looked for changes in both content (topic changes) and flow (periods of silence and participant interruptions).

Because this graphical analysis was a visual analysis, exact numbers could not be calculated for changes in neural entropy. In order to approximate a 90-95% CI, I looked for large changes in neural entropy that were at least 2-3 times larger than the regular changes that were occurring, relative to the mean entropy for that region. To ensure that I could interpret the changes in the neural entropy based on an estimated confidence interval, thus assuming a normal distribution, I calculated D'Agostino's K-squared tests on all 120 distributions. According to the D'Agostino's K-squared test results, 67.5% of the distributions were significantly non-normal; however, this appeared to be largely due to kurtosis, rather than skew. To determine how many distributions were significantly skewed, I calculated the skew of the distributions and compared the skew to the ±1 rule-of-thumb, where skewness greater than or less than ±1 is considered significantly skewed

(Bulmer, 1979). 22.5% of the neural entropy distributions were positively or negatively skewed more than ±1. For highly skewed distributions, I interpreted changes in neural entropy differently to account for the positive and negative skew (e.g., for a negatively skewed distribution, large positive changes were interpreted more cautiously than large negative changes).

In my graphical analyses of the NEO task trials, I found that changes in neural entropy across both frequency bands and all regions were associated with both the communication content and flow. For example, in Figure 8A, large changes in neural entropy for team 23 were associated with a topic change from discussing environmental conditions (E) to vehicles (V), environmental conditions (E) to their plan (Pl), vehicles (V) to their route (R), and vehicles (V) to time (T). These changes in entropy appeared to be driven by changes in the EEG power for the second participant, whose EEG power changed from below baseline, baseline level, and above baseline while the first participant often stayed around baseline EEG power during the task session (Fig. 8B). Changes in neural entropy were also observed due to silence or changes from silence to talking, an extreme example of which is shown in Figure 9 for team 3. These changes seemed largely driven by changes in EEG power for both participants, whose EEG power changed variability relative to baseline during transitions from silence to talking and vice versa (Fig. 9B). For team 12, shown in Figure 10, there was a change in neural entropy due to several interruptions from one of the participants to the other participant. These effects were driven by changes in EEG power for both participants, where the EEG power changed variability relative to baseline across the entire task session (Fig. 10B). These patterns of results suggest that within the NEO task, changes in neural entropy across the brain are associated with changes in both communication content and flow.

A



B

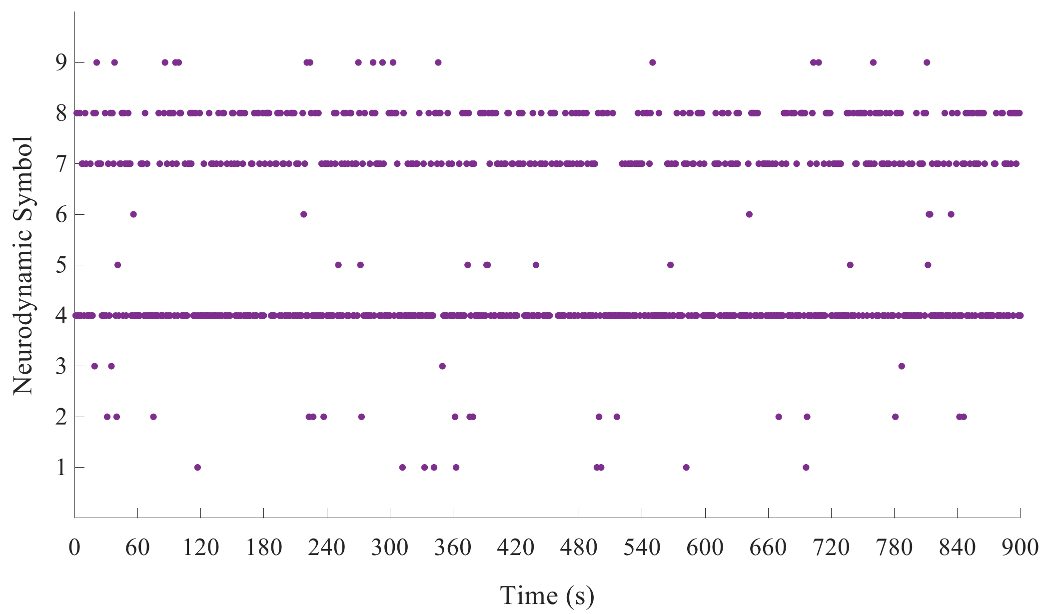


Figure 8 – Graphical Analysis of NEO Team 23. A) This graph is the neural entropy time series is for the alpha frequency range. This example illustrates changes in neural entropy due to topic changes and silence. The parentheses refer to topic changes, where E = Environmental conditions, V = Vehicles, Pl = Plan, R = Route, and T = Time. All arrow placements are approximate. B) This graph is an example of one of the neurodynamic symbol series for this team, namely, the alpha frequency band of the occipital region.

A

B

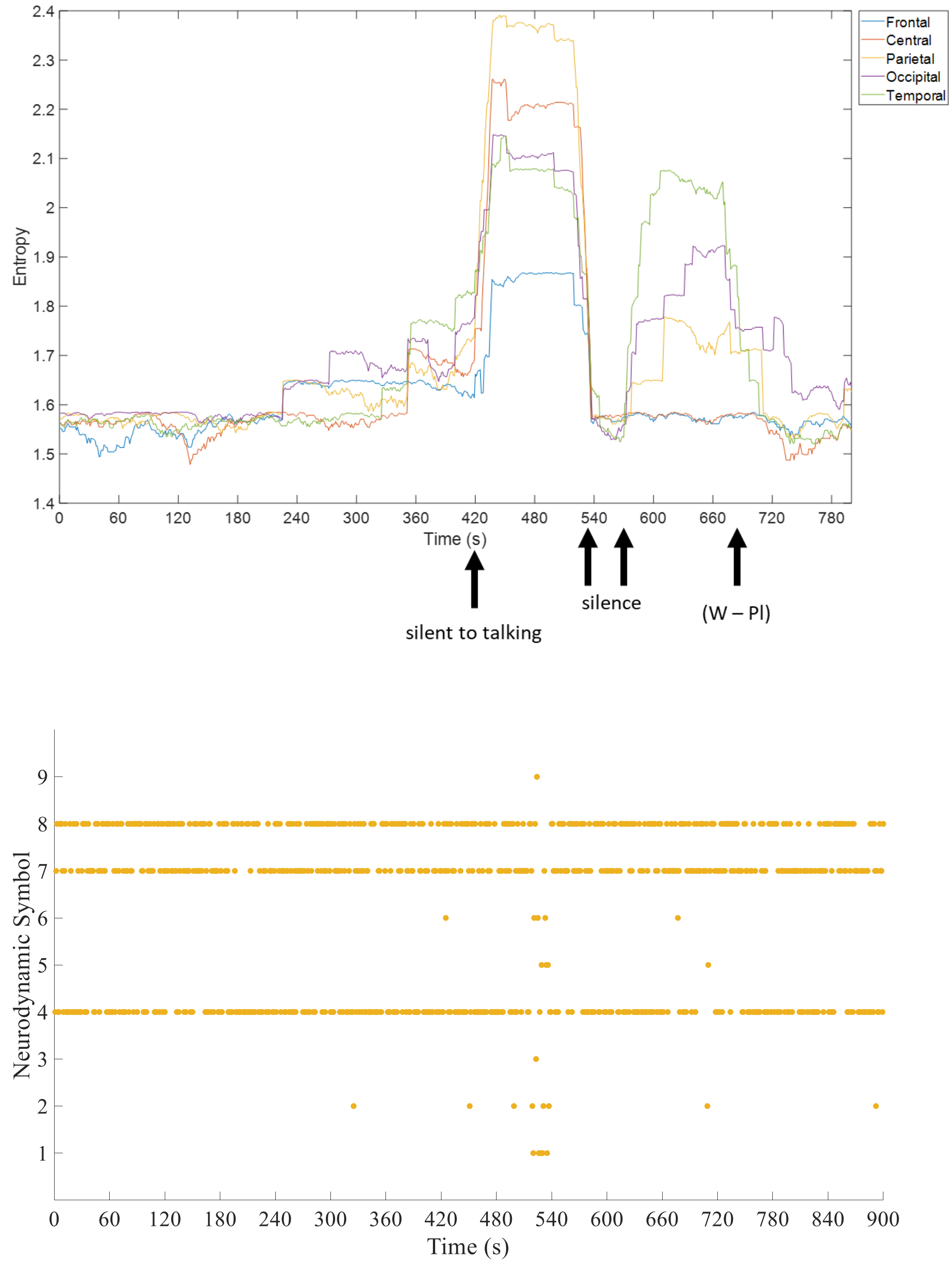


Figure 9 – Graphical Analysis of NEO Team 3. A) This neural entropy time series is for the alpha frequency range. This example illustrates a large increase in neural entropy due to silence. The parentheses refer to topic changes, where W = (Red Cross) Workers and Pl = Plan. All arrow placements are approximate. B) This graph is the neurodynamic symbol series for this team in the alpha frequency band of the parietal region.

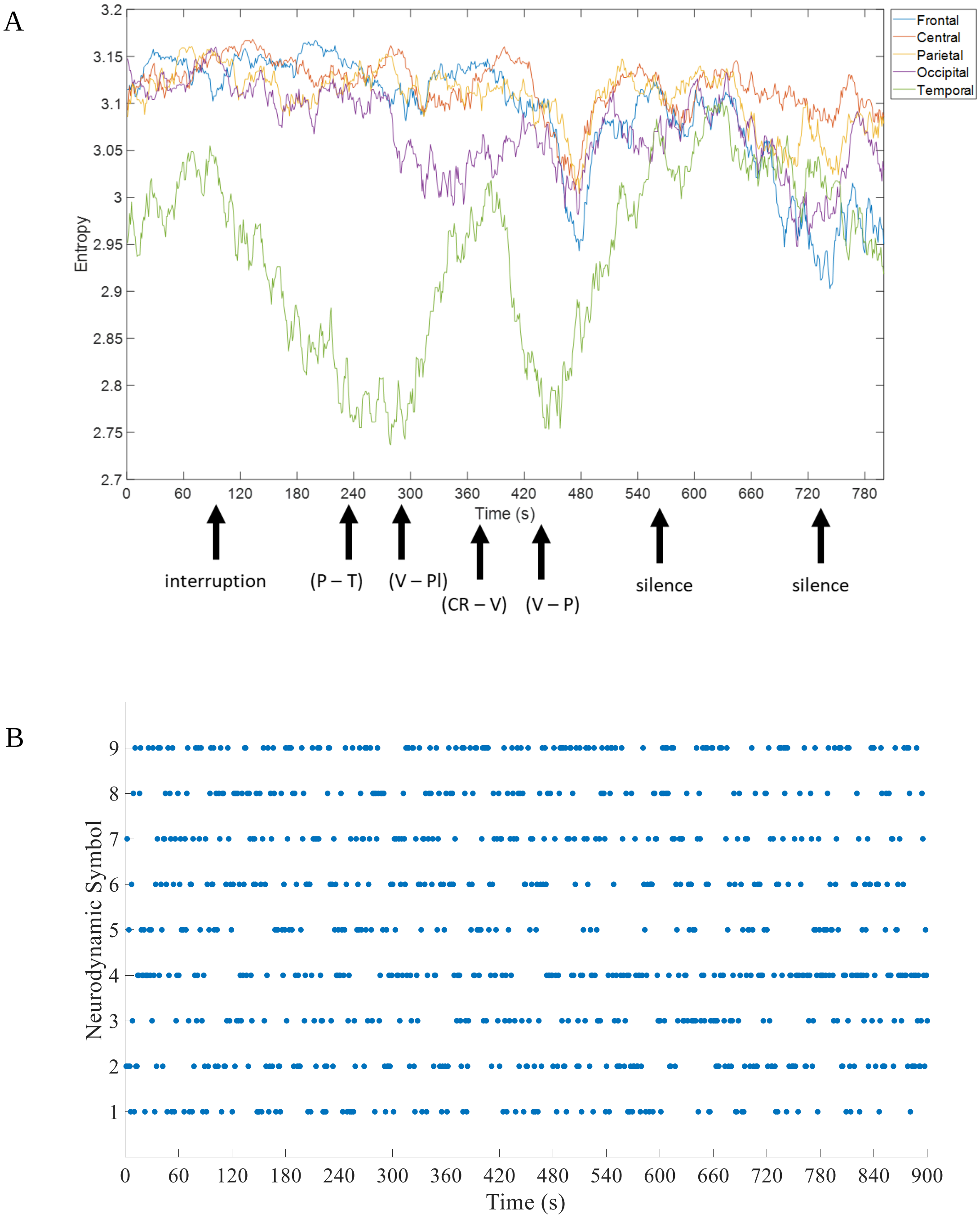
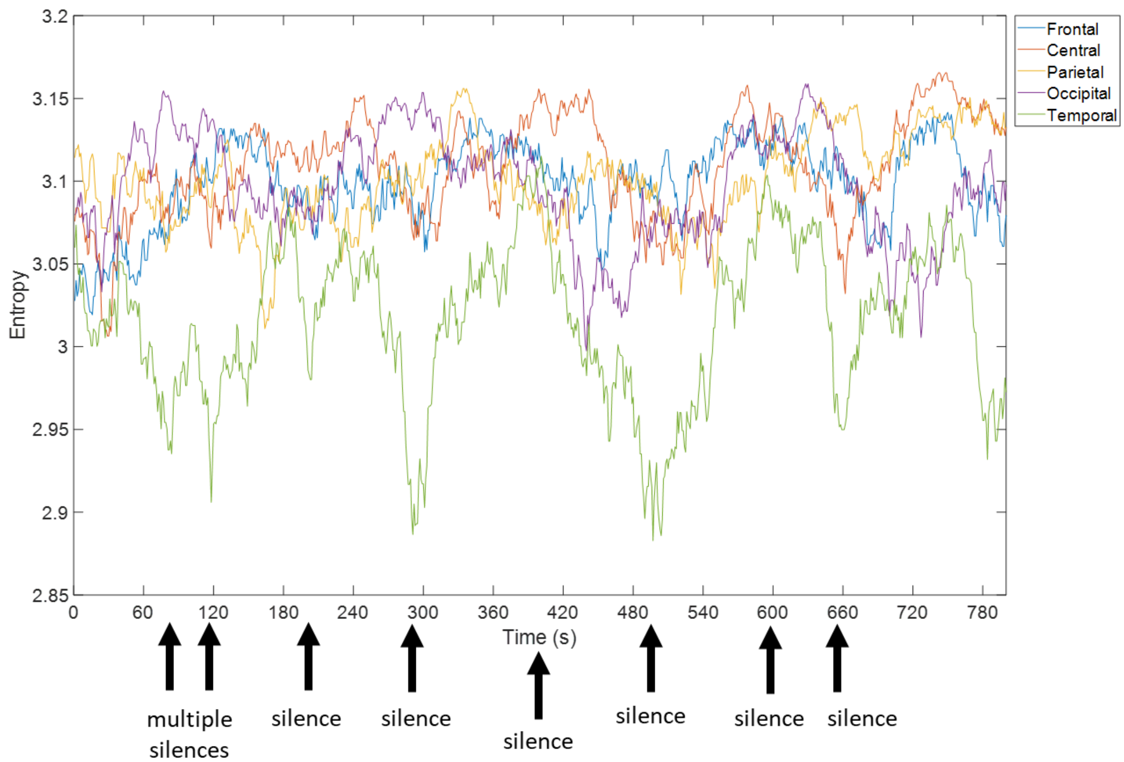


Figure 10 – Graphical Analysis of NEO Team 12. A) This neural entropy time series is for the beta frequency range. This example illustrates changes in neural entropy due to an interruption, topic changes, and silence. The parentheses refer to topic changes, where P = Personnel, T = Time, V = Vehicle, Pl = Plan, and CR = Conversation regulation. All arrow placements are approximate. B) This graph is the neurodynamic symbol series for this team in the beta frequency band of the frontal region.

For the Minecraft task, I observed small changes in neural entropy across both frequency bands, primarily in the temporal region, that were associated with communication flow. For example, in Figure 11 for team 11, small abrupt changes in neural entropy in the temporal region were associated with periods of silence, some of which were periods of multiple silences. These effects seemed driven by changes in EEG power for both participants, where the EEG power changed variability relative to baseline across the entire task session (Fig. 11B). An extreme example of this can be seen in Figure 12 for team 5, where a period of long silence resulted in a sharp decrease in neural entropy. These entropy changes appeared driven by changes in EEG power for both participants, where the EEG power became less variable and more similar to their baseline measurement during silence (Fig. 12B). Some changes in neural entropy were due to interruptions or topic changes, but this only occurred for team 15. In Figure 13, changes in neural entropy in the occipital and temporal regions occurred during long silences, several interruptions, and topic changes from off-topic (OT) to participant 2's blocks (B2) and from participant 1's blocks (B1) to off-topic (OT). These changes in entropy appeared to be largely driven by changes in the EEG power for the second participant, whose EEG power changed from below baseline, baseline level, and above baseline during one of the topic changes (Fig. 13B). These patterns of results suggest that within the Minecraft task, changes in neural entropy, particularly in the temporal region, are associated with mostly with changes in communication flow.

A



B

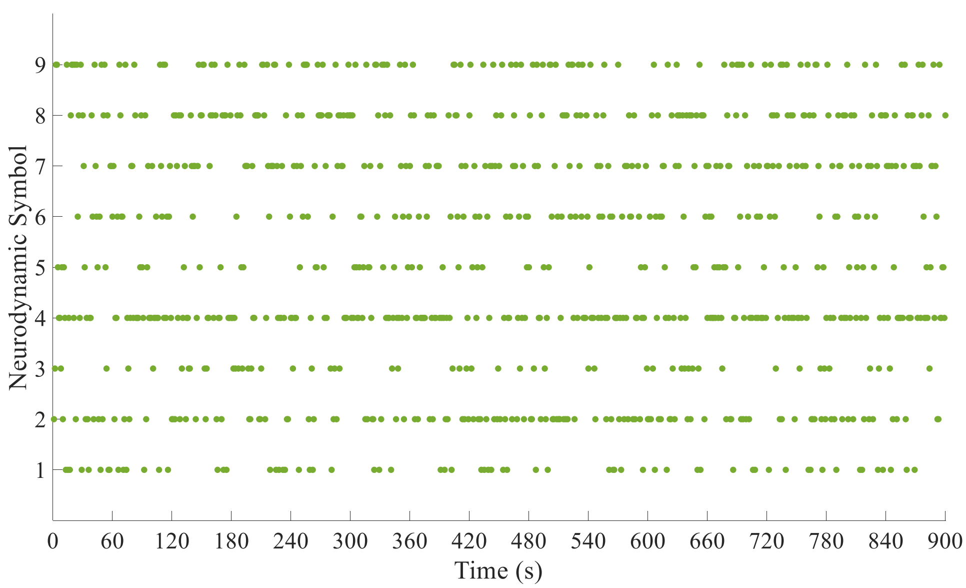
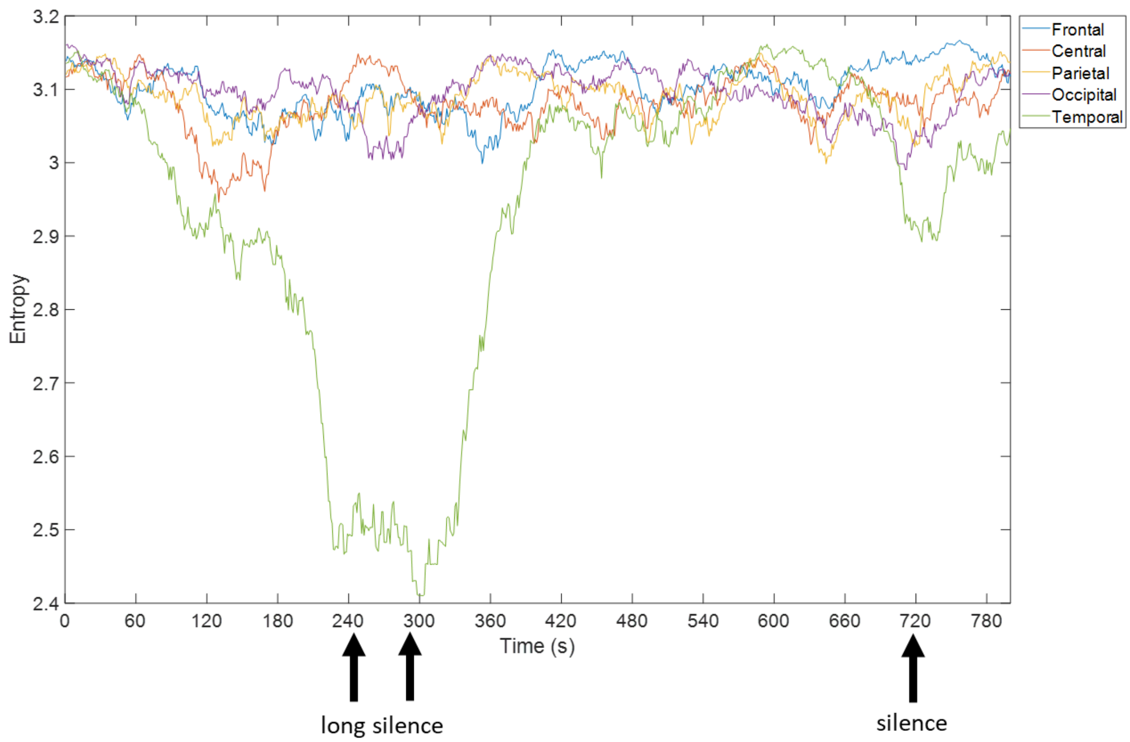


Figure 11 – Graphical Analysis of Minecraft Team 11. A) This neural entropy time series is for the alpha frequency range. This example illustrates changes in neural entropy due to silence. All arrow placements are approximate. B) This graph is the neurodynamic symbol series for this team in the alpha frequency band of the temporal region.

A



B

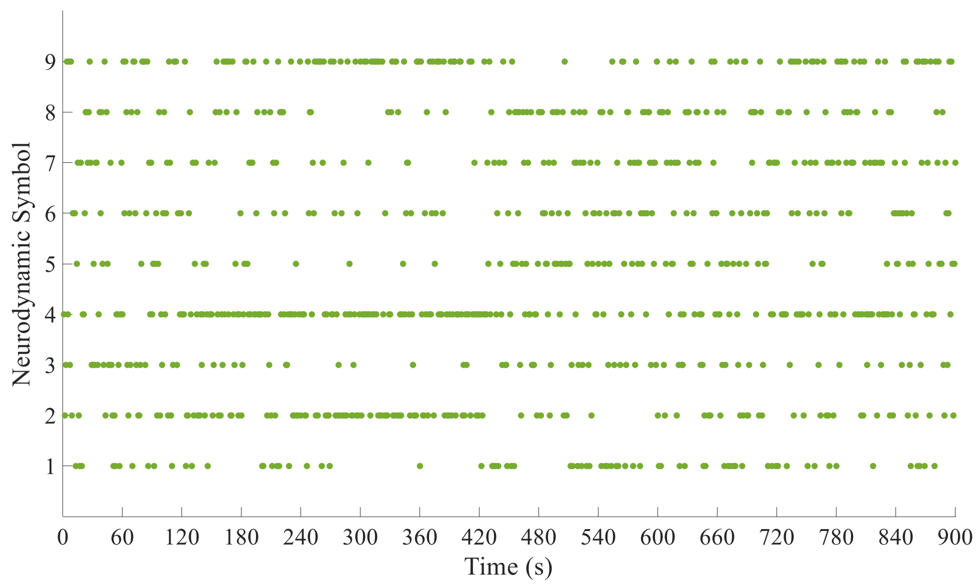


Figure 12 – Graphical Analysis of Minecraft Team 5. A) This neural entropy time series is for the beta frequency range. This example illustrates a large decrease in neural entropy due to a long period of silence. All arrow placements are approximate. B) This graph is the neurodynamic symbol series for this team in the beta frequency band of the temporal region.

A

B

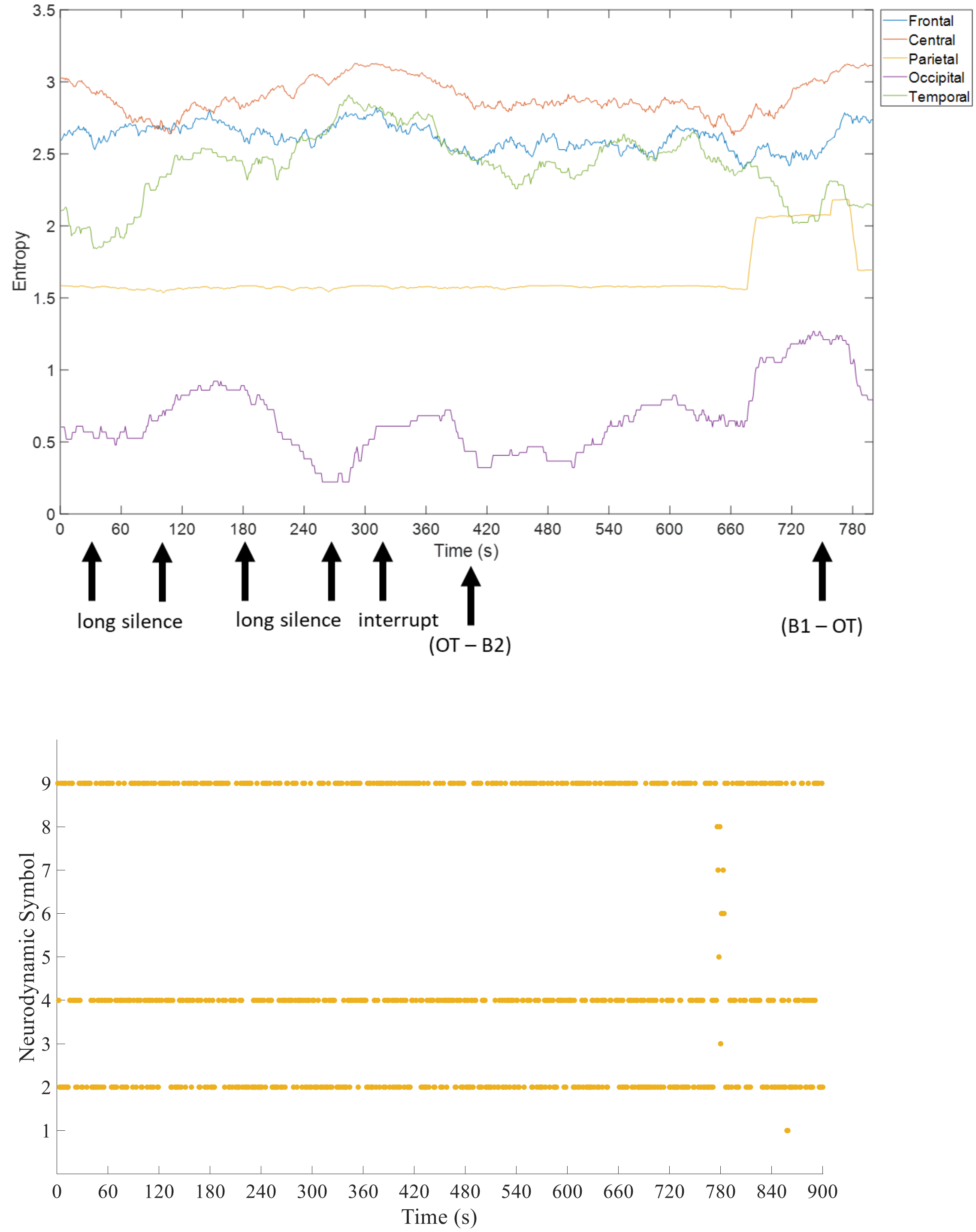


Figure 13 – Graphical Analysis of Minecraft Team 15. A) This neural entropy time series is for the alpha frequency range. This example illustrates changes in neural entropy due to an interruption, silence, and topic changes. The parentheses refer to topic changes, where OT = Off-topic, B1 = Participant 1's blocks, and B2 =

Participant 2's blocks. All arrow placements are approximate. B) This graph is the neurodynamic symbol series for this team in the alpha frequency band of the parietal region.

CHAPTER 4. DISCUSSION

This study illustrates how communication dynamics structure neural dynamics, over time, within specific task constraints. Specifically, I found significant relationships between changes in the neural synchronization of teams and changes in the team's communication flow and content across time, which were affected by the type of task the team was performing and who the team member was performing the task with. Additionally, I replicated my previous research findings where manipulating the type of task alters the dynamical structure of the team's communication. However, I did not find support for the effect of task type and interaction partner on average neural synchronization across different electrodes or brain regions.

4.1 Communication Dynamics

My first hypothesis was a manipulation check based on my previous work (Dunbar & Gorman, 2014) during a shorter task period (15 minutes compared to 45 minutes). In H1, I predicted that the Minecraft task would lead to a dynamical communication structure in fact-based communication and the NEO task would lead to a dynamical communication structure in interpretation-based communication. In support of H1, I found that both facts and interpretations were significantly better fit by a power-law and that the Minecraft task sessions were dynamically structured around fact-based communication whereas the NEO task sessions were dynamically structured around interpretation-based communication. Conversation regulation, unrelated to any particular task, was better fit by the null distribution (exponential). This pattern of results suggests that the task type differences during a shorter time period elicit similar communication dynamics.

Unexpectedly, I found a different pattern of results emerge in the surrogate analysis compared to my prior research. Similar to my prior research, the surrogates lost the dynamic patterns that were present in the original data based on the change in the R^2 fit. However, unlike my previous research findings, the surrogates still showed the same significant differences in the scaling exponents as the original data did. This difference in the surrogate results could mean one of two things: That the dynamics in the communication data are illusory or that the 15 minute time frame for the task is too short to produce enough data for a fractal analysis. Time series shorter than 256 data points can produce inaccurate estimates of the time series' true scaling exponent (Delignieres, Ramdani, Lemoine, et al., 2006). Based on change in the R^2 fit for the surrogate data, the first interpretation seems unlikely because randomizing the data made the data no longer fit a power-law, indicating a loss of dynamical structure due to randomization. The second interpretation may be plausible given that dyads varied in the amount that they communicated with one another. On average, dyads spent less than half the task session communicating (time (s) spent speaking M = 419.00, SD = 189.75). The average length of verb phrases (verb phrase M = 259.97, SD = 104.54) for each task session is near the point where the fractal analysis may not accurately capture the scaling exponent, potentially impacting the reliability of the scaling exponents for the teams that communicated less frequently. However, the amount that participants spoke during the task should not have any impact on the reliability of the other dependent measures because the reliability of the measure itself is not dependent on the amount of communication; rather, I predicted that the value of the measure itself should change as a function of the amount of communication. A lack of communication or communicating for the entire task session would have been more problematic for my other measurements. Additionally, I expected participants to communicate for a portion of the session. Future research would be necessary to determine the optimal task length to circumvent this issue for the scaling exponents.

4.2 Neural Synchronization

My second and third hypotheses pertained to the effect of the Interaction (H2) and Task Type (H3) conditions on the average neural entropy. In H2, I predicted that neural synchronization would be higher in the team member condition compared to the experimenter condition. In H3, I predicted increased neural synchronization in the alpha band in the Fz, POz, and P4 electrodes for the NEO task and increased neural synchronization in the beta band in the Fz, Cz, C3, and C4 electrodes for the Minecraft task. Neither hypothesis was supported by the results from my study, although I did find evidence that the Fz electrode can identify differences in neural synchronization between teams performing the NEO task and the Minecraft task. There may be a few possible reasons for the null results: Data loss due to averaging, lack of events to change neural entropy, the task type manipulation does not impact neural dynamics the same way it manipulates communication dynamics, or the interaction manipulation does not impact neural dynamics the same way it manipulates motor dynamics.

One possible reasons for my null results may be because I was averaging entropy across the entire task session. Averaging across time series data results in loss of the internal data structure. By averaging across the task session, I may have removed nuances in the neural entropy over time that could have been due to the task type or interaction conditions. This argument is further supported by the differences in the averaged results compared to the time series results, which are discussed in the next section **Cross-level Effects**.

Another possible reason for my null results may be because the teams were coordinating during ‘typical conditions.’ Other research has used neural measures of entropy as an indicator of uncertainty, where high entropy represents high uncertainty, or ‘surprise’ that needs to be resolved by the team (Stevens & Galloway, 2017). Prior research has found that teams tend to have fairly average entropy as they work in typical conditions and that entropy increases with uncertainty and decreases after uncertainty reaches a tipping point, or threshold, where the team needs to resolve the uncertainty during the task session through synchronization or neural reorganization (e.g., Stevens, Galloway, Halpin, & Willemsen-Duynlap, 2016b). Uncertainty can be inherent to the task setting, task performance, or introduced artificially in the task session by perturbing the team during task performance. I did not include perturbations in this study, which may have resulted in a lack of change in neural entropy. In addition, both the NEO and Minecraft tasks have less uncertainty, or surprise, built in to them than more realistic tasks, such as medical simulations (e.g., Stevens et al., 2016b). It may also be plausible that the relationship between entropy and uncertainty is mediated by attention, where entropy is an indicator of when joint attention is needed from the team to resolve an uncertainty in the task. The tasks selected for this study had few incidents where participants would need to jointly attend to an event on their screen, the exception being when participants were typing up their plan together for the NEO task.

It may also be that neither of my manipulations affect neural dynamics. The task type manipulations, although they manipulate the dynamics of the communication content, might not affect neural synchronization similarly across the brain. In the average neural entropy results, I only found that the Fz electrode identified reliable differences in neural entropy between the Minecraft and NEO tasks, but not any of the other electrodes I identified. My cross-correlation analyses indicated that there were some differences in the task type when examining neural entropy over time; however, there was a fair amount of overlap between the cortical regions involved in the relationship between the neural activity and communication across the two task types. These results provide only limited support for extending the theory of interactive team cognition (Cooke et al., 2013) to neural coordination.

My interaction manipulation was based on prior research with motor dynamics; namely, postural sway (Shockley et al., 2003). In prior studies, this interaction manipulation served as a convenient control condition to disentangle dynamics due to the experimental task from dynamics due to the shared interaction medium (i.e., coupling). In the average neural entropy results, I did not find any differences due to the shared interaction medium. My null results for the interaction condition may be because there were differences in how the experimenters and participants approached their task session. Experimenters were more experienced with the task, which may have led to unintentional differences between the experimenter and participant session based on expertise rather than on their interaction partner. Although the Interaction condition may not have successfully manipulated neural dynamics alone, it did successfully manipulate cross-level effects between neural synchronization and communication content and flow.

4.3 Cross-level Effects

My fourth hypothesis was an exploratory hypothesis. In H4, I expected to find reciprocal relationships between the communication and neural activity of the teams based on predictions from the dynamical systems theory of team coordination (Gorman et al., 2017; Gorman, 2014). I addressed this hypothesis using two methods: Cross-correlation and graphical analysis. I found support for this hypothesis, where changes in both communication content and flow were reflected in the neural entropy time series of the teams. These results provide support for the dynamical systems theory of team coordination, extending cross-level effects to the task constraints of the team.

Unlike the average neural entropy results, I found that the relationship of neural entropy with communication flow was affected by the Interaction condition. Specifically, I found significant zero-lag relationships between neural entropy and communication flow entropy in the experimenter condition, whereas I found significant pure lead-lag with seasonality relationships in the participant condition. The results for the experimenter condition suggest that the relationship between changes in neural activity and who is speaking and when is more superficial or spurious because it is only related momentarily in time. If this relationship was meaningful (e.g., tied to the speaker), there would be significant relationships across time. Conversely, I found significant relationships across time for the participant condition. I expected to find significant relationships across time for the participant condition because in this condition, the communication flow was relevant to what was going on in the task now, previously, and in the future for *both* participants. For the experimenter condition, communication flow was only relevant for one participant at a time because the participants were performing the task separately with different experimenters. This finding suggests that the interaction condition successfully manipulated the relationship between the team's communication flow and neural activity over time.

In addition, I found that the relationship between neural entropy and communication (flow and content) was also affected by the Task Type condition. I found pure lead-lag with seasonality patterns primarily in the central, frontal, and occipital regions for the Minecraft task in the alpha band and the frontal region in the beta band. For the NEO task, I found pure lead-lag with seasonality patterns in the central, frontal, parietal, and occipital regions in the alpha band and the central region with some parietal electrodes in the beta band. In the graphical analysis, differences in neural entropy for the Minecraft task were primarily due to changes in flow (silence), whereas for the NEO task, it was due to both content (topic changes) and flow.

Although I performed these analyses to explore H4, the differences I found in the relationship between the communication and neural activity of teams were not at all similar to the predictions in H3. In contrast to H3, it seems that multiple cortical regions contribute to the relationship between the neural activity and communication content of teams, which overlap somewhat between the two task types. My predictions for H3 were derived from prior research investigating the neural coordination between interacting individuals performing different types of tasks, but much of this research focused primarily on the frontal (e.g., Stevens & Galloway, 2014, 2015, 2017) and central regions (e.g., Stevens & Galloway, 2014, 2015; Moreno et al., 2013), with some emphasis on the parietal-occipital region (e.g., Stevens & Galloway, 2015, 2017). In contrast, similar to the results I found in the current study, basic speaker-listener coupling research suggests that neural coupling occurs widely across the brain, relative to both language production and comprehension (Stephens et al., 2010). My findings suggest that in addition to the frontal and central regions, future research on team coordination should additionally measure the parietal, occipital, and temporal regions in conjunction with team communication to determine how these cortical regions differentially contribute to the team's communication. With communication flow, I found that the temporal region seems to contribute most to the relationship between the neural activity and communication flow, which is compatible with findings from speaker-listener coupling in the temporal regions in relation to language production (Stephens et al., 2010).

The differences in the graphical analyses were also unexpected, although these differences may relate to how participants approach each type of task. In the NEO task, participants can approach the task in numerous ways. There are several pieces of information that are necessary to discuss for the plan: Which vehicles to use, what personnel to bring for the extraction, the route to take on the island, the timing of events in the plan and on the island itself, the environmental conditions of the island, the extraction process, and various other topics. Conversely, in the Minecraft task, participants only need to convey which blocks the other participant needs to place in the game world. Participants tend to perform the Minecraft sequentially, completing their sets of blocks by going across either the rows or columns, whereas the NEO task is started differently by every team. Perhaps the communication content within and across each Minecraft session is too similar to detect changes in neural entropy over time, whereas in the NEO task the communication content changes more frequently, resulting in detectable changes in neural entropy.

However, both types of tasks are similarly affected by changes in flow since changes in flow affect all types of verbal communication.

4.4 Limitations and Future Directions

Although I controlled for how much participants and experimenters communicated and participants self-reported movement during speech in my analyses, I did not control for experimenter experience with the task. Prior research has shown that task experience affects the relationship between neural activity and communication (Gorman et al., 2016). The trained experimenters were quite experienced with the task and tended to run their task sessions similarly across sessions, whereas the participant sessions differed in how much the participants communicated and how the participants approached the task. It may be possible that the experimenter's expertise with the task influenced the participants neural and communication dynamics in unintended ways. Future research will be necessary to disentangle this by recruiting four naïve participants at a time, rather than having two participants work separately with trained experimenters.

In my communication surrogate analysis, I found that the surrogate data showed similar patterns in the scaling exponents as did my original data. This lack of change may be due to the length of time in the task sessions, which may not have produced enough data for my fractal analysis. Future research may be necessary to determine the minimum time boundary to elicit changes in the communication dynamics by manipulating the length of the task and calculating the changes in the dynamical parameters as a function of task length.

Another complication with this study was that it was difficult to find changes in neural entropy for the Minecraft task. The Minecraft task is a predictable and relatively unchanging task with little uncertainty. Prior research usually inserts identifiable events meant to disrupt the team's coordination to make it easier to find changes in dynamical parameters in the time series (e.g., Gorman et al., 2016). Future research should perturb the team as the team members are coordinating on these tasks to make it easier to identify changes in the neural dynamics or use tasks with more built in uncertainty (e.g., during healthcare simulation training; Stevens et al., 2016b).

Another possible limitation of the study was the neural analysis. Individual participant's neural data was discretized into a team level time series by averaging into one second epochs and converting the two team member's neural data into NSs prior to running the entropy analysis. This discretization process could have destroyed some of the information in the time series relevant to neural synchronization. However, prior research has suggested that neural synchronization occurs at a delay of a few seconds (Kuhlen et al., 2012; Stephens et al., 2010), so it may be possible that the discretization process did not destroy relevant information. Future research should examine differences between neural analyses to determine which analysis best measures team neural synchronization.

4.5 Conclusion

The current findings illustrate that teams dynamically structure the content and flow of their communication in relation to their neural activity. This dynamical structuring across multiple levels of analysis occurs around both the task constraints and who the team is working with on the task, but only when looking at the time series; this difference does not appear in the aggregate. These findings highlight the need to examine the nuances of the relationship between levels of analysis in teams in relation to the experimental manipulations we use across time. Thus, the relationship might not be exact or veridical or illusory, depending on how finely grained the variables are measured. Ultimately, investigating the causal nature of this relationship may reveal how these levels of analysis are nested within one another, providing possible new sources of measurement for team assessment.

APPENDIX A. CODING RULES

The following is a description of the coding rules used for the verb phrases in this study (Butner, Pasupathi, & Vallejos, 2008; Pasupathi & Hoyt, 2009; Pasupathi & Wainryb, 2010).

1. Facts – truthful statements that can be objectively tested; something that can be sensed and/or perceived.
    a. Actions – references to a person's actions.
    b. Descriptions – descriptions of something that can be sensed and/or perceived.
    c. Causal information – factual information that explains the reason for a behavior or event.
    d. Emotional behaviors – internal emotions described in terms of overt behaviors.
    e. Quotes – a phrase that that was said out loud or from the task materials.
2. Interpretations – references to mental processes and subjective interpretations that cannot be objectively tested.
    a. Emotions/Evaluations – refer to how people feel, and/or how they judge things (e.g., whether they are good or bad, positive or negative).
    b. Goals – intentions, goals, and desires.
    c. Thoughts/ other interpretations – all other thoughts and interpretations that cannot be categorized as goals or evaluations.
3. Conversation regulation – statements aimed at regulating the conversation.

    a. Backchanneling – non-lexical (i.e., vocalized sounds that have no semantic meaning other than to acknowledge the listener), phrasal (i.e., one word responses that acknowledge the listener), and substantive responses (i.e., asking for clarification or repeating what the other person said).

4. Uncodeable – does not fit in any of the previous categories.

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