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UNIVERSITY OF CALIFORNIA
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Neural, Linguistic, and Vocal Mechanisms of Successful Communication

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Psychology

by

Eleanor Collier

September 2024

Dissertation Committee:
Dr. Brent L. Hughes, Chairperson
Dr. Kalina J. Michalska
Dr. Sonja Lyubomirsky

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2024

The Dissertation of Eleanor Collier is approved:

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Committee Chairperson

University of California, Riverside

DEDICATION

To my husband, parents, and sister, the bonus parents and siblings I've acquired through my husband, and all our other family, through blood and through serendipity, who have shaped me, sustained me, and given me the gift of connection

ABSTRACT OF THE DISSERTATION

Neural, Linguistic, and Vocal Mechanisms of Successful Communication

by

Eleanor Collier

Doctor of Philosophy, Graduate Program in Psychology
University of California, Riverside, September 2024
Dr. Brent L. Hughes, Chairperson

Self-disclosure is a powerful way for people to connect, yet few studies have examined how disclosers can build a sense of shared meaning with listeners. We investigated possible neural, linguistic, and vocal mechanisms through which listeners may come to understand disclosers more intimately. We found that across numerous brain regions, greater neural *asynchrony* between speakers and listeners was associated with greater shared meaning-making. We also found that people who felt more connected at baseline had greater neural asynchrony, and that asynchrony partially explained the positive relationship between baseline connection and shared meaning-making. In addition, we found that neural asynchrony during key moments of speech may facilitate shared meaning-making. In particular, greater neural asynchrony when speakers (1) talked more slowly and (2) paused more was associated with greater shared meaning. These findings shed light on key processes that enable successful communication, and contribute to a more nuanced theoretical framework for how people build shared understanding through self-disclosure.

TABLE OF CONTENTS

List of Figures ..... **vii**

List of Tables ..... **viii**

List of Abbreviations ..... **ix**

Introduction **1**

Does Neural Synchrony Between Speakers and Listeners Lead to Shared Meaning Making? 2
What Features of Speech Facilitate Successful Communication? 5

Methods **10**

Participants 10
Procedures 13
Data Analysis 19

Results **32**

Shared Meaning is Associated With Positive Relationship Outcomes and Greater Baseline Connection 32
Neural Asynchrony, Rather Than Synchrony, is Associated With Shared Meaning-Making 33
Neural Asynchrony May Facilitate Greater Shared Meaning-Making Between More Connected Individuals 35
Neural Asynchrony During Key Moments of Speech May Facilitate Shared Meaning-Making 37

Discussion **41**

References **46**

Supplementary Materials **52**

LIST OF FIGURES

Figure 1. Participants' social network **11**
Figure 2. Story-listening structure **12**
Figure 3. fMRI task design **16**
Figure 4. Behavioral task design **18**
Figure 5. Neural synchrony analysis method **23**
Figure 6. Results for neural synchrony and shared meaning **34**
Figure 7. Results for mediation analysis of connection, neural asynchrony, and shared meaning **36**
Figure 8. Results for speech features, neural asynchrony, and shared meaning **40**
Supp. Figure 1. Results for average synchrony **54**

LIST OF TABLES

Table 1. Linguistic and vocal features analyzed **30**
Table 2. Results for mediation analysis of connection, neural asynchrony, and shared meaning **36**
Supp. Table 1. Results for neural synchrony and shared meaning **52**
Supp. Table 2. Results for average synchrony **55**
Supp. Table 3. Results for emotional language, synchrony, and shared meaning **56**
Supp. Table 4. Results for vivid language, synchrony, and shared meaning **57**
Supp. Table 5. Results for reflective language, synchrony, and shared meaning **58**
Supp. Table 6. Results for third-person pronouns, synchrony, and shared meaning **59**
Supp. Table 7. Results for big words, synchrony, and shared meaning **60**
Supp. Table 8. Results for vocal pitch, synchrony, and shared meaning **61**
Supp. Table 9. Results for vocal intensity, synchrony, and shared meaning **62**
Supp. Table 10. Results for vocal roughness, synchrony, and shared meaning **63**
Supp. Table 11. Results for speech rate, synchrony, and shared meaning **64**
Supp. Table 12. Results for silent pauses, synchrony, and shared meaning **66**
Supp. Table 13. Results for high and low speech rate, synchrony, and shared meaning **67**
Supp. Table 14. Results for high and low pause proportion, synchrony, and shared meaning **68**

LIST OF ABBREVIATIONS

Abbreviation	Definition
ACC	anterior cingulate cortex
accumbens	nucleus accumbens
AG	angular gyrus
aHipp	anterior hippocampus
aINS	anterior insula
amyg	amygdala
ATL	anterior temporal lobe
auditory	auditory cortex
dlPFC	dorsolateral prefrontal cortex
dmPFC	dorsomedial prefrontal cortex
FEF	frontal eye field
FFA	fusiform face area
IFG	inferior frontal gyrus
INS	insula
IPL	inferior parietal lobule
ITG	inferior temporal gyrus
LiG	lingual gyrus
lOFC	lateral orbital frontal cortex
lPFC	lateral prefrontal cortex
MCC	midcingulate cortex
motor	motor cortex
mPFC	medial prefrontal cortex
MTG	middle temporal gyrus
OFC	orbitofrontal cortex
OTC	occipitotemporal cortex
PCC	posterior cingulate cortex
PHG	parahippocampal gyrus
pHipp	posterior hippocampus
pINS	posterior insula

premotor	premotor cortex
preSMA	pre-supplementary motor area
pSTS	posterior superior temporal sulcus
SMA	supplementary motor area
somatosensory	somatorsensory cortex
SPL	superior parietal lobule
STS	superior temporal sulcus
temp pole	temporal pole
TPJ	temporal parietal junction
V1	primary visual area
visual	visual cortex
vlPFC	ventrolateral prefrontal cortex
vmPFC	ventromedial prefrontal cortex

Social connection is an essential human nutrient. A key process through which people connect with others is *self-disclosure:* sharing thoughts, feelings, and experiences. When successful, self-disclosure enables listeners to understand speakers' experiences and gain insight into who speakers are. However, self-disclosure does not always succeed at this. This study aims to identify when and how self-disclosure leads to social connection.

To do this, we examine two likely links between self-disclosure and social connection: *neural synchrony* and *speech features*. Speech is the primary vehicle through which people disclose their experiences, and consists of vocal and linguistic features combined strategically to convey meaning. Once speech reaches listeners' ears, it gets converted to neural signals from which meaning is interpreted. When the neural signals of listeners align with those of speakers (i.e., neural synchrony occurs), listeners comprehend the details of speakers' experiences more accurately (Liu et al., 2022; Stephens et al., 2010).

Neural synchrony (computed as the correlation between two people's brain activity across time) has been identified as a candidate mechanism through which listeners come to understand speakers' experiences. Yet more remains to be discovered about the role of neural synchrony in real-world social connection. Specifically, it remains unknown whether neural synchrony enables listeners to go beyond a basic understanding of speakers' experiences and gain deeper insight into *who speakers are* (e.g., their personality traits, driving forces, and life stories). In this study, we leverage a new measure of shared meaning to explore

the extent to which neural synchrony helps listeners understand speakers more intimately.

Despite the unknowns about neural synchrony, given its strong association with narrative comprehension, it provides a useful metric for at least one form of successful communication. In addition, neural synchrony's high temporal resolution and objectivity as a measure enables us to capture shared understanding on a moment-to-moment basis. Thus, in this study, we investigate how linguistic and vocal features of speech impact moment-to-moment neural synchrony between speakers and listeners, with the aim of shedding light on potential strategies disclosers could use to help listeners understand them.

Does Neural Synchrony Between Speakers and Listeners Lead to Shared Meaning-Making?

Social neuroscience research in the past decade has begun to investigate shared understanding by identifying when brains dynamically couple across time. This dynamic coupling, or neural synchrony, has been shown to correlate with narrative comprehension when matching listeners' brain activity with the prerecorded brain activity of a storyteller (Liu et al., 2022; Stephens et al., 2010). Synchrony between multiple listeners has also been linked to more linguistically similar accounts of events (Nguyen et al., 2019) and more similar interpretations of events (Lahnakoski et al., 2014; Van Baar et al., 2021; Yeshurun et al., 2017).

Ever since neural synchrony was first developed as a measure, researchers have speculated that it could be the physiological basis for social connection

(Wheatley et al., 2012). However, studies of neural synchrony so far have employed research paradigms that are several steps removed from real-world social interactions. For example, participants listened to an unknown stranger tell a story (Liu et al., 2022; Stephens et al., 2010), watched short video clips (Dziura et al., 2021; Parkinson et al., 2018), or watched animations with moving shapes (Nguyen et al., 2019). Though neural synchrony is uniquely suited to measure shared moment-to-moment information processing, it has yet to be utilized to study actual conversation partners engaging in self-disclosure. The present study employs a more naturalistic paradigm in which members of a social network take turns disclosing about their experiences and listening to each other.

This more naturalistic paradigm enables us to probe neural synchrony's role in real-world social connection in a deeper way than previous studies have been able to. So far, no studies have examined the degree to which neural synchrony facilitates shared interpretations of the nuanced information people seek to convey about themselves during self-disclosure. Past studies have linked neural synchrony between speakers and listeners to the more basic communication outcome of narrative comprehension: the degree of detail and accuracy with which listeners can recount the stories they heard (Liu et al., 2022; Stephens et al., 2010). Colloquially, this could be thought of as "getting the facts straight"—who did what, when and where. Though narrative comprehension is certainly crucial for understanding others' experiences, it only captures

understanding of a story's surface-level content, rather than its deeper interpretation.

A key ingredient for social connection is forming a sense of shared reality, which requires interpreting events the same way (Higgins et al., 2021). Several studies suggest that neural synchrony may also facilitate shared interpretations of events, not just narrative comprehension (Lahnakoski et al., 2014; Van Baar et al., 2021; Yeshurun et al., 2017). However, these studies measured synchrony between multiple *listeners* (or viewers), rather than between speakers and listeners. It is possible that listener-listener synchrony and speaker-listener synchrony capture different forms of shared information processing. In addition, these studies examined fairly basic, high-level aspects of shared interpretation (e.g., whether viewers of a TV show paid attention to characters or physical objects [Lahnakoski et al., 2014]; whether listeners interpreted a character in a story as cheating on her husband [Yeshurun et al., 2017]; or whether listeners agreed with political statements during debates [Van Baar et al., 2021]). These high-level forms of shared interpretation do matter for understanding others' experiences, but still fail to capture the deeper, self-relevant information people seek to convey during self-disclosure.

People are motivated to disclose about themselves because they find revealing information about *who they are* to be intrinsically rewarding (Tamir & Mitchell, 2012). Thus, the gamut of what disclosers wish for listeners to interpret from their experiences may be as multifaceted and multi-tiered as the self. Dan

McAdams' seminal paper "What Do We Know When We Know a Person?" provides a useful, three-level template for organizing features of the self (McAdams, 1995): 1) traits, 2) driving forces (e.g., goals, motives, and coping mechanisms), and 3) self-narratives (one's autobiographical identity). Listeners' ability to accurately interpret this subtext from disclosers' stories may be crucial for social connection. To capture shared understanding of these three features, we developed a novel measure of *shared meaning* between listeners and disclosers, which we define as shared interpretations about how a given experience relates to who the discloser is. (See Methods section for details.)

Our study leverages this new measure of shared meaning to examine the extent to which neural synchrony enables listeners to gain deeper insight into *who speakers are*. By doing so, we aim to clarify whether neural synchrony lives up to the hype about its importance for real-world social connection—whether its role in communication is limited to the important, but more simple function of enabling listeners to understand the *what, when, and where*; or whether it further enables listeners to understand *why* an experience matters, by promoting shared interpretations of how an experience relates to who the speaker is.

What Features of Speech Facilitate Successful Communication?

Self-disclosure can be a powerful tool for social connection and, more broadly, for well-being. A large body of research has demonstrated the benefits of self-disclosure for disclosers' health and well-being (Kelley et al., 1997; Pennebaker et al., 1988). Listeners can also benefit from hearing others'

disclosures, especially when they respond supportively (Inagaki & Eisenberger, 2016; Inagaki & Orehek, 2017). However, the success of self-disclosure depends on the extent to which disclosers can build shared understanding with listeners. Indeed, research shows that disclosers benefit the most from self-disclosure when they feel understood by listeners (Goldstein et al., 2014; Gramling et al., 2016; Lun et al., 2008). Thus, finding ways to create shared understanding between listeners and disclosers could enable conversation partners to connect more deeply and experience greater well-being.

Self-disclosure is fundamentally an act of communication. To increase the effectiveness of self-disclosure for connection and well-being, it is therefore necessary to identify communication strategies that disclosers can use to help listeners understand them. However, past research has largely ignored the communicative nature of self-disclosure, and instead focused on what *listeners* can do to make disclosers feel more understood (e.g., expressing emotional support [Weber et al., 2004] and engaging in active listening [Bodie et al., 2015]). Very little research has examined what *disclosers themselves* can do to help listeners understand them.

While listeners' response styles matter a great deal for social connection, disclosers typically have little control over how listeners respond. Thus, existing research leaves individuals who seek connection in an unfortunate predicament: the best they can do is find someone to disclose to, and hope that person does a good job of making them feel understood. It would be more directly beneficial if

research could equip *disclosers themselves* with strategies to help listeners understand them. This would not only help listeners respond more supportively (Collier & Meyer, 2020), but would also help people build deeper and more supportive relationships in the long run by creating a well of shared meaning to draw from when discussing future experiences. In addition, knowing successful communication strategies could empower people to engage in self-disclosure more often, as people often refrain from disclosing due to rejection sensitivity (Butler et al., 2007) and fear of consequences like embarrassment, upsetting others, or not being supported (Pasupathi et al., 2009).

Our study aims to identify features of disclosers' speech that could aid in successful communication by examining how listeners' moment-to-moment understanding changes with disclosers' use of linguistic and vocal patterns. Based on past research linking neural synchrony to shared understanding of narratives (Liu et al., 2022; Stephens et al., 2010), we chose to use neural synchrony as a marker of moment-to-moment understanding. Neural synchrony is uniquely suited to capture the moment-to-moment success of communication due to its high temporal resolution and objectivity, unlike other measures that simply capture overall understanding across an entire story (e.g., the accuracy of listeners' recounts of stories). By comparing the time series of speakers' and listeners' brain activations, one can uncover a fine-grained picture of how listeners' brains track with, anticipate, and lag behind speakers' brains in order to encode information conveyed by speakers (Stephens et al., 2010). This opens the

possibility of analyzing moment-to-moment effects of speech features—for example, how disclosers' use of emotional language *during a given window of time* influences listeners' understanding *in that same window*. Although one could simply test the average effect of emotional language on shared understanding, doing so may not adequately capture its role in communication.

To illustrate this, imagine person A, who uses a high degree of emotional language when describing some parts of her experience, but less emotional language when describing other parts. Now imagine person B, who uses a moderate amount of emotional language throughout her disclosure. Person A's disclosure style might lead to spikes in neural synchrony during crucial parts of the story and thus result in better listener understanding (Nummenmaa et al., 2012; Smirnov et al., 2019). However, averaging emotional language across disclosures would equate these two very different disclosure styles. Neural synchrony's high temporal resolution makes it an ideal tool for identifying features of disclosures that promote successful communication, not just on average, but from moment-to-moment.

While moment-to-moment self-report measures of shared understanding do exist and might be easier to obtain, neural synchrony is less disruptive to measure, less unidimensional, and more sensitive to fluctuations. For example, the most common behavioral measure of moment-to-moment shared understanding—empathic accuracy—can be measured by having speakers and listeners each make continuous valence ratings of the speaker's experience, then

computing the correlation between the two. However, measuring empathic accuracy requires participants to interrupt their natural experience of listening to a disclosure to make subjective assessments, which may change how participants experience what they are listening to. Empathic accuracy also only captures a single dimension of interpersonal understanding (emotional valence). In addition, despite having a high degree of temporal resolution in theory, empathic accuracy is ill-suited to capture moment-to-moment fluctuations in understanding; participants in a previous study we conducted (Collier et al., Under Review) tended to only change their ratings of valence every ten to twenty seconds.

Neural synchrony transcends these shortcomings by "catching" brains "in the act" of communication, without interrupting participants' experiences to do so. Rather than imposing a unidimensional measure of shared understanding (i.e., valence), neural synchrony can provide a complex, dynamic marker of speakers' and listeners' shared processing of language, social meaning, and emotions. Our study leverages neural synchrony's high temporal resolution and sensitivity to shared information processing to identify speech features that promote successful communication on a moment-to-moment basis. By doing so, we aim to elucidate the extent to which listeners pick up on the linguistic and vocal patterns people use to express themselves, and which ones matter most for successful communication. We hope our findings will lead to an improved theoretical framework for how people build shared understanding through self-

disclosure, and will pave inroads for future research on ways to increase people's social connection.

Methods

Participants

Ten participants in the same social network were recruited from the community at and around UC Riverside (M_{age} = 24.7, SD = 3.4; 60% female; 40% White, 30% Mixed, 20% Hispanic, 10% Asian). We define being in the same social network as knowing at least one other person in the study. This resulted in a set of participants with a range of closeness levels (33.3% friends and 66.7% strangers; among friends, $M_{closeness}$ = 46.3 on a 100-point scale, SD = 34.5; Figure 1). Each participant shared personal stories and listened to each of the other nine participant's stories in a round robin design (Figure 2), resulting in 90 unique speaker-listener pairs. Each participant shared four stories, resulting in a total of 360 story-listening sessions: the main unit of analysis for testing the association between neural synchrony and shared meaning. One participant's shared meaning ratings are missing (N=36) due to failing to fill out the surveys, resulting in 324 datapoints for the shared meaning analysis.

Participants were screened for any sources of metal in their bodies, as well as medical conditions such as claustrophobia and epilepsy, to ensure their safety in the scanner. Participants were also screened for mental health conditions that might affect their neural activity patterns in social and emotional processing regions of the brain.

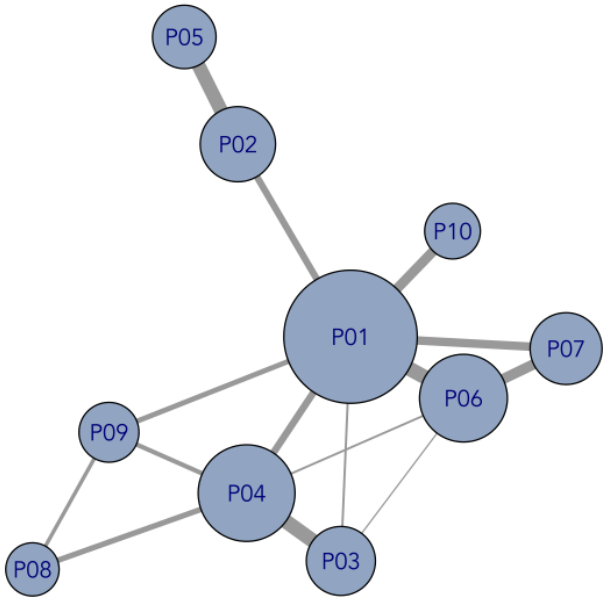


Figure 1. Participants' social network at the time of recruitment. Node size represents how central a given participant is to the network. Thickness of edges between nodes represents how close participants felt (averaged between participant pairs).

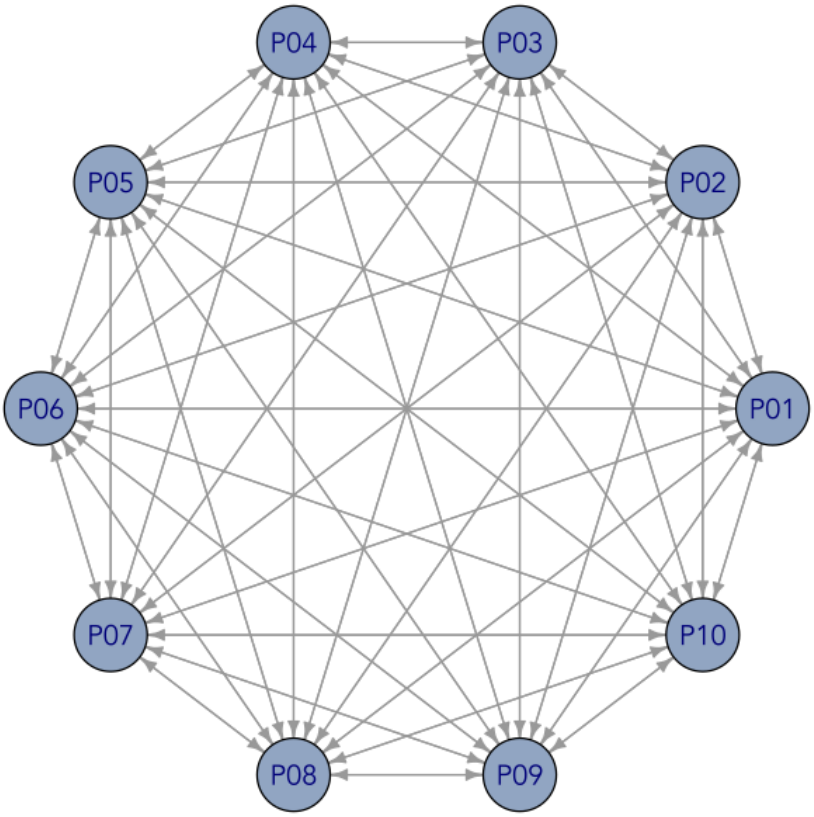


Figure 2. Story-listening structure in a round robin design with 10 participants. Each participant listened to the other 9 participants' stories, resulting in 90 unique speaker-listener pairs (10 speakers x 9 listeners for each speaker). Each participant shared four stories, resulting in a total of 360 story-listening sessions.

Procedures

Participants Share and Interpret Their Own Self-Disclosures

During the initial scan session, participants were audio-recorded while describing four personal experiences they had not previously shared with anyone else in the study (Figure 3). These experiences consisted of two positive and two negative events, to capture a range of emotional expression. The order in which participants shared their stories (positive stories first vs. negative stories first) was counterbalanced. Participants were instructed to discuss each event for three minutes, and were shown a timer to keep track of time. Aside from these instructions, disclosure specifics were left open-ended to make the disclosures as naturalistic as possible. Disclosures were recorded using the FOMRI III Optoacoustics microphone, a MRI-compatible microphone that filters out background noises from the scanner. Participants were instructed not to speak for the first 9 s of the recording, to allow the microphone's noise-reduction algorithm time to normalize. To reduce head motion, a strip of masking tape was applied across participants' foreheads and attached to either side of the head coil, which provided participants with tactile feedback if they moved their heads (Krause et al., 2019). In addition, before sharing their stories, participants first practiced talking in the scanner by discussing their weekly routines while moving their heads as little as possible. Participants succeeded in moving their heads very little while speaking (mean motion relative to the middle timeframe of the scan = 0.15 mm; max = 0.3 mm).

After recording their disclosures in the scanner, participants were asked to describe their interpretations of their *own* experiences. For each disclosure, participants listed everything they wished listeners to understand about them based on that disclosure. To capture the different levels of information about the self that participants may wish to convey to listeners (McAdams, 1995), participants were prompted on separate pages of a Qualtrics survey to list what they wanted listeners to understand about: 1) their traits, 2) their driving forces, 3) their life story, and 4) anything else they want to convey about themselves. Participants were given examples of features that fit each of these categories, and were instructed to list as many distinct features as they could think of. Participants typed each feature into a separate box so the text they wrote could be used in the final behavioral task. Below are examples of actual features listed by participants for each of the categories.

1. Traits: *"I can easily fit in with people who I don't know."*
2. Driving forces: *"I wanted to show my girlfriend to my spiritual family since I knew they would be happy for my positive experience."*
3. Life story: *"The cake meant more to me than food because it showed that I have grown and am able to understand more things about life now."*
4. Other information: *"I felt excited but also a bit resentful for the blindfolding of my eyes."*

Participants Listen to and Interpret Others' Self-Disclosures

After all participants shared their disclosures, they then listened to everyone else's recorded disclosures (Figure 3). To avoid participant fatigue, the listening task was split into three separate scan sessions. Within a given scan session, participants listened to the disclosures shared by three other participants. For each speaker's disclosures, participants listened to the recordings in the order they were originally shared. After each listening to all four of a given speaker's disclosures, participants were given one minute to rest in order to consolidate memories of that speaker's stories (Collier & Meyer, 2020; Meyer, 2019). Following this rest period, participants engaged in a 30-second arithmetic task as a "palette cleanser" before listening to the next speaker's stories.

Afterward, participants were asked to describe their interpretations of the *speakers'* experiences. For each disclosure, participants listed everything they understood about the speaker based on that disclosure. While doing so, participants had access to the disclosure recordings to jog their memories if needed. Participants were once again instructed to list as many distinct features as they could think of, and were prompted with the same four categories of features described above. This time, after typing their responses, participants were also recorded while reading their interpretations out loud. These recorded interpretations were then shared with the original speakers in the next part of the study.

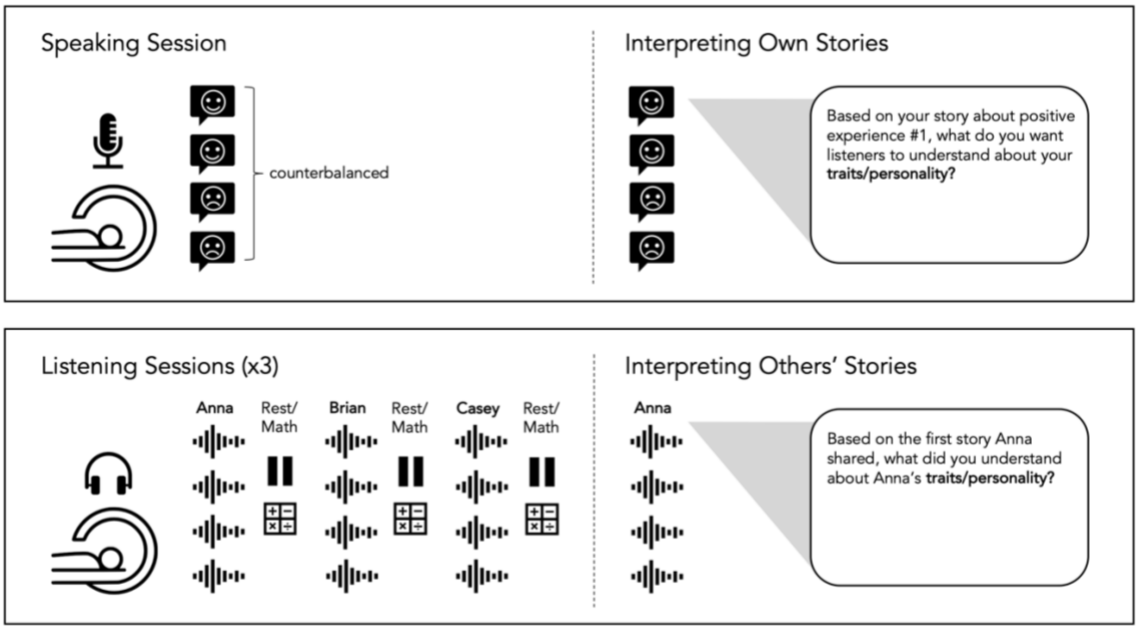


Figure 3. *Upper panel:* Participants first shared their stories while undergoing fMRI scanning. For each story, participants listed what they wished listeners to understand about their traits, driving forces, life story, and anything else about them. *Lower panel:* Once all participants' stories were recorded, participants listened to the stories shared by the other participants while undergoing fMRI scanning. Between each set of stories, participants rested for one minute, then completed 30 seconds of math problems. This was split into three sessions, with participants listening to three other participants' stories per session. For each story they listened to, participants listed their interpretations of the speaker's traits, driving forces, life story, and anything else about them.

Participants Rate the Similarity of Listeners' Interpretations to Their Own

Finally, participants rated the similarity between their own interpretations of their experiences and listeners' interpretations of their experiences (Figure 4). To do so, participants first listened to the recordings of what a given listener understood about them from their disclosures. Next, for each disclosure, a new page of the Qualtrics survey reminded participants of all the things they wished

listeners to understand about them. Under each feature, participants saw a continuous rating scale asking them to indicate how well the listener understood that feature (0=Not at all, 100=Completely). Based on the corresponding recording of the listener's interpretations, participants rated the listener's understanding of each feature of their experience. Understanding was averaged across features to compute a shared meaning score for each disclosure.
Each participant repeated this process for the nine listeners who listened to their disclosures. To avoid participants' judgments of any given listener being influenced by previous listeners, participants rated each listener on a different day.

To test how shared meaning relates to other relevant interpersonal outcomes, we additionally asked participants to complete some questionnaires before and after they rated shared meaning for each listener. These included questions about how connected they felt with the listener ("How close do you feel to the listener?" and "How connected do you feel with the listener"?); questions about how responsive they felt the listener was, adapted from the Perceived Partner Responsiveness Scale ("How understood do you feel by the listener?", "How validated do you feel by the listener?", and "How cared for do you feel by the listener?" [Reis et al., 2017]); and the Inclusion of the Other in the Self (IOS) Scale, which asks participants to represent their perceived degree of self-other overlap with the listener via a venn diagram (Woosnam, 2010). As these measures were highly correlated (Cronbach's $\alpha = 0.97$ for the pre-test and 0.95

for the post-test), we scaled and averaged all items to create a single measure, which we will simply refer to as "connection." Participants were also asked to rate their emotions in the pre-test and post-test using the Positive and Negative Affect Schedule (Watson et al., 1988). Finally, for each individual disclosure, participants were asked to rate perceived understanding based on the listener's response ("Overall, how well do you feel the listener understood your story?") This differs from the shared meaning measure because it does not capture shared interpretations of specific features of participants' experiences, but rather captures how understood participants felt overall.

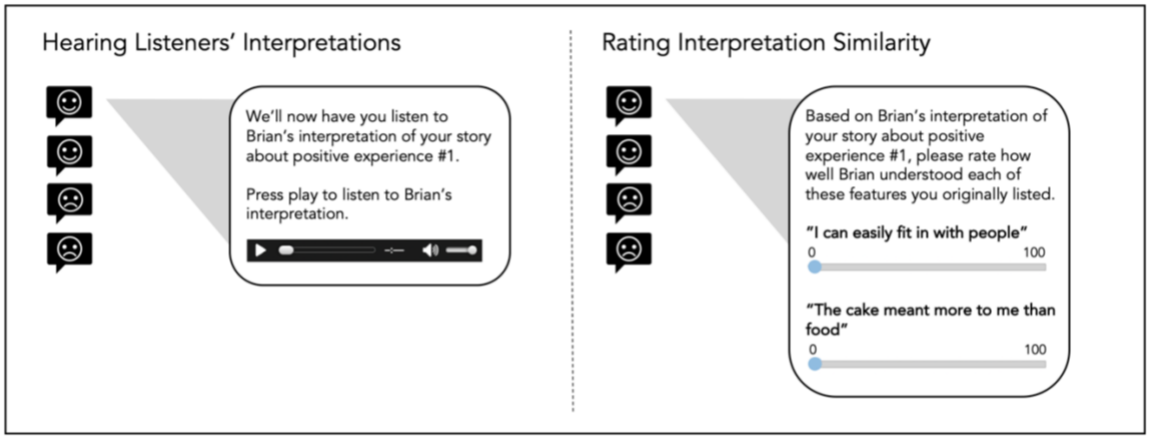


Figure 4. Participants first heard listeners' recorded interpretations of the each of the four stories they shared. Based on these interpretations, participants then rated how well listeners understood the features they originally wanted listeners to understand about them. Understanding was averaged across features to compute a shared meaning score for each story.

fMRI Acquisition

Scanning was performed on a Siemens Trio 3T MRI Scanner. A T_1-weighted structural image was acquired coplanar with the functional images (TR = 2400 ms, TE = 2.72 ms, voxel size = 0.8 x 0.8 x 0.8 mm^3, multiband factor = 1, FOV = 240 x 256 mm^2, matrix = 320 × 300, flip angle = 8°). Functional images were acquired using a T_2-weighted EPI gradient-echo sequence (TR = 1500 ms, TE = 32 ms, voxel size = 2.5 x 2.5 x 2.5 mm^3, multiband factor = 2, FOV = 210 x 230 mm^2, matrix = 92 × 84, flip angle = 75°). A pair of spin echo EPI acquisitions with identical spatial parameters and bandwidth but opposite phase encoding directions (anterior to posterior and posterior to anterior) were collected to correct for magnetic field distortions.

Data Analysis

Behavioral Analysis

Given the newness of our measure of shared meaning, we evaluated the relationship between shared meaning and other interpersonal outcomes that we expected to correlate. To test how shared meaning relates to perceived understanding, we modeled shared meaning for each listening session as a regressor in a linear mixed effects model predicting perceived understanding. To account for the multilevel structure of the data (listening sessions nested within speaker-listener pairs), random slopes and intercepts were estimated at the speaker-listener pair level. (To ensure model convergence, random slopes were not included.) To test how shared meaning relates to changes in connection,

positive mood, and negative mood, we first averaged shared meaning across listening sessions within speaker-listener pairs, as these other outcomes were collected only once before and after each shared meaning survey for a given speaker-listener pair. For each outcome variable, we then modeled average pair-level shared meaning as a regressor in a linear model predicting the post-test outcome, controlling for the pre-test outcome.

In addition, given that shared meaning captures similarity of interpretations between the speaker and the listener, we expected that people with a higher baseline level of connection (as reported in the pre-test) would achieve greater shared meaning. To test this, we modeled speakers' perceptions of connection with the listener as a regressor in a linear model predicting speaker's average perceptions of shared meaning with the listener.

fMRI Data Preprocessing

fMRI data was preprocessed in FSL (Jenkinson et al., 2012) to remove noise from the BOLD signal, following steps consistent with past approaches to neural synchrony analysis (e.g., Nastase et al., 2019; Parkinson et al., 2018). Anatomical images were skull-stripped using FSL's Brain Extraction Tool (BET). For use in computing nuisance regressors, white matter and cerebrospinal fluid masks were generated from each anatomical image using FMRIB's Automated Segmentation Tool in FSL. Each EPI volume underwent the following preprocessing steps: field map unwarping using FSL's Topup Tool, removal of low-frequency noise below 0.009 Hz with a high-pass filter, skull-stripping using

BET, spatial smoothing with a 6mm radius, and registration to the anatomical image using Boundary-Based Registration. The six standard motion parameters and their derivatives were computed using FMRIB's Linear Image Registration Tool. These motion parameters, as well as the signal extracted from white matter and cerebrospinal fluid regions, were regressed out of the data in a GLM, using a high-pass filter to remove any frequencies in the regressors below 0.009 Hz.

Computing Average Neural Synchrony

For each of the 360 story-listening sessions, neural synchrony was assessed between the speaker and the listener. To reduce data dimensionality while searching across the entire brain, synchrony was computed at the level of individual brain regions of interest (ROIs). Specifically, we used the Shen 268 Atlas, a whole brain parcellation spanning 268 cortical and subcortical ROIs (Shen et al., 2013). We excluded 14 ROIs (in the cerebellum and brainstem) that fell outside the coverage of our BOLD acquisition.

To compute neural synchrony, BOLD activation timeseries were extracted from each ROI for both the speaker and the listener. Timepoints before the speaker started speaking were removed, assuming a delay of 4.5 s between the first instance of speech and the start of the corresponding BOLD time course. As previous research has found that listeners' neural activity can lag behind that of speakers in some brain regions and anticipate it in others (Stephens et al., 2010), we searched for synchrony across a range of lags, from -6 s (listener follows speaker) to +6 s (listener precedes speaker). (Note that our TR was 1.5 s, so this

equates to a range of ± 4 TRs.) For a given listening session, we computed synchrony using the peak correlation between the speaker's and listener's BOLD timeseries across the entire range of lags (Figure 5). For example, if the speaker and listener were most strongly correlated at a lag of -3 s, the correlation value at a lag of -3 s would be used to estimate synchrony. Using this method, it is possible for the maximum correlation value to be a spike rather than a true peak (e.g., there might be a strong correlation at -3 s but no correlation at -4.5 s or -1.5 s). To keep such scenarios from inflating synchrony estimates, peaks correlations were smoothed by averaging them together with the correlation at the preceding and the following time lag. In addition, peaks were not allowed to occur at the edges of the lag range. The resulting synchrony values were normalized with Fisher's z transformation before further statistical analyses.

To examine where in the brain speaker-listener synchrony emerges on average, we computed median synchrony across all listening sessions and speaker-listener pairs. The statistical significance of median synchrony in each ROI was assessed using permutation testing with 1,000 permutations. For each permutation, listeners' BOLD activation timeseries were circularly shifted such that the non-overlapping edge of the shifted time series was concatenated to the beginning or end. *P*-values were corrected for multiple comparisons across ROIs by controlling the false discovery rate (FDR) at $q < 0.05$.

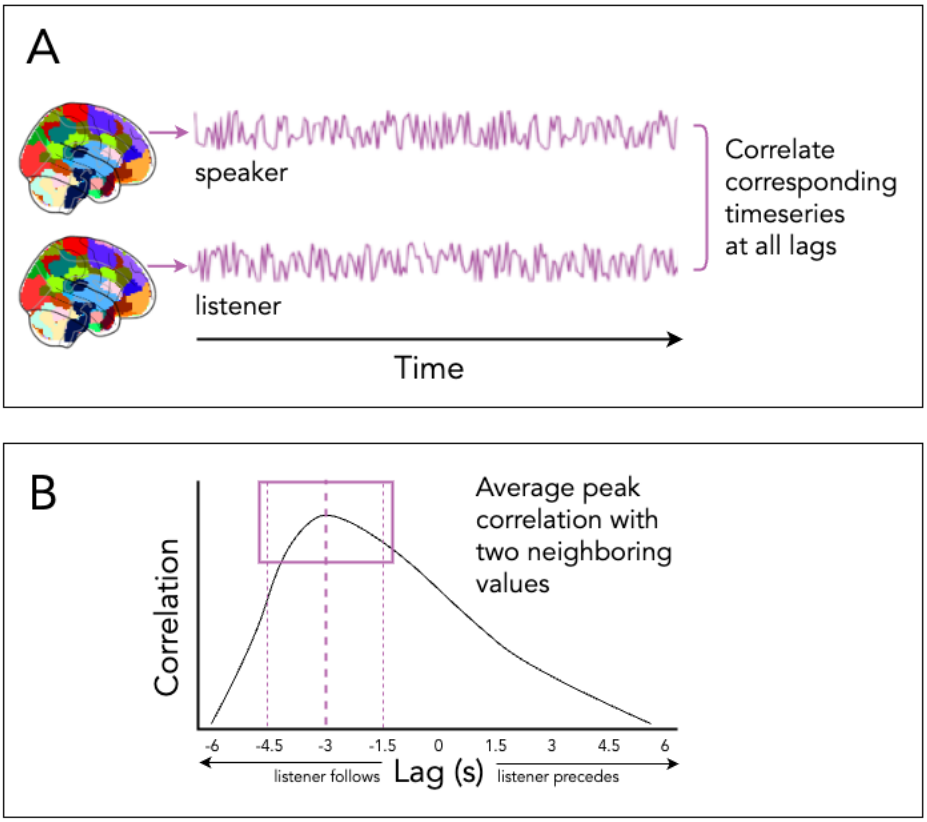


Figure 5. (A) Neural synchrony was calculated between the speaker and the listener by computing the correlation between BOLD signals in corresponding regions of interest across the two brains. Synchrony was calculated at all time lags in the range of ± 6 s (± 4 TRs) (B). For a given listening session, a smoothed peak synchrony value was estimated as the peak correlation between the speaker's and listener's BOLD timeseries across the entire range of lags, averaged together with the correlation at the preceding and the following lag.

Testing the Association Between Neural Synchrony and Shared Meaning

To test the extent to which neural synchrony correlates with shared meaning, we modeled average synchrony across each listening session as a regressor in a linear mixed effects model predicting shared meaning. A separate model was fitted for each ROI. To account for the multilevel structure of the data

(listening sessions nested within speaker-listener pairs), random slopes and intercepts were estimated at the speaker-listener pair level. To distinguish the within- and between-pair effects of synchrony, synchrony was centered by speaker-listener pair, and pair-level synchrony means were also included as a regressor. Results are reported at the pair-level. *P*-values were corrected for multiple comparisons across ROIs by controlling the FDR at $q < 0.05$.

Testing Neural (A)Synchrony's Role in Facilitating Greater Shared Meaning Between More Connected Individuals

The results of our behavioral analysis of shared meaning, as well as our analysis of the relationship between neural synchrony and shared meaning (see Results), suggested that neural *asynchrony* might explain the relationship between baseline feelings of connection and shared meaning. To formally test this, we first analyzed the relationship between speakers' perceptions of baseline connection (as reported in the pre-test) and mean pair-level neural asynchrony (averaged across the set of 72 regions for which asynchrony was associated with significantly greater shared meaning). We then tested the extent to which asynchrony mediates the relationship between baseline connection and mean pair-level shared meaning using R's mediation package (Tingley et al., 2014), with a quasi-Bayesian approximation for confidence intervals based on 10,000 samples.

Identifying Speech Features That Facilitate Successful Communication on a Moment-to-Moment Basis

To identify speech features that facilitate successful moment-to-moment understanding, we originally planned to test the extent to which the speakers' use of certain speech features correlates with moment-to-moment neural synchrony. This analysis approach was based on a theoretical model in which speaker-listener neural synchrony was a proxy for shared understanding. However, our findings regarding the relationship between synchrony and shared meaning challenge this model (see Results section). Thus, we decided to change our analysis strategy. In our revised approach, we tested the extent to which neural *asynchrony* during key moments of speech (i.e., moments with greater presence of certain speech features) is associated with greater shared meaning.

Computing Moment-to-Moment Neural Synchrony. Moment-to-moment neural synchrony was computed using a moving average with a window of 15 s (10 TRs; Nummenmaa et al., 2012). Synchrony for a given window was computed using the same method for computing average synchrony described above. The resulting synchrony timeseries were shifted backward by 4.5 s before aligning them to the speech timeseries to account for hemodynamic delay.

Computing Moment-to-Moment Speech Features. To analyze linguistic features of disclosures, disclosure recordings were first cleaned lightly to reduce background noise and enhance clarity of speech using the software Cleanvoice AI. Recordings were then converted to time-stamped transcripts using

the automated transcription software Sonix AI. To analyze moment-to-moment linguistic features, a moving window of the same size used to compute moment-to-moment neural synchrony (15 s) was applied, with a 1.5 s timestep, and linguistic metrics for a given time point were calculated using all the words within the window for that time point.

To analyze vocal features of disclosures, disclosure recordings were cleaned extensively using the software program Audacity to remove background noise from the scanner. This was achieved by separately targeting two components of scanner noise: a rhythmic, high-pitched "chirping" noise, and a constant, lower-pitched "rumbling" noise. Audacity's noise reduction effect was applied twice (with a strength of 48 dB), first using the sound profile of a single instance of chirping noise, and second using the sound profile of the entire 9 s of background noise before the speaker started speaking. To filter out the small amount of remaining noise, a noise gate was applied to remove low-level sounds beneath 44 dB, then a low-pass filter was applied to remove high-frequency sounds above 2,000 Hz. This process results in some distortion of speakers' voices, but the vocal features of interest (see below) can still be compared on a moment-to-moment basis. Once recordings were cleaned, the speech analysis program Praat (Boersma, 2002) was used to extract raw acoustic features from the speech waveform at the 1.5 s level. (Pitch was first calculated at the 0.001 s level for greater accuracy, then downsampled to 1.5 s.) A window of 15 s was then

slid across the data, and mean levels of vocal features were computed for each window.

The linguistic and vocal features we analyzed are features that have been found to increase when speakers express emotional experiences in research on storytelling, linguistics, and paralinguistics. This research includes a previous study we conducted to test how speakers' use of linguistic and vocal features influences listeners' empathic accuracy (Collier et al., Under Review). In this study, we examined the extent to which average use of speech features across an entire disclosure affected listeners' average ability to identify speakers' emotions. While this approach only captures listeners' understanding of one dimension of speakers' experiences (emotional valence), and does not answer how speech features affect communication on a moment-to-moment level, it does provide clues about speech features that may contribute to other forms of shared understanding. These features and the methods we used to compute them are summarized in Table 1 below. The table also includes references to the research findings that motivated us to analyze each feature.

Regression Models. To test the extent to which neural *asynchrony* during key moments of speech (i.e., moments with greater presence of certain speech features) correlates with shared meaning, we first computed the alignment between each speech feature and moment-to-moment neural (a)synchrony as the correlation between them. The resulting correlation values were then normalized with Fisher's z transformation. Next, we modeled speech-

synchrony alignment as a regressor in a linear mixed effects model predicting shared meaning. A separate model was fitted for each ROI and each speech feature. To account for the multilevel structure of the data (listening sessions nested within speaker-listener pairs), random slopes and intercepts were estimated at the speaker-listener pair level. To distinguish the within- and between-pair effects of speech-synchrony alignment, speech-synchrony alignment was centered by speaker-listener pair, and pair-level speech-synchrony alignment means were also included as a regressor. Results are reported at the pair-level. *P*-values were corrected for multiple comparisons across ROIs and speech features by controlling the FDR at $q < 0.05$.

Note that the results of this analysis can be interpreted bidirectionally—that is, significant effects could be the result of greater *asynchrony* when the speaker uses *more* of a given speech feature, or greater *synchrony* when the speaker uses *less* of a certain speech feature. Thus, to evaluate whether effects are driven by asynchrony or synchrony in key moments, we split speakers' stories into moments of high (≥ +1 SD) and low (≤ -1 SD) use of each speech feature for which there were clear findings in the previous analysis. We then tested the extent to which neural asynchrony vs. synchrony in these moments correlated with shared meaning by modeling (a)synchrony as a regressor in a linear mixed effects model predicting shared meaning. A separate model was fitted for each ROI and each level of each speech feature. Random slopes and intercepts were estimated at the speaker-listener pair level. To distinguish the within- and

between-pair effects of (a)synchrony, (a)synchrony was centered by speaker-listener pair, and pair-level (a)synchrony means were also included as a regressor. Results are reported at the pair-level.

Table 1. Linguistic and vocal features analyzed. The "previous study" we refer to examined how speakers' use of linguistic and vocal features influences listeners' empathic accuracy (Collier et al., Under Review).

Speech Feature	Motivation for Analyzing	Computation Method
Emotional language	Correlated with listeners' empathic accuracy in a past study (Zaki et al., 2009) as well as in our previous study.	VADER package in R (Hutto & Gilbert, 2014): Gives emotional intensity score for each word
Vivid language	Correlated with higher degrees of narrative immersion (Nelson et al., 2008) and episodic detail (Bucci et al., 2009); also correlated with listeners' empathic accuracy in our previous study.	DAAP Software (Ma Bucci et al., 2006): Measures the extent to which words refer clearly to detailed cognitive, sensory, and emotional experiences via the weighted number of function words (Murphy et al., 2015)
Reflective language	Found to facilitate processing of difficult events, and to help organize experiences into cohesive stories (Pennebaker et al., 1997; Petrie et al., 1998).	LIWC Software (Pennebaker et al., 2015) "causal" and "insight" language categories: Measures the proportion of language in these categories
Third-person pronouns	Found to increase with negative affect (Bernard et al., 2015); also correlated with listeners' empathic accuracy in our previous study.	LIWC Software: Measures the proportion of third person pronouns
Big words	Found to convey more information compared to shorter words (Piantadosi et al., 2011); also correlated with listeners' empathic accuracy in our previous study.	LIWC Software: Measures the proportion of words with > 6 letters
Emotional vocal patterns (pitch, intensity, jitter)	Pitch and intensity (perceived as loudness), have been found to increase with more intense emotions (Juslin & Laukka, 2003). Jitter (perceived as vocal roughness) has been found to increase with more intense negative emotions (Juslin & Laukka, 2001).	Praat Software (Boersma, 2002), accessed via Python package Parselmouth (Jadoul et al., 2018): Computes log pitch (f0), intensity (log amplitude), and jitter (cycle-to-cycle variability in f0) across a specified window of time
Speech rate	Found to increase with more intense emotions (Juslin & Laukka, 2003); also correlated with listeners' empathic accuracy in our previous study.	Word count divided by time

Silent pauses	Found to improve listening comprehension (Blau, 1990) and also to improve listeners' memory of words following pauses (MacGregor et al., 2010).	Proportion of time without speech

Results

Shared Meaning is Associated With Positive Relationship Outcomes and Greater Baseline Connection

Our theoretical model of communication positions shared meaning-making as an important interpersonal outcome. Given the newness of our measure of shared meaning, we evaluated its importance in the context of other interpersonal outcomes that are known to positively impact people's health and well-being, such as perceived understanding, connection, and mood. In line with our predictions, we found that shared meaning was associated with significantly greater perceived understanding (β = 1.10, *SE* = 0.05, $t(310) = 24.06$, $p < 0.001$), increased feelings of connection (β = 0.42, *SE* = 0.06, $t(78) = 6.55$, $p < 0.001$), and increased positive mood (β = 0.23, *SE* = 0.06, $t(78) = 3.93$, $p < 0.001$); though not with significantly reduced negative mood (β = -0.06, *SE* = 0.10, $t(78) = -0.62$, $p = 0.54$).

In addition, given that shared meaning captures similarity of interpretations between the speaker and the listener, we expected that people with a higher baseline level of connection would achieve greater average shared meaning. Indeed, speaker-listener pairs with higher baseline connection achieved significantly greater shared meaning (β = 0.36, *SE* = 0.10, $t(79) = 3.47$, $p < 0.001$). Taken together, these findings suggest that shared meaning-making both emerges from and facilitates closer relationships between people.

Neural Asynchrony, Rather Than Synchrony, is Associated With Shared Meaning-Making

Based on past research, we predicted that speakers and listeners would achieve more shared meaning when they had greater neural synchrony in regions associated with processing language, social meaning, and emotion (Liu et al., 2022; Stephens et al., 2010). Contrary to our hypothesis, we found that across 72 brain regions, greater *asynchrony* at the pair-level was associated with significantly greater shared meaning (βs ranging from -0.26 to -0.46). In other words, the less a given listener synchronized with a given speaker across all four of the speaker's stories, the more they converged on similar interpretations of speakers' experiences. This effect emerged in regions associated with language processing (e.g., ATL, ITG), social reasoning (e.g., vmPFC, dmPFC, PCC, temporal pole), and emotion (e.g., aINS, NAcc), as well as regions in the visual, premotor, and motor cortices, and the cerebellum (Figure 6; Supplementary Table 1). There were only five regions in which greater synchrony was associated with greater shared meaning (βs ranging from 0.25 to 0.47), all in the brainstem or cerebellum.

Given this surprising departure from past findings on synchrony and shared understanding, we also investigated the extent to which speakers and listeners synchronized overall in our study. Consistent with past research (Liu et al., 2022; Silbert et al., 2014; Stephens et al., 2010), we found significant average synchrony across 27 regions (smoothed peak *r*-values ranging from 0.03 to 0.09),

including regions in the auditory and visual cortices, and regions associated with language processing (e.g., ATL, STS, AG) and social reasoning (e.g., TPJ, temporal pole) (Supplementary Figure 1; Supplementary Table 2). Average synchrony and the asynchrony-shared meaning effect emerged in largely non-overlapping regions; only six regions contained both effects (cerebellum, ATL, SPL, lOFC, and two visual cortex regions). It is possible that the average synchrony we observed facilitates more basic forms of understanding that have been found to correlate with synchrony in previous studies (e.g., content comprehension), whereas shared meaning-making requires the listener's brain to deviate more from the speaker's while listening. However, as we did not measure content comprehension in our study, we cannot make this comparison directly.

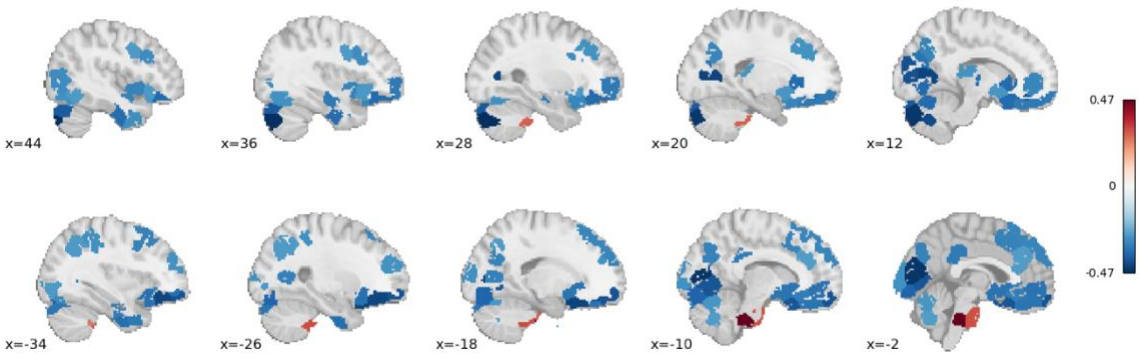


Figure 6. Brain regions showing significant average effects of speaker-listener neural synchrony on shared meaning. Synchrony was negatively correlated with shared meaning in most regions. Brain slices with positive and negative x-coordinates belong to the right and left hemispheres, respectively. The scale is in units of β-values.

Neural Asynchrony May Facilitate Greater Shared Meaning-Making Between More Connected Individuals

Given our earlier finding that speaker-listener pairs who were more connected at baseline achieved greater shared meaning—as well as our finding that neural *asynchrony* was associated with greater shared meaning—it seemed plausible that more connected individuals might achieve greater shared meaning due to stronger neural asynchrony. To assess this, we first analyzed the relationship between baseline connection and overall neural asynchrony (averaged across the set of 72 regions for which asynchrony was associated with significantly greater shared meaning). Higher baseline connection was associated with significantly stronger neural asynchrony ($\beta = 0.22$, $SE = 0.11$, $t(79) = 2.03$, $p = 0.045$), supporting the case for mediation. We then tested the extent to which asynchrony mediates the relationship between baseline connection and shared meaning, and indeed found a significant partial mediation effect (proportion mediated = 27%, CI = 2%, 68%, p = 0.04; Figure 7; Table 2). These findings suggest that more connected individuals may, in part, succeed more at shared meaning-making through synchronizing *less* in certain brain regions.

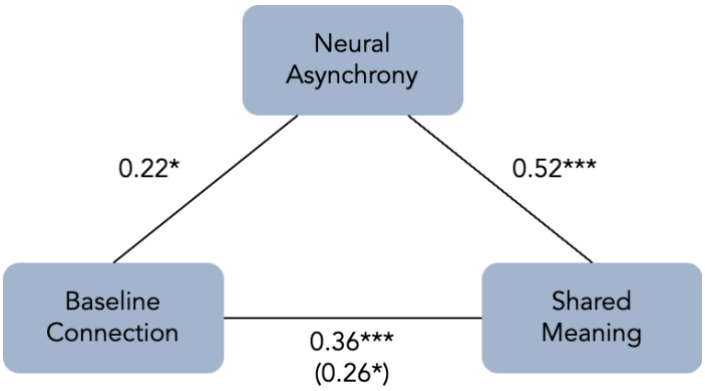


Figure 7. Results from the mediation model demonstrating that neural asynchrony partially explains the relationship between how connected participants felt at baseline and their perceptions of shared meaning after exchanging self-disclosures and listening to each other's responses. Neural asynchrony was averaged across the set of 72 brain regions for which asynchrony was associated with significantly greater shared meaning.

		Quasi-Bayesian CI		
	β	**Lower**	**Upper**	***p*-value**
Indirect Effect	0.10	0.00	0.21	0.04
Direct Effect	0.26	0.08	0.44	0.01
Total Effect	0.36	0.16	0.56	< 0.001
Proportion of Total Effect Mediated	0.27	0.02	0.63	0.04

Table 2. Test of mediation with results for the effect of baseline connection on shared meaning, with neural asynchrony as a mediator.

Neural Asynchrony During Key Moments of Speech May Facilitate Shared Meaning-Making

We originally predicted that certain speech features would correlate positively with moment-to-moment neural synchrony, and considered features that did so to be markers of successful communication. This hypothesis was based on a theoretical model in which speaker-listener neural synchrony was a proxy for shared understanding. However, our finding that neural *asynchrony,* rather than synchrony, is associated with greater shared meaning challenges this model. Thus, to identify speech features that facilitate greater understanding on a moment-to-moment basis, we instead tested the extent to which neural *asynchrony* during key moments of speech (i.e., moments with greater presence of certain speech features) was associated with greater shared meaning.

Two related speech features emerged as possible facilitators of moment-to-moment understanding: talking more slowly and pausing more (Supplementary Tables 11-12). Across 36 brain regions, greater speaker-listener asynchrony when speakers talked more slowly was associated with greater shared meaning (βs ranging from 0.30 to 0.53). Similarly, across 25 brain regions, greater speaker-listener asynchrony when speakers paused more was associated with greater shared meaning (βs ranging from 0.30 to 0.58). This effect was bidirectional—in other words, another possible interpretation could be that greater *synchrony* when speakers talked more *quickly* (or paused *less*) was associated with greater shared meaning. Thus, to evaluate whether these findings

were driven by asynchrony or synchrony in key moments, we split speakers' stories into moments of high (≥ +1 SD) speech rate or pause proportion and low (≤ -1 SD) speech rate or pause proportion. We then analyzed the extent to which neural asynchrony vs. synchrony in these moments correlated with shared meaning. Across most ROIs, *asynchrony* when speakers talked slowly or paused more was significantly associated with greater shared meaning (βs ranging from -0.21 to -0.51 for speech rate and -0.22 to -0.49 for pause proportion), whereas *synchrony* when speakers talked quickly or paused less was not significantly associated with shared meaning; though there were some exceptions (Figure 8; Supplementary Tables 13-14). Overall, this indicates that the effects of speech rate and pause proportion on shared meaning are largely driven by asynchrony, rather than synchrony.

For other speech features, findings were difficult to interpret; asynchrony correlated more strongly with shared meaning in some regions when the speaker's use of a given speech feature was low, and in other regions when the speaker's use of that same speech feature was high (Supplementary Tables 3-12). Due to the mixed directions of these findings, it is difficult to determine how these other speech features may impact moment-to-moment understanding. It is possible that some brain regions attempt meaning-making in response to higher levels of a given feature (e.g., more emotional language), while other brain regions do so in response to lower levels of a given feature (e.g., less emotional

language). If so, the other speech features we tested may still facilitate moment-to-moment understanding, but in a more complex way.

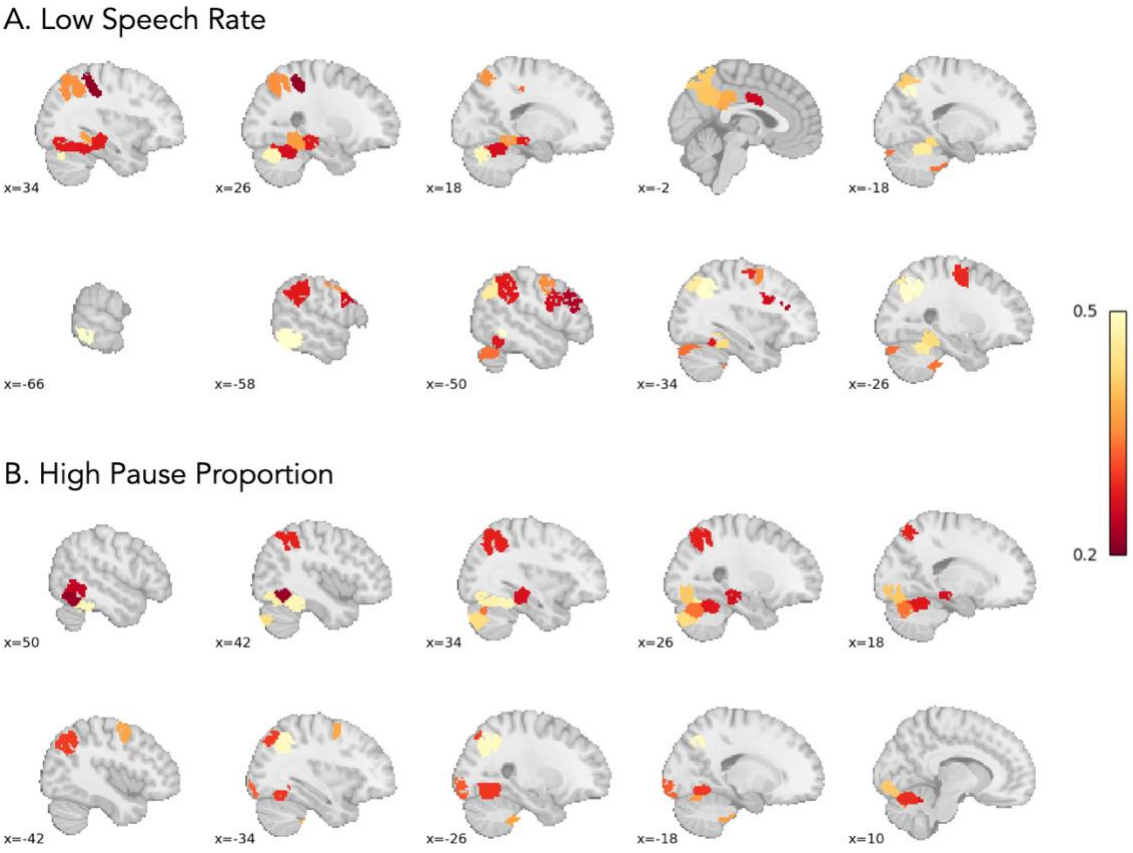


Figure 8. Brain regions for which shared meaning was significantly greater when there was more speaker-listener neural *asynchrony* during key moments of speech. (A) Effect of asynchrony on shared meaning when speakers talked relatively slowly (≤ -1 SD). (B) Effect of asynchrony on shared meaning when speakers paused relatively more (≥ +1 SD). Brain slices with positive and negative x-coordinates belong to the right and left hemispheres, respectively. The scale is in units of β-values.

Discussion

Self-disclosure is a powerful way for people to connect, yet few studies have examined how disclosers can build a sense of shared meaning with listeners. We investigated possible neural, linguistic, and vocal mechanisms through which listeners may come to understand speakers more intimately. We found that across numerous brain regions, greater neural *asynchrony* between speakers and listeners was associated with greater shared meaning-making. We also found that people who felt more connected at baseline had greater neural asynchrony, and that asynchrony partially explained the positive relationship between baseline connection and shared meaning-making. In addition, we found that neural asynchrony during key moments of speech may facilitate shared meaning-making. In particular, greater neural asynchrony when speakers (1) talked more slowly and (2) paused more was associated with greater shared meaning. Collectively, these findings shed light on key processes that enable successful communication between disclosers and listeners.

It was surprising to find that neural asynchrony, rather than synchrony, was associated with greater shared meaning. Given that past research has demonstrated a clear positive relationship between *synchrony* and various forms of shared understanding, we expected that synchrony between speakers and listeners would also correlate with shared meaning in our study. However, a closer examination of the literature reveals some key differences between past studies and ours. For one, most studies linking neural synchrony to shared

higher-level interpretations of narratives have actually measured synchrony between multiple *listeners* (or viewers), rather than between speakers and listeners (Lahnakoski et al., 2014; Van Baar et al., 2021; Yeshurun et al., 2017). Only a handful of studies have tested the association between speaker-listener synchrony and shared understanding (Liu et al., 2022; Nguyen et al., 2022; Stephens et al., 2010). In these studies, the measure of shared understanding was oriented around accurate memory of factual details. Our study is the first to our knowledge to examine the relationship between speaker-listener synchrony and shared higher-level interpretations of narratives.

It is possible that between speakers and listeners, neural synchrony and asynchrony may contribute to different forms of shared understanding. This is supported by our finding that average synchrony emerged in brain regions that were mostly distinct from those where the asynchrony-shared meaning effect emerged. When it comes to comprehending factual details, perhaps synchrony is beneficial because it reflects shared linguistic and conceptual processing. On the other hand, when it comes to interpreting the subtext of self-disclosures (e.g., understanding what a story says about the speaker's traits, driving forces, and life story), perhaps asynchrony is beneficial because the listener's brain needs to *deviate* from the speaker's in order to arrive at the same mental model. From that perspective, it would actually be more surprising if listeners were able to achieve a shared sense of meaning with speakers without their brains needing to do some "extra work." In the same vein, listener-listener synchrony may reflect listeners'

brains doing that "extra work" in the same way—hence the positive association between listener-listener synchrony and shared higher-level interpretations in past research. Future work should explicitly measure and compare these different forms of understanding (fact-based and interpretation-based) at both the speaker-listener level and the listener-listener level, to further test this new theoretical model of how neural synchrony and asynchrony may work together to facilitate shared understanding.

Our findings contribute to an emerging picture of neural synchrony and asynchrony playing complex roles in social interaction. Though our study is the first to find an association between speaker-listener asynchrony and shared meaning-making, some very recent research has begun to identify other ways neural asynchrony may contribute to positive social outcomes. For example, in one study, pairs of participants engaged in the Fast Friends paradigm (a structured conversation in which partners take turns answering personal questions) while undergoing simultaneous fMRI scanning (Speer et al., Under Review). In that study, friends had greater neural *asynchrony* compared to strangers, and pairs with greater asynchrony enjoyed their conversations more. This aligns with our own finding that more connected individuals had greater neural asynchrony, and that asynchrony partially mediated the relationship between baseline connection and shared meaning-making. It is possible that people who are closer to each other have already done the basic work to understand the facts about each other, and thus their brains are more "free" to

diverge and interpret conversational content. Future research should continue to examine differences in neural synchrony and interpersonal outcomes between people of different closeness levels, as most past work has examined synchrony between strangers.

Our study is also the first to test how linguistic and vocal features of speech interact with moment-to-moment neural (a)synchrony to facilitate shared meaning-making. Though most of the speech features we tested did not have a consistent positive or negative effect on the relationship between asynchrony and shared meaning, two features did. Greater neural asynchrony when speakers (1) talked more slowly and (2) paused more was associated with greater shared meaning. The finding for pause proportion aligns with past research showing that silent pauses improve language comprehension (Blau, 1990) and memory for words after pauses (MacGregor et al., 2010). However, the finding for speech rate appears to contradict previous research on the role of speech rate in communication. For example, faster speech rate has been found to signal greater emotional intensity (Juslin & Laukka, 2003), and past work has shown that listeners more accurately rate speakers' emotional valence when speakers talk faster on average (Collier et al., Under Review). These differences in findings may be driven by differences in outcome measures: In the examples from past research, listeners' understanding was measured in terms of accurately identifying emotions, whereas in our study, understanding was measured in terms of shared meaning-making. Perhaps the work of interpreting speakers'

experiences is easier to do when speakers talk more slowly because it gives listeners time to think, whereas reading speakers' emotional states is easier when speakers talk more quickly because speakers sound more animated. Just as the role of neural synchrony vs. asynchrony may differ based on the type of shared understanding being examined, the role of linguistic and vocal features may also differ on this basis. Future work should continue to investigate the complex interplay between speech, synchrony, and various forms of shared understanding.

In summary, neural *asynchrony* between speakers and listeners appears to play a surprising yet important role in successful communication. Moments when speakers talk more slowly or pause more may present opportune windows for listeners' brains to diverge and interpret speakers' deeper meanings. Overall, these findings contribute to a more nuanced theoretical framework for how people build shared understanding through self-disclosure. T.S. Elliot wrote, "The end of all our exploring will be to arrive where we started and know the place for the first time" (Eliot, 1943). Though he was describing knowing oneself, perhaps a similar process applies to knowing others: To arrive where the speaker started, the listener must do some exploring.

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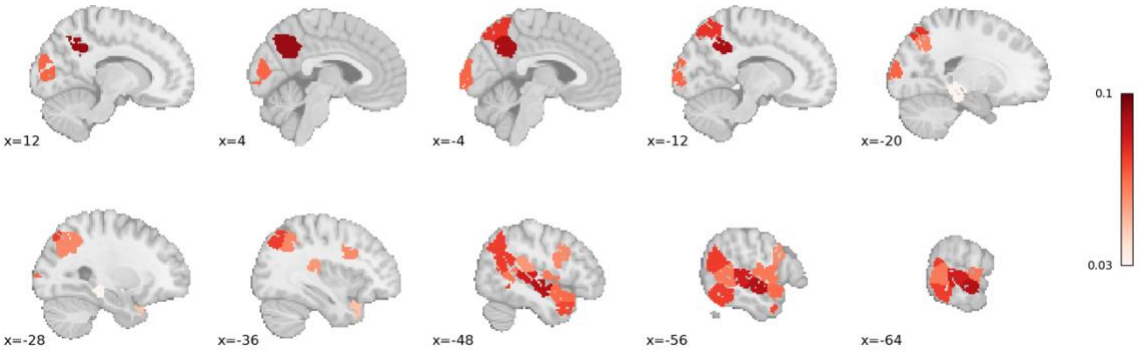
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SUPPLEMENTARY MATERIALS

Supp. Table 1. Brain regions showing significant average effects of speaker-listener neural synchrony on shared meaning. Negative β-values represent that *asynchrony* was associated with greater shared meaning. Adjusted p-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
1	R	vmPFC	-0.33	0.10	-3.25	79	0.01
2	R	OFC	-0.36	0.10	-3.67	79	0.006
3	R	vmPFC	-0.41	0.10	-4.25	79	0.002
4	R	OFC	-0.33	0.10	-3.27	79	0.01
5	R	ACC	-0.30	0.10	-2.97	79	0.02
7	R	lPFC	-0.33	0.10	-3.27	79	0.01
13	R	dlPFC	-0.28	0.10	-2.79	80	0.03
17	R	lOFC	-0.36	0.10	-3.65	79	0.006
18	R	lOFC	-0.30	0.10	-3.02	79	0.02
22	R	dlPFC	-0.29	0.10	-2.86	79	0.02
31	R	premotor	-0.26	0.10	-2.59	79	0.04
34	R	aINS	-0.31	0.10	-3.11	79	0.01
36	R	aINS	-0.27	0.10	-2.67	80	0.03
42	R	precuneus	-0.30	0.10	-2.99	79	0.02
56	R	ATL	-0.35	0.10	-3.56	79	0.006
57	R	temp pole	-0.29	0.10	-2.89	80	0.02
58	R	ATL	-0.35	0.10	-3.63	79	0.006
66	R	FFA	-0.27	0.10	-2.59	79	0.04
67	R	FFA	-0.28	0.10	-2.75	79	0.03
74	R	visual	-0.29	0.10	-2.84	79	0.02
77	R	cuneus	-0.34	0.10	-3.41	79	0.008
79	R	LiG	-0.36	0.10	-3.63	79	0.006
80	R	V1	-0.40	0.10	-4.22	79	0.002
82	R	LiG	-0.43	0.09	-4.55	79	< 0.001
94	R	aHipp	-0.33	0.10	-3.33	79	0.009
100	R	cerebellum	-0.46	0.09	-5.18	80	< 0.001
102	R	cerebellum	-0.39	0.10	-4.04	80	0.002
104	R	cerebellum	0.28	0.10	2.91	80	0.02
105	R	cerebellum	-0.42	0.09	-4.60	80	< 0.001
106	R	cerebellum	-0.36	0.10	-3.66	79	0.006
111	R	cerebellum	-0.45	0.09	-5.01	81	< 0.001
123	R	caudate	-0.36	0.10	-3.73	80	0.005
125	R	accumbens	-0.27	0.10	-2.75	80	0.03
127	R	thalamus	-0.28	0.10	-2.77	79	0.03
128	R	thalamus	-0.35	0.10	-3.63	80	0.006
134	L	vmPFC	-0.32	0.10	-3.20	79	0.01
135	L	OFC	-0.43	0.10	-4.48	79	< 0.001
136	L	OFC	-0.40	0.10	-4.10	79	0.002

137	L	OFC	-0.34	0.10	-3.44	79	0.008
138	L	ACC	-0.34	0.10	-3.48	79	0.007
139	L	vmPFC	-0.40	0.10	-4.12	79	0.002
143	L	lPFC	-0.35	0.10	-3.56	79	0.006
144	L	dlPFC	-0.28	0.10	-2.80	80	0.03
145	L	dmPFC	-0.30	0.10	-3.04	79	0.02
148	L	dmPFC	-0.30	0.10	-3.01	79	0.02
149	L	dlPFC	-0.31	0.10	-3.11	79	0.01
150	L	preSMA	-0.31	0.10	-3.11	79	0.01
151	L	IFG	-0.31	0.10	-3.13	80	0.01
152	L	lOFC	-0.42	0.10	-4.44	79	< 0.001
153	L	aINS	-0.35	0.10	-3.47	79	0.007
176	L	precuneus + cuneus	-0.31	0.10	-3.06	79	0.02
177	L	SPL	-0.26	0.10	-2.55	79	0.04
179	L	motor	-0.28	0.10	-2.73	79	0.03
185	L	temp pole	-0.33	0.10	-3.27	79	0.01
187	L	ATL + temp pole	-0.34	0.10	-3.45	79	0.008
190	L	ATL	-0.32	0.10	-3.14	79	0.01
194	L	ATL	-0.37	0.10	-3.82	79	0.004
195	L	ATL	-0.32	0.10	-3.21	79	0.01
196	L	ITG	-0.34	0.10	-3.37	79	0.009
202	L	temp pole	-0.35	0.10	-3.58	79	0.006
206	L	FFA	-0.30	0.10	-2.94	79	0.02
210	L	visual	-0.27	0.10	-2.61	79	0.04
211	L	LiG	-0.40	0.10	-4.08	79	0.002
212	L	visual	-0.28	0.10	-2.77	79	0.03
213	L	visual	-0.37	0.10	-3.78	79	0.005
215	L	V1	-0.45	0.09	-4.95	80	< 0.001
216	L	LiG	-0.31	0.10	-3.09	79	0.01
219	L	ACC	-0.26	0.10	-2.62	80	0.04
223	L	PCC	-0.33	0.10	-3.22	79	0.01
236	L	cerebellum	-0.26	0.10	-2.50	79	0.05
241	L	cerebellum	-0.34	0.10	-3.54	80	0.006
248	L	cerebellum	-0.27	0.10	-2.67	79	0.03
252	L	cerebellum	0.25	0.10	2.48	80	0.05
256	L	cerebellum	0.30	0.10	3.13	80	0.01
259	L	accumbens	-0.34	0.10	-3.43	79	0.008
267	L	brainstem	0.47	0.09	5.01	79	< 0.001
268	L	brainstem	0.30	0.10	3.10	80	0.01



Supp. Figure 1. Brain regions showing significant speaker-listener neural synchrony, averaged across all listening sessions and speaker-listener pairs. Brain slices with positive and negative x-coordinates belong to the right and left hemispheres, respectively. The scale is in units of *r*-values.

Supp. Table 2. Brain regions showing significant speaker-listener neural synchrony, averaged across all listening sessions and speaker-listener pairs. Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at q < 0.05).

Shen Atlas Index	Hemisphere	Brain Region	Smoothed Peak *r*	*p*-adj
18	R	lOFC	0.06	0.03
37	R	pINS	0.05	0.05
43	R	SPL	0.07	0.03
51	R	temp pole	0.05	0.03
54	R	STS	0.07	< 0.001
62	R	pINS	0.05	0.02
80	R	V1	0.07	0.03
90	R	precuneus	0.09	< 0.001
100	R	cerebellum	0.06	< 0.001
124	R	putamen	0.06	0.02
157	L	premotor	0.06	< 0.001
163	L	somatosensory	0.06	< 0.001
177	L	SPL	0.06	0.03
178	L	SPL	0.08	0.02
180	L	pINS + somatosensory	0.06	0.03
182	L	AG	0.07	0.03
183	L	TPJ	0.07	< 0.001
186	L	temp pole	0.05	0.02
187	L	ATL + temp pole	0.07	< 0.001
188	L	ATL	0.06	< 0.001
191	L	auditory + STS	0.08	< 0.001
192	L	pSTS	0.06	0.02
197	L	auditory	0.09	< 0.001
199	L	ITG	0.07	0.03
212	L	visual	0.07	0.05
225	L	precuneus	0.09	< 0.001
233	L	pHipp	0.03	0.04

Supp. Table 3. *Emotional language*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers using more (positive β) or less (negative β) emotional language. Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
13	R	dlPFC	-0.35	0.10	-3.42	77	0.02
33	R	motor	0.38	0.10	3.76	77	0.01
40	R	pINS	0.50	0.09	5.36	77	< 0.001
85	R	PCC	-0.36	0.10	-3.51	77	0.02
88	R	PCC	-0.31	0.10	-3.01	77	0.04
90	R	precuneus	-0.36	0.10	-3.57	77	0.02
93	R	pHipp	0.32	0.10	3.09	77	0.04
107	R	cerebellum	0.43	0.10	4.41	77	0.003
108	R	cerebellum	0.50	0.09	5.33	77	< 0.001
124	R	putamen	-0.31	0.10	-3.03	77	0.04
141	L	mPFC	0.34	0.10	3.32	77	0.03
142	L	lOFC	-0.31	0.10	-3.03	77	0.04
144	L	dlPFC	0.34	0.10	3.36	77	0.02
156	L	IFG	0.31	0.10	2.99	77	0.05
161	L	motor	0.38	0.10	3.83	77	0.009
182	L	AG	0.31	0.10	3.09	77	0.04
189	L	temp pole	-0.32	0.10	-3.08	77	0.04
191	L	auditory + STS	-0.33	0.10	-3.24	77	0.03
196	L	ITG	0.34	0.10	3.32	77	0.03
197	L	auditory	-0.36	0.10	-3.60	77	0.02
208	L	visual	-0.41	0.10	-4.24	77	0.005
215	L	V1	-0.34	0.10	-3.35	77	0.02
233	L	pHipp	0.39	0.10	3.97	77	0.007
262	L	thalamus	0.31	0.10	3.06	77	0.04

Supp. Table 4. *Vivid language.* Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers using more (positive β) or less (negative β) vivid language. Adjusted p-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
43	R	SPL	-0.38	0.10	-3.81	77	0.01
52	R	temp pole	0.32	0.10	3.11	77	0.04
71	R	FFA	-0.33	0.10	-3.20	77	0.03
106	R	cerebellum	-0.37	0.10	-3.66	77	0.01
107	R	cerebellum	0.38	0.10	3.84	77	0.009
137	L	OFC	0.35	0.10	3.48	77	0.02
152	L	lOFC	0.35	0.10	3.42	77	0.02
153	L	aINS	0.53	0.09	5.85	77	< 0.001
172	L	motor	-0.38	0.10	-3.84	77	0.009
218	L	PCC	0.34	0.10	3.33	77	0.02
235	L	PHG	0.38	0.10	3.76	77	0.01
248	L	cerebellum	-0.34	0.10	-3.35	77	0.02

Supp. Table 5. *Reflective language*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers using more (positive β) or less (negative β) reflective language. Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
18	R	lOFC	-0.44	0.10	-4.59	77	0.002
28	R	preSMA	-0.32	0.10	-3.07	77	0.04
69	R	OTC	0.43	0.10	4.45	77	0.003
83	R	ACC	0.44	0.09	4.65	77	0.002
125	R	accumbens	-0.34	0.10	-3.31	77	0.03
128	R	thalamus	-0.37	0.10	-3.75	77	0.01
139	L	vmPFC	-0.41	0.10	-4.12	77	0.006
153	L	aINS	-0.50	0.09	-5.43	77	< 0.001
191	L	auditory + STS	-0.32	0.10	-3.08	77	0.04
199	L	ITG	0.34	0.10	3.34	77	0.02
200	L	FFA	-0.32	0.10	-3.21	77	0.03
226	L	precuneus	-0.39	0.10	-3.87	77	0.009
227	L	PCC	0.40	0.10	4.06	77	0.006
267	L	brainstem	-0.39	0.10	-4.00	77	0.007

Supp. Table 6. *Third-person pronouns*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers using more (positive β) or fewer (negative β) third-person pronouns. Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
11	R	dlPFC	0.45	0.11	4.15	60	0.006
14	R	dlPFC	0.35	0.12	3.06	60	0.04
22	R	dlPFC	0.40	0.11	3.54	60	0.02
29	R	SMA	-0.34	0.11	-3.01	60	0.05
41	R	somatosensory	-0.34	0.12	-2.96	60	0.05
60	R	temp pole	-0.37	0.11	-3.31	60	0.03
71	R	FFA	-0.40	0.11	-3.61	60	0.02
85	R	PCC	-0.44	0.11	-3.92	60	0.009
90	R	precuneus	-0.37	0.11	-3.23	60	0.03
93	R	pHipp	-0.38	0.11	-3.37	60	0.02
117	R	cerebellum	-0.57	0.10	-5.76	60	< 0.001
132	R	brainstem	-0.34	0.11	-3.01	60	0.05
146	L	dlPFC	-0.35	0.11	-3.09	60	0.04
177	L	SPL	-0.38	0.11	-3.39	60	0.02
195	L	ATL	0.44	0.11	4.01	60	0.008
196	L	ITG	0.35	0.11	3.14	60	0.04
225	L	precuneus	-0.41	0.11	-3.63	60	0.02
233	L	pHipp	-0.40	0.11	-3.57	60	0.02
234	L	PHG	0.36	0.11	3.11	60	0.04
253	L	cerebellum	-0.39	0.11	-3.56	60	0.02
259	L	accumbens	-0.36	0.11	-3.15	60	0.04

Supp. Table 7. *Big words*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers using more (positive β) or fewer (negative β) big words. Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
11	R	dlPFC	-0.34	0.10	-3.34	77	0.02
18	R	lOFC	-0.39	0.10	-3.97	77	0.007
54	R	STS	0.37	0.10	3.70	77	0.01
57	R	temp pole	0.35	0.10	3.52	77	0.02
69	R	OTC	0.32	0.10	3.13	77	0.04
122	R	caudate	-0.32	0.10	-3.11	77	0.04
125	R	accumbens	-0.38	0.10	-3.85	77	0.009
132	R	brainstem	0.36	0.10	3.60	77	0.02
141	L	mPFC	-0.50	0.09	-5.33	77	< 0.001
149	L	dlPFC	0.31	0.10	2.97	77	0.05
153	L	aINS	-0.35	0.10	-3.49	77	0.02
154	L	dlPFC	0.31	0.10	3.02	77	0.04
156	L	IFG	-0.39	0.10	-3.95	77	0.008
165	L	motor	0.33	0.10	3.27	77	0.03
166	L	FEF	0.41	0.10	4.21	77	0.005
181	L	somatosensory	0.34	0.10	3.39	77	0.02
185	L	temp pole	0.34	0.10	3.36	77	0.02
187	L	ATL + temp pole	0.44	0.10	4.59	77	0.002
190	L	ATL	0.50	0.09	5.50	77	< 0.001
198	L	PHG	0.31	0.10	3.02	77	0.04
221	L	ACC	0.31	0.10	3.03	77	0.04
244	L	cerebellum	0.43	0.10	4.38	77	0.003
259	L	accumbens	-0.34	0.10	-3.38	77	0.02
265	L	brainstem	0.30	0.10	2.95	77	0.05
268	L	brainstem	-0.30	0.10	-2.94	77	0.05

Supp. Table 8. *Vocal pitch*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers' vocal pitch being higher (positive β) or lower (negative β). Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
25	R	motor	0.35	0.10	3.51	77	0.02
43	R	SPL	-0.40	0.10	-4.12	77	0.006
48	R	AG	-0.34	0.10	-3.40	77	0.02
56	R	ATL	-0.37	0.10	-3.63	77	0.01
58	R	ATL	-0.38	0.10	-3.84	77	0.009
71	R	FFA	-0.34	0.10	-3.34	77	0.02
73	R	visual	0.36	0.10	3.56	77	0.02
79	R	LiG	0.38	0.10	3.76	77	0.01
81	R	visual	0.31	0.10	3.02	77	0.04
82	R	LiG	0.35	0.10	3.40	77	0.02
121	R	caudate	0.36	0.10	3.62	77	0.01
144	L	dlPFC	0.37	0.10	3.64	77	0.01
148	L	dmPFC	0.33	0.10	3.26	77	0.03
156	L	IFG	-0.33	0.10	-3.22	77	0.03
161	L	motor	0.39	0.10	3.97	77	0.007
187	L	ATL + temp pole	0.36	0.10	3.57	77	0.02
211	L	LiG	0.56	0.09	6.32	77	< 0.001
213	L	visual	-0.33	0.10	-3.23	77	0.03
215	L	V1	0.50	0.09	5.34	77	< 0.001
216	L	LiG	0.44	0.10	4.61	77	0.002
218	L	PCC	0.38	0.10	3.85	77	0.009
227	L	PCC	-0.33	0.10	-3.23	77	0.03
248	L	cerebellum	-0.34	0.10	-3.35	77	0.02
260	L	caudate	0.36	0.10	3.54	77	0.02
267	L	brainstem	-0.31	0.10	-3.05	77	0.04
268	L	brainstem	-0.36	0.10	-3.60	77	0.02

Supp. Table 9. *Vocal intensity*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers' vocal intensity being higher (positive β) or lower (negative β). Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
1	R	vmPFC	0.40	0.10	3.99	77	0.007
3	R	vmPFC	0.40	0.10	4.11	77	0.006
8	R	vlPFC	0.33	0.10	3.23	77	0.03
11	R	dlPFC	0.31	0.10	3.03	77	0.04
13	R	dlPFC	0.32	0.10	3.18	77	0.03
26	R	motor	-0.30	0.10	-2.96	77	0.05
29	R	SMA	-0.30	0.10	-2.95	77	0.05
32	R	FEF	-0.33	0.10	-3.31	77	0.03
63	R	auditory	-0.32	0.10	-3.18	77	0.03
65	R	pSTS	-0.31	0.10	-3.14	78	0.04
84	R	MCC	0.38	0.10	3.83	77	0.009
92	R	amyg	-0.31	0.10	-3.01	77	0.04
94	R	aHipp	-0.32	0.10	-3.10	77	0.04
98	R	PHG	0.43	0.10	4.40	77	0.003
134	L	vmPFC	0.37	0.10	3.75	77	0.01
139	L	vmPFC	0.35	0.10	3.42	77	0.02
145	L	dmPFC	0.38	0.10	3.88	77	0.009
156	L	IFG	-0.39	0.10	-3.99	77	0.007
161	L	motor	0.41	0.10	4.11	77	0.006
171	L	somatosensory	0.36	0.10	3.59	77	0.02
187	L	ATL + temp pole	0.41	0.10	4.16	77	0.005
211	L	LiG	0.35	0.10	3.45	77	0.02
213	L	visual	-0.30	0.10	-2.95	77	0.05
222	L	PCC	-0.34	0.10	-3.39	77	0.02
235	L	PHG	0.37	0.10	3.67	77	0.01
253	L	cerebellum	-0.35	0.10	-3.48	77	0.02
256	L	cerebellum	-0.35	0.10	-3.48	77	0.02
261	L	putamen	0.30	0.10	2.95	77	0.05
267	L	brainstem	-0.33	0.10	-3.24	77	0.03
268	L	brainstem	-0.32	0.10	-3.14	77	0.04

Supp. Table 10. *Vocal roughness (jitter).* Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers' vocal roughness being higher (positive β) or lower (negative β). Adjusted p-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
9	R	dlPFC	-0.40	0.10	-4.10	77	0.006
31	R	premotor	0.31	0.10	2.99	77	0.05
53	R	ATL	-0.39	0.10	-3.97	77	0.007
80	R	V1	0.55	0.09	5.95	77	< 0.001
82	R	LiG	0.31	0.10	2.98	77	0.05
85	R	PCC	0.38	0.10	3.91	77	0.008
93	R	pHipp	-0.34	0.10	-3.37	77	0.02
134	L	vmPFC	-0.36	0.10	-3.59	77	0.02
148	L	dmPFC	-0.43	0.10	-4.34	77	0.004
151	L	IFG	-0.44	0.10	-4.54	77	0.002
152	L	lOFC	0.33	0.10	3.22	77	0.03
169	L	aINS	-0.35	0.10	-3.50	77	0.02
182	L	AG	0.34	0.10	3.34	77	0.02
186	L	temp pole	-0.31	0.10	-3.02	77	0.04
188	L	ATL	-0.42	0.10	-4.24	77	0.005
200	L	FFA	0.30	0.10	2.94	77	0.05
212	L	visual	0.35	0.10	3.44	77	0.02
215	L	V1	0.33	0.10	3.22	77	0.03
222	L	PCC	0.32	0.10	3.06	77	0.04
227	L	PCC	0.31	0.10	3.01	77	0.04
254	L	cerebellum	-0.41	0.10	-4.17	77	0.005
256	L	cerebellum	0.39	0.10	3.91	77	0.008
257	L	corpus callosum	-0.34	0.10	-3.39	77	0.02
267	L	brainstem	0.34	0.10	3.36	77	0.02

Supp. Table 11. *Speech rate*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was positively correlated with speakers talking more slowly. Adjusted *p*-values are shown (corrected for multiple comparisons by controlling the FDR at q < 0.05).

Shen Atlas Index	Hemisphere	Brain Region	*β*	*SE*	*t*	*df*	*p*-adj
38	R	motor	0.35	0.10	3.41	77	0.02
43	R	SPL	0.45	0.10	4.65	77	0.002
67	R	FFA	0.39	0.10	3.90	77	0.008
68	R	PHG	0.34	0.10	3.41	77	0.02
70	R	ITG	0.36	0.10	3.62	77	0.01
71	R	FFA	0.51	0.09	5.63	77	< 0.001
89	R	PCC	0.36	0.10	3.62	77	0.01
90	R	precuneus	0.32	0.10	3.10	77	0.04
95	R	hipp + PHG	0.43	0.10	4.43	77	0.003
101	R	cerebellum	0.31	0.10	3.11	77	0.04
106	R	cerebellum	0.38	0.10	3.90	77	0.008
110	R	cerebellum	0.35	0.10	3.49	77	0.02
114	R	cerebellum	0.36	0.10	3.61	77	0.01
140	L	dmPFC + ACC	0.31	0.10	3.05	77	0.04
147	L	dlPFC	0.40	0.10	4.00	77	0.007
157	L	premotor	0.49	0.09	5.16	77	< 0.001
165	L	motor	0.45	0.10	4.74	77	0.002
166	L	FEF	0.33	0.10	3.35	77	0.02
177	L	SPL	0.45	0.10	4.64	77	0.002
178	L	SPL	0.35	0.10	3.42	77	0.02
182	L	AG	0.53	0.09	5.93	77	< 0.001
183	L	TPJ	0.39	0.10	4.05	77	0.006
184	L	IPL	0.37	0.10	3.68	77	0.01
198	L	PHG	0.35	0.10	3.43	77	0.02
199	L	ITG	0.50	0.09	5.48	77	< 0.001
200	L	FFA	0.39	0.10	3.92	77	0.008
220	L	MCC	0.35	0.10	3.53	77	0.02
221	L	ACC	0.34	0.10	3.31	77	0.03
223	L	PCC	0.35	0.10	3.51	77	0.02
225	L	precuneus	0.47	0.10	4.93	77	< 0.001
226	L	precuneus	0.30	0.10	2.95	77	0.05
241	L	cerebellum	0.31	0.10	2.96	77	0.05
248	L	cerebellum	0.39	0.10	4.03	77	0.007

254	L	cerebellum	0.50	0.09	5.36	77	< 0.001
255	L	cerebellum	0.35	0.10	3.51	77	0.02
256	L	cerebellum	0.41	0.10	4.19	77	0.005

Supp. Table 12. *Silent pauses*. Brain regions for which shared meaning was significantly greater when moment-to-moment speaker-listener neural *asynchrony* was correlated with speakers pausing more (positive β) or less (negative β). Adjusted p-values are shown (corrected for multiple comparisons by controlling the FDR at $q < 0.05$).

Shen Atlas Index	Hemisphere	Brain Region	β	*SE*	*t*	*df*	*p*-adj
17	R	lOFC	-0.37	0.10	-3.63	77	0.01
36	R	aINS	0.32	0.10	3.17	77	0.03
43	R	SPL	0.52	0.09	5.71	77	< 0.001
66	R	FFA	0.30	0.10	2.96	77	0.05
67	R	FFA	0.54	0.09	5.96	77	< 0.001
69	R	OTC	0.31	0.10	3.01	77	0.04
70	R	ITG	0.34	0.10	3.33	77	0.02
71	R	FFA	0.58	0.09	6.71	77	< 0.001
76	R	visual	0.39	0.10	3.93	77	0.008
87	R	LiG	-0.31	0.10	-3.04	77	0.04
93	R	pHipp	-0.43	0.10	-4.44	77	0.003
95	R	hipp + PHG	0.41	0.10	4.22	77	0.005
100	R	cerebellum	0.32	0.10	3.08	77	0.04
106	R	cerebellum	0.43	0.10	4.41	77	0.003
110	R	cerebellum	0.41	0.10	4.16	77	0.005
114	R	cerebellum	0.35	0.10	3.43	77	0.02
122	R	caudate	-0.32	0.10	-3.06	77	0.04
131	R	brainstem	0.33	0.10	3.20	77	0.03
138	L	ACC	-0.39	0.10	-3.88	77	0.009
150	L	preSMA	0.33	0.10	3.26	77	0.03
157	L	premotor	0.45	0.10	4.73	77	0.002
165	L	motor	0.38	0.10	3.78	77	0.01
177	L	SPL	0.31	0.10	3.06	77	0.04
182	L	AG	0.36	0.10	3.62	77	0.01
183	L	TPJ	0.33	0.10	3.28	77	0.03
199	L	ITG	0.41	0.10	4.12	77	0.006
207	L	LiG	0.34	0.10	3.35	77	0.02
214	L	visual	0.34	0.10	3.36	77	0.02
229	L	pHipp	-0.31	0.10	-3.01	77	0.04
234	L	PHG	-0.33	0.10	-3.19	77	0.03
248	L	cerebellum	0.38	0.10	3.88	77	0.009
256	L	cerebellum	0.45	0.10	4.66	77	0.002

Supp. Table 13. *High vs. low speech rate comparison.* β-values for the effect of synchrony on shared meaning when speakers talked relatively slowly (≤ -1 SD) or quickly (≥ +1 SD). Negative β-values represent that *asynchrony* was associated with greater shared meaning. Significance codes: * < 0.05, ** < 0.01, *** < 0.001

			Speech Rate	
Shen Atlas Index	**Hemisphere**	**Brain Region**	**Fast**	**Slow**
38	R	motor	0.15	-0.21*
43	R	SPL	0.02	-0.35***
67	R	FFA	0.03	-0.28**
68	R	PHG	-0.11	-0.37***
70	R	ITG	0.32**	-0.02
71	R	FFA	0.17	-0.27*
89	R	PCC	0.02	-0.32**
90	R	precuneus	0.12	-0.3**
95	R	hipp + PHG	0.22*	-0.27**
101	R	cerebellum	0.23*	-0.03
106	R	cerebellum	0.11	-0.3**
110	R	cerebellum	0.17	-0.26*
114	R	cerebellum	-0.18	-0.48***
140	L	dmPFC + ACC	0.15	-0.16
147	L	dlPFC	0.11	-0.23*
157	L	premotor	0.24*	-0.26*
165	L	motor	-0.16	-0.35**
166	L	FEF	0.15	-0.29**
177	L	SPL	0.02	-0.51***
178	L	SPL	0.06	-0.41***
182	L	AG	0.21*	-0.46***
183	L	TPJ	0.36***	0.11
184	L	IPL	0.16	-0.27**
198	L	PHG	-0.01	-0.43***
199	L	ITG	0.18	-0.51***
200	L	FFA	0.12	-0.27*
220	L	MCC	0.18	-0.25*
221	L	ACC	0.22*	-0.14
223	L	PCC	-0.01	-0.38***
225	L	precuneus	-0.12	-0.41***
226	L	precuneus	0.28**	-0.12
241	L	cerebellum	0.17	-0.33**
248	L	cerebellum	0.04	-0.20
254	L	cerebellum	0.12	-0.46***
255	L	cerebellum	0.14	-0.01
256	L	cerebellum	0.20	-0.33**

Supp. Table 14. *High vs. low pause proportion comparison*. β-values for the effect of synchrony on shared meaning when speakers paused relatively more (≥ +1 SD) or less (≤ -1 SD). Negative β-values represent that *asynchrony* was associated with greater shared meaning. Significance codes: * < 0.05, ** < 0.01, *** < 0.001

			Pause Proportion	
Shen Atlas Index	**Hemisphere**	**Brain Region**	**Low**	**High**
36	R	aINS	0.27*	-0.2
43	R	SPL	0.37***	-0.28**
66	R	FFA	0.07	-0.22*
67	R	FFA	0.17	-0.47***
69	R	OTC	-0.07	-0.24*
70	R	ITG	0.38***	0.02
71	R	FFA	0.21*	-0.48***
76	R	visual	-0.02	-0.41***
95	R	hipp + PHG	0.24*	-0.26*
100	R	cerebellum	-0.09	-0.43***
106	R	cerebellum	0.17	-0.29**
110	R	cerebellum	0.21*	-0.27*
114	R	cerebellum	-0.19	-0.34**
131	R	brainstem	0.21*	-0.2
150	L	preSMA	0.2	-0.3**
157	L	premotor	0.38***	-0.15
165	L	motor	0	-0.38***
177	L	SPL	-0.19	-0.49***
182	L	AG	0.19	-0.3**
183	L	TPJ	0.36***	0.04
199	L	ITG	0.25*	-0.33**
207	L	LiG	-0.04	-0.3**
214	L	visual	-0.07	-0.32**
248	L	cerebellum	0.16	-0.36***
256	L	cerebellum	0.1	-0.37***