

Dartmouth College

Dartmouth Digital Commons

Dartmouth College Master's Theses

Theses and Dissertations

Summer 2023

Left inferior frontal gyrus connectivity with the dorsomedial subsystem of default network tracks real-world conversation behaviour

Dhaval M. Bhatt

Dartmouth College, dhaval.m.bhatt.gr@dartmouth.edu

Follow this and additional works at: https://digitalcommons.dartmouth.edu/masters_theses



Part of the [Applied Behavior Analysis Commons](#), and the [Social Psychology Commons](#)

Recommended Citation

Bhatt, Dhaval M., "Left inferior frontal gyrus connectivity with the dorsomedial subsystem of default network tracks real-world conversation behaviour" (2023). *Dartmouth College Master's Theses*. 83. https://digitalcommons.dartmouth.edu/masters_theses/83

This Thesis (Master's) is brought to you for free and open access by the Theses and Dissertations at Dartmouth Digital Commons. It has been accepted for inclusion in Dartmouth College Master's Theses by an authorized administrator of Dartmouth Digital Commons. For more information, please contact dartmouthdigitalcommons@groups.dartmouth.edu.

**LEFT-INFERIOR FRONTAL GYRUS CONNECTIVITY WITH THE
DORSOMEDIAL SUBSYSTEM OF DEFAULT NETWORK TRACKS
REAL-WORLD CONVERSATION BEHAVIOUR**

A Thesis

Submitted to the Faculty

in partial fulfilment of the requirements for the
degree of

Master of Arts

in

Psychological and Brain Sciences

by Dhaval M. Bhatt

Guarini School of Graduate and Advanced Studies
Dartmouth College
Hanover, New Hampshire

July, 2023

Examining Committee:

(chair) Dr. Meghan L. Meyer

Prof. Luke J. Chang

Dr. Jeremy R. Manning

F. Jon Kull, Ph.D.

Dean of the Guarini School of Graduate and Advanced Studies

Abstract

Social interactions are multifaceted, complex, and critical to social behaviour as they help gather information, develop social connections, and regulate social behaviour (Lakey & Orehek, 2011; Testard et al., 2021; Jolly & Chang, 2021). Among social interactions, conversations find a special place for humans due to the nuances associated with language, conversational behaviour (e.g., gestures), and context (e.g., where conversations occur and what is discussed). Researchers have studied aspects of single conversation behaviour, content related to conversations, and brain function (Sievers et al., 2020). However, little is known about the brain function of densely-sampled in-person conversation behaviour. Filling this gap is important, given that real-world conversation happens frequently and is an index of social connectedness. We utilise the passive-mobile sensing approach from the StudentLife study (Wang et al., 2014; daSilva et al., 2021) to track real-world conversations and relate the features to resting-state functional connectivity via fMRI. In this thesis, we show that resting state functional connectivity of left inferior frontal gyrus (LIFG, a region associated with language; Turken & Dronkers, 2011; Klaus & Hartwigsen, 2019) with the dorsomedial prefrontal cortex (dMPFC) subsystem of the default mode network (DMN), which is a network associated with social-cognitive processes (Collier & Meyer, 2020; Sippel et al., 2021), of an individual is related to the time they spend in the vicinity of conversations. Consistent with social psychological literature (Delormier, Frohlich, & Potvin, 2009; Dunbar, 2017), we also find that features of conversation – average time spent, the variance associated with, and total time spent around conversations – at places associated with ‘social eating’ was related to the same brain function. Our results suggest that the importance of LIFG within the dMPFC subsystem may be associated with (1) average time spent around conversations generally, and (2) conversations occurring specifically in socially relevant situations. This thesis also supports that passive-mobile sensing can be useful to study real-world conversations, and that adding neuroimaging modalities to otherwise densely-sampled behavioural features can open new avenues of research to better understand the brain-basis of social interactions.

Acknowledgements

I am grateful to my advisor, Dr. Meghan L. Meyer, for guiding me through the project that I present here and my thesis committee, Prof. Luke J. Chang and Dr. Jeremy R. Manning, both of whom I also thank for their advice on how I may strengthen my analyses and results. I thank Prof. Andrew Campbell, who envisioned the StudentLife study, and Prof. James Haxby, whose aid led to the completion of data collection for this study. I am grateful to Dr. Jeremy Huckins for their help in understanding and parsing the data. I also extend my thanks to all the students, researchers, and research assistants who helped build the application for data collection and storage, who helped operate the fMRI to collect the brain scans, and those who administered the process at every point of this study and my project.

I give a special set of thanks to Dr. Meyer and extend this gratitude to my lab-mates, who created a positive and comfortable environment to aid my research, and to my family and friends who supported, applauded, and with whom I shared these past two years at Dartmouth College.

Table of Contents

Abstract	ii
Acknowledgements	iii
Table of Contents	iv
List of Tables	v
List of Figures	v
Introduction	1
Data and Methods	5
Participants.....	5
Resting State fMRI.....	5
fMRI Data Acquisition.....	5
Resting state fMRI preprocessing.....	5
Resting state functional connectivity.....	6
Passive Mobile Sensing.....	9
Tracking Conversation Time.....	9
Tracking Location.....	10
Personality Questionnaires.....	12
Results	14
LIFG-dMPFC connectivity relates to average time spent around conversations.....	15
LIFG RSFC is related to the average duration.....	15
Only LIFG RSFC is related to the average duration.....	17
LIFG-dMPFC RSFC relates to average time spent around conversations at eateries.....	18
LIFG-dMPFC RSFC relates to variance and total duration in conversations at eateries..	19
Discussion	22
Limitations.....	24
Conclusion.....	25
Appendix A	26
Appendix B	28
References	33

List of Tables

Table 01	Regions in the three DMN subsystems	7
Table 02	Spatial clustering of tracked locations	11
Table 03	Statistics of the data and features used	14
Table A1	Statistics of all the variables mentioned in the thesis	26

List of Figures

Figure 01	Functional atlas of the dorsomedial subsystem of DMN	8
Figure 02	Correlations between LIFG-dMPFC subsystem fc and behavioural conversation features	16
Figure 03	Correlations between LIFG-dMPFC subsystem fc and behavioural features for conversations at eateries	20
Figure B1	Correlations between L-IFG resting state functional connectivity within the dorsomedial subsystem and behavioural features for conversations at various locations	28

Introduction

Social integration is critical for human health and development (Barnett & Gotlib, 1988; Diener & Seligman, 2002; Holt-Lunstad, Smith, & Layton, 2010; Holt-Lunstad, Robles, & Sbarra, 2017; Dunbar, 2018). Greater social connectedness is linked to better mental health (Holt-Lunstad, Smith, & Layton, 2010; Dunbar, 2018), better physical health (Baumeister & Leary, 1995; Holt-Lunstad, Robles, & Sbarra, 2017), and overall increased happiness (Diener & Seligman, 2002). On the flipside, isolation tends to make individuals more stressed (Barnett & Gotlib, 1988), vulnerable to depression (Barnett & Gotlib, 1988; Cacioppo et al., 2006), less physically healthy (Hawley & Cacioppo, 2003; Holt-Lunstad, Smith, & Layton, 2010; Holt-Lunstad, Robles, & Sbarra, 2017), and more susceptible to substance abuse (Åkerlind & Hörnquist, 1992; Hawley & Cacioppo, 2003). Studying interaction behaviours have led scientists to show that humans, among other higher-order social animals, actively seek out social connections (Dunbar, 2018; Templer et al., 2018; Testard et al., 2021), leading to the belief that perhaps, the brain may have evolved to be “social by default” (Dunbar, 1998; Meyer, 2019).

Studies in modern social psychology have focussed on interactions in various forms (Dunbar, Marriott, & Duncan, 1997; Momennejad, Duker, & Coman, 2019; Dunbar, 2018). Recent social cognitive research has focussed on the multiple aspects of social integration from large networks of communities (Sallet et al., 2011; Baek et al., 2022; Baek & Parkinson, 2022) to solitary individuals (Hawley & Cacioppo, 2003; Hyon et al., 2020), from synchrony between folks (Dikker et al., 2017; Czeszumski et al., 2022) to self-regulating effects of mental health (daSilva et al., 2021; Sippel et al., 2021; Baek et al., 2022), and from well-defined conversations (Bögels & Levinson, 2017; Templeton et al., 2022) to more ambiguous everyday interactions (Dunbar, 2017). However, there is a gap in literature for studying the brain function behind real-world social integration. Most neuroscience studies mentioned earlier use blood oxygen level-dependent functional magnetic resonant imaging (BOLD-fMRI) as the chief neuroimaging modality as the technology provides greater spatial resolution while limiting mobility and temporal resolution. Although some studies have used more real-world-like paradigms (e.g., participants converse while undergoing fmri or converse

in a lab before and after fMRI; [Bögels & Levinson, 2017](#); [Sievers et al., 2020](#)), ecological validity of social interactions largely remain questionable when one is confined to a small space and/or in a lab setting. Contemporary social-cognitive neuroimaging studies favour more mobile, comparatively inexpensive technologies like electroencephalography (EEG; [Dikker et al., 2017](#)) or functional near-infrared spectroscopy (fNIRS; [Burns & Lieberman, 2020](#); [Hirsch et al., 2021](#); [Czeszumski et al., 2022](#)) which may offer opportunities for ecologically valid conversation sampling. Despite this push, more ecological studies on neural bases of social interactions remain few.

To begin the neural exploration of real-world social interactions, for ecological human social behaviours are multifaceted and complex, we propose combining passive mobile sensing methods designed to detect time spent conversing with people with resting state functional magnetic resonance imaging. Such an integration of methods is done in the *StudentLife* project ([Wang et al., 2014](#)). *StudentLife* is a large-scale passive mobile sensing study that recruits and tracks the undergraduate students at Dartmouth College over the duration of their academic year. The project uses a mobile app to track the mental health of students with self-reports, their physical location with GPS, and their resting-state brain function with regular fMRI scans. Previous research combining everyday student behaviour assessed with mobile sensing and brain function has implicated resting state functional connectivity (RSFC) between subgenual cingulate cortex (sgCC) and ventromedial/orbitofrontal cortex (OFC) to predict phone usage ([Huckins et al., 2019a-2019b](#)). Per the ethical requirements of Dartmouth College's Institutional Review Board (IRB), the mobile application removes all identity-level and content-level information from the records. Instead, the *StudentLife* application uses online HMM-based vocal-classification to differentiate conversations from soliloquy or any other noise ([Rabbi et al., 2011](#); [Lane et al., 2012-2014](#)). While we do not record the language or voice in conversations, we were able to capture time spent in and close to real-world conversations. Our method utilises the mobile-sensed conversation log over a period of 8 weeks per subject to calculate persistent conversation behaviours. This thesis connects some of the conversation data to brain function as collected from the fMRI scans at the centre of these 8-week tracking periods.

Although our primary aim targets an exploration of general conversation-traits, there is contextual relevance to these behaviours. That is, *how* one interacts with others strongly depends on *where* the social interaction is taking place. To this extent, we take advantage of the global positioning system (GPS) coordinates that the *StudentLife* mobile application tracks. Among the conversations happening in everyday life, literature in social psychology has implicated those over meals as being important to share impactful social knowledge, establish alliances, and form social bonds (Dunbar et al., 1997; Dunbar, 2017). Hence, it becomes important to explore the brain-basis of interaction behaviour at such socially salient locations.

Research from the *StudentLife* project connect brain function with everyday behaviours (Huckins et al., 2019a-2019b) and implicates mental health with social interactions (daSilva et al., 2021), providing the opportunity to bridge conversation behaviours with brain function. Human social cognitive research has implicated neural processes occurring in the default mode network (DMN; Amodio & Frith, 2006; Heatherton et al., 2006; Andrews-Hanna et al., 2010; Denny et al., 2012; Mars et al., 2012; Meyer et al., 2019). Graph theoretic tools have been used to distribute the network into three major subsystems, of which the dorsomedial prefrontal cortex (dMPFC) subsystem (also shortened to ‘dorsomedial subsystem’) has regions that, research shows, engage in mentalizing (Tamir & Thornton, 2018; Saxe & Kanwisher, 2003), value-perception (Behrens et al., 2008), and social learning (Lieberman et al., 2019; Meyer et al., 2019; Collier & Meyer, 2020). Particular to the dorsomedial subsystem of the DMN is left inferior frontal gyrus (L-IFG), a region participating in language (Uddén & Bahlmann, 2012; Klaus & Hartwigsen, 2019) and size of active-participation social networks (Mori & Haruno, 2022), processes that are important for conversations. Hence, we predict that the connectivity of left IFG within the dMPFC subsystem may be important in conversation-related behaviours. Moreover, we hypothesise that L-IFG functional connectivity may be related to trait-level real-world behaviours that occur in situations furthering social interactions.

The aim of this thesis is to investigate associations between brain function (here, assessed by resting state functional connectivity) and real-world social interactions. Specifically, we establish that the connectivity of left IFG within the dMPFC subsystem

of DMN plays a key role in how long an individual tends to be exposed to conversations. Honing in on the location-specificity of conversations, we show that the same brain-to-conversation relationship exists when examining time spent in conversations over meals. Our analyses support the theories from social neuroscience that suggest that regions of the DMN and the dMPFC subsystem are integral to social cognition and social network maintenance (Collier & Meyer, 2020; Inagaki & Meyer, 2020; Sippel et al., 2021). Our analyses also support the theories from social psychology that emphasise the importance of conversations happening over meals for social bonding (Dunbar, Marriott, & Duncan, 1997; Dunbar, 2017). Moreover, our method of combining passive mobile sensing with neuroimaging presents an avenue on how one may study the brain functions associated with complex, densely-sampled, real-world human behaviours for future research.

Data and Methods

Participants

115 Dartmouth first-year college students between the ages of 18-22 years agreed to participate in this study. Subjects with poor quality or incomplete data were removed. The study retained 88 participants (ages = 18.25 Mean \pm 0.64 SD; 70.5% Females; 60.2% white, 22.7% asian, 3.4% black, 10.2% multi-racial, and 3.5% did not report) with 8 weeks of mobile-sensing data and a complete resting-state fMRI scan, collected across the Winter and Spring quarters of the academic year. The following subsections discuss the data in further detail. All participants provided informed consent in accordance with the Dartmouth College Institutional Review Board (IRB).

Resting State fMRI

fMRI Data Acquisition

The Dartmouth Brain Imaging Center uses a 3T Siemens Magnetom Prisma MRI scanner with a 32-channel phased array head coil. Blood oxygen level dependent (BOLD) functional MR images were acquired using an EPI gradient echo sequence with $2.5 \times 2.5 \times 2.5$ mm isotropic voxels, reaction time (TR) of 1000 msec and echo time (TE) of 33 ms, 3.5 mm slice thickness with 0.5 mm skip between slices, Field of View (FoV) = 240 mm \times 240 mm, matrix size of 96×96 , 90° flip angle, and a sense factor of 2. A T2-weighted structural image was acquired coplanar with the functional images (MP-RAGE; 160 sagittal slices; 1 mm \times 1 mm \times 1 mm voxels; 9.9 ms TR and 4.6 ms TE; 0.9-mm slice thickness; 240 mm \times 240 mm FoV; 8° flip angle; sense factor of 4). The resting state scan lasted 12 minutes and 54 seconds during which time participants were instructed to lie still and let their mind wander.

Resting state fMRI preprocessing

fMRI data was preprocessed using the Power et al. (2014) and Huckins et al. (2019a-2019b) processing streams, with frame-displacement (FD) thresholded at 0.25

mm and 24 motion parameters. Additional slice-correction, rigid-body realignment, and within-run intensity normalisation were performed to correct for head-movement and voxel activation scaled to set the modal intensity of 1000 units with a signal-change of 1%. The brain scans were transformed to standardised MNI atlas space with frame-censoring. The resulting, uncensored fMRI signals were nuisance-regressed with interpolation and band-pass filtered between 0.009 Hz and 0.08 Hz, per Huckins et al. (2019a-2019b). We used the python library *nitools* (Chang et al., 2020) to regress out 24 motion parameters that included the head motion and rotation, square of the head motion and rotation, change in head motion and rotation, and the square of change in head motion and rotation. We also regressed out the global, white-matter, and cerebrospinal fluid (CSF) signals alongside those corresponding up to two orders of polynomial powers and activity related to brain spikes.

Resting state functional connectivity

We parcelled the preprocessed BOLD signals into Thomas Yeo et al. (2011) 17 networks functional atlas with 100 regions-of-interest (ROI) and removed voxel-clusters with fewer than 5 voxels. This parcellation scheme is derived from a large sample size (1,000 subjects) and their default network (or default mode network; DMN) regions are anatomically similar to those determined with task-based fMRI studies examining social cognition (Saxe & Kanwisher, 2003; Amodio & Frith, 2006; Denny et al., 2012), making the functional atlas useful for us. Thomas Yeo et al. (2011) also provide clustering of three default network subsystems with regions divided to fall in the dorsomedial (or, the dorsoMedial PreFrontal Cortex; dMPFC) subsystem, the core DMN (a.k.a. Core) subsystem, and the Medial-Temporal (or, the Medial Temporal Lobe; MTL) subsystem. Table 01 lists the regions in the three DMN subsystems.

Table 01: Regions in the three DMN subsystems: *the centroids listed here are as derived from Thomas Yeo et al. (2011). ROIs with fewer than 5 voxels have been removed. The MNI coordinates follow the MNI-152 system with 2 mm × 2 mm × 2 mm voxel dimensions.*

Network	Centroid			Larger Anatomical Region	Voxels
	X	Y	Z		
MTL	-39	-80	32	L Middle Occipital Lobule	82
Subsystem	48.2	-70.8	27.2	R Middle Occipital Gyrus	111
	-12.4	-55.4	12.6	L Calcarine Gyrus, L Precuneus	119
	13.8	-53.2	13.8	R Cuneus, R Precuneus	141
	27.4	-28	-20.2	R Fusiform Gyrus	189
	-26.8	-33	-18	L Fusiform Gyrus	271
Core	61.8	-6.8	-18.2	R Middle Temporal Gyrus	232
Subsystem	23.4	-48.8	44	R Superior Frontal Gyrus	352
	-22.4	28.8	46.6	L Middle Frontal Gyrus / L Superior Frontal Gyrus	377
	-44.4	-68.2	37.4	L Angular Gyrus	570
	51.4	-57.4	29.6	R Angular Gyrus / R Middle Temporal Gyrus	622
	-0.6	-50.8	31	R / L PCC	1494
	0.6	50	5.2	MPFC / ACC	2648
dMPFC	55.6	24.6	8.2	R Inferior Frontal Gyrus	98
Subsystem	61.8	-25.8	-6.2	R middle Temporal Gyrus	183
	-40.4	12.6	50.4	L Middle Frontal Gyrus	241
	43	29.6	-13.8	R Inferior Frontal Gyrus	282
	-52.4	-55.6	28.6	L Angular Gyrus	423
	51.8	3.8	-30.2	R Medial Temporal Pole	424
	-46.6	26.8	-2.2	L Inferior Frontal Gyrus	1201
	-56.6	-12.2	-19	L Middle Temporal Gyrus	1667
	-2.4	45.6	41.2	Bilateral dMPFC	1783

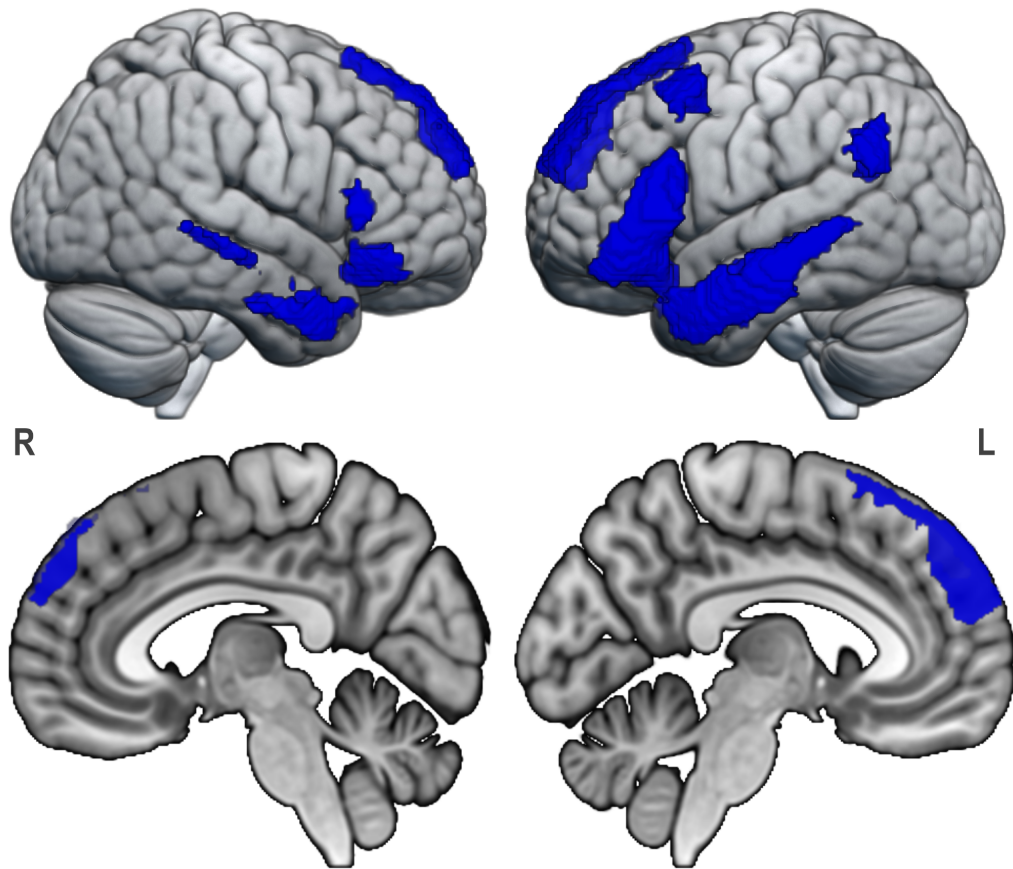


Figure 01: Functional atlas of the dorsomedial subsystem of DMN: *Shaded in blue are all the regions of the dorsomedial prefrontal cortex (dMPFC) subsystem of the default mode network (DMN) as derived from Thomas Yeo et al. (2011). ROIs with fewer than 5 voxels were removed.*

Of the three DMN sub-networks, literature has shown that regions of the dMPFC subsystem participate in theory of mind (ToM; [Saxe & Kanwisher, 2003](#)), social value perception ([Behrens et al., 2008](#); [Kable & Glimcher, 2007](#); [Piva et al., 2019](#)), and social learning ([Meyer et al., 2019](#); [Collier & Meyer, 2020](#)), making the subsystem important to study in the context of real-world social interaction. Within this subsystem is the region of Left Inferior Frontal Gyrus (L-IFG), which research has shown to be linked with language comprehension ([Uddén & Bahlmann, 2012](#); [Klaus & Hartwigsen, 2019](#)) and size of active-participation social networks ([Mori & Haruno, 2022](#)), making it important to study the connectivity of L-IFG with other dorsomedial ROIs when examining real-world conversation behaviour in particular. To that end, we used Fisher's

z-transformed Pearson's correlation between the time-course of the parcellated ROI pairs to create a resting state functional connectivity (RSFC) network for each subject. From this network, we extracted the adjacency matrices for the ROIs belonging to the three DMN subsystems. From the adjacency matrix, we extract all the between-ROI edge-weights and average them to calculate the within-network RSFC. The mean of column-vectors affiliated to each ROI in the adjacency matrix, without self-loops, is calculated as the average ROI connectivity. For each analysis, we treated subjects with functional connectivity, conversation, and/or self-report trait scores (e.g., self-esteem), more than 2.5 standard deviations from the respective means as outliers excluded from analyses. Furthermore, each analysis was followed-up with complementary sets of analyses into other ROIs and features to distil the results for clearer inferences.

Passive Mobile Sensing

Wang et al.'s (2014) StudentLife iOS and Android applications were used to collect mobile-sensing data. Enrolled participants downloaded the app at the onset of the study and the application passively sensed audio, screen-based, text-message, call-based, and gps features. Further and detailed information on the preprocessing and analyses of passively-sensed data can be found in related publications (Rabbi et al., 2011; Lane et al., 2012; Chen et al., 2013; Wang et al., 2014). Given that the subjects in this study were freshmen undergraduates at Dartmouth College, temporal periods were chunked in order of weeks (multiples of 7 days) to remove any inconsistencies due to the students' class schedules. In other words, any structure to conversation behaviour specific to certain days of the week was held constant by creating week-specific values. Trait-level conversation features were thus calculated over an 8-week (56 days) period. A period of 8-weeks also allowed us to retain a larger population size.

Tracking Conversation Time

Smartphone microphones were used as sensors to collect audio features with a sampling ratio of 1 min ON to 3 min OFF. The detected features were fed into a Hidden Markov Model (HMM) to classify the audio as human voice and to detect if the audio

may resemble a conversation (Lane et al., 2014). HMM-based classifiers have been shown to have high audio-based feature-detection accuracy (84–94%; Rabbi et al., 2011; Lane et al., 2012). Once determined that the participant was exposed to conversations occurring in close vicinity, the microphone keeps logging the features until the detected conversation has ended. For ethical practices and in accordance with Dartmouth College’s IRB, all personal and identity-based information, including voice and content of the conversations, were not saved. All the feature-detection was carried out on-line, and only the features approved by the IRB were logged.

From the logged conversation data per subject, four main conversation-based features were extracted. First is the total duration of conversation, calculated as the sum of all individual conversation durations over a subject’s 8-week period. Second was the total number of conversations over the 8-week period. Third was the average duration of conversations, defined as the mean of all individual conversations per subject over the 8-week period. Last was the variance in conversation durations, calculated as the variance of all individual conversations durations.

Tracking Location

Primarily, the GPS coordinates were logged to track the movement of a subject on and around the campus. However, we take advantage of these GPS logs to track interaction behaviour of our participants at various locations, particularly at and around eateries. We reason that conversations around meals are important, which aligns with the literature in social psychology suggesting that they convey socially salient information (Dunbar, Marriott, & Duncan, 1997; Dunbar, 2017).

The mobile application logged the GPS coordinates every 10 minutes, sampling a total of 144 location points a day per subject. This spatial data consisted of altitude (not used), latitude, longitude, and accuracy in metres, the last of which implies higher accuracy for lower values. The spatial data was collected parallel to the conversation data, and we merged these two streams of data in a rolling fashion, since a conversation log will have a location ping recorded within 5 minutes of either occurring. Observations containing more than 20 minutes of inconsistencies were dropped, resulting in an average 3% data loss (daSilva et al., 2021). Density-based spatial clustering of applications with

noise (DBSCAN; Ester et al., 1996) was used to cluster the cleaned data to spatial locations on and around Dartmouth Campus. These locations were then further grouped into twelve ‘types,’ as reported in Table 02.

Table 02: Spatial clustering of tracked locations: *Each cluster gives a list of locations found on or around the campus. The location lists (the column ‘Locations’) also include those locations found outside the town of Hanover, NH, that are often visited by the students. Locations with an asterisk (*) next to the cluster name have a comparatively larger population size ($N > 40$).*

Location Cluster	Locations
Athletic Facilities*	'berry_sports_center', 'canoe', 'chase-field', 'football', 'ladyard_cacoe', 'leverone', 'lodge', 'softballfield', 'sport-venues', 'sport-venues-press', 'tennis', 'thompson_arena'
Classroom Buildings*	'Hillel', 'Mckenzie', 'Tuck_hall', 'batrlett', 'buchanan', 'burke', 'butterfield', 'byrnehall', 'carpenterhall', 'chasehall', 'cummings', 'currier', 'hallgarten', 'hopkins', 'hopkins-spaulding', 'kemeny', 'lsb', 'maclean', 'massrow', 'mclaughlin', 'moore', 'morano', 'murdough', 'raven-house', 'remsen', 'ripley', 'robinson', 'rockefeller-center', 'rockefeller-social-sciences', 'russell-sage', 'silbsby-rocky', 'smith', 'steele', 'streater', 'sudikoff', 'thayer_secure', 'thornton', 'vail', 'webster_cottage', 'websterhall', 'wentworth', 'whittemore', 'wilson', 'woodburyhall', 'woodward'
Culture and Arts*	'hood', 'hopkins', 'hopkins-spaulding', 'lodge', 'native_american_house', 'rockefeller-center', 'rockefeller-social-sciences', 'sphinx', 'vac'
Eateries*	'53_commons', 'candela', 'capizza', 'collis', 'domino', 'hopkins-food', 'HanoverInn', 'indian_food', 'mexican-food', 'mollys', 'murphy', 'noodle', 'orient', 'pine', 'ramunto', 'salt-hill', 'starbucks', 'sushiya', 'tuktuk', 'umpleby'
Greek Housing*	'ACA', 'AD', 'AP', 'AT', 'AXD', 'BAO', 'BG', 'CGE', 'CH', 'DDD', 'EKT', 'GDC', 'KD', 'KDE', 'KKG', 'KKK', 'PDA', 'PT', 'SAE', 'SN', 'SPE', 'TDC', 'ZP', 'tabard'
The Green	'green'

Location Cluster	Locations
Student Housing*	'13-EWL', '19-EWL', '9-EWL', 'Cohen', 'andres', 'bissell', 'brown_hall', 'channing-cox', 'east-wheelock', 'fahey-mclane', 'fairchild', 'fayerweather', 'fayerweather-south', 'french', 'gile', 'judge', 'lacasa', 'ledyard', 'little_hall', 'lord', 'maxwell', 'mcCulloch', 'morton', 'native_american_house', 'north-park', 'richardson', 'six-south', 'south-house', 'tlc', 'topliff', 'wheeler', 'zimmerman'
Libraries*	'baker-berry', 'dana-library', 'feldberg_library', 'library-default-services', 'lsl', 'sanborn'
Marketplace*	'NuggetTheaters', 'carson-tech_services', 'post-office', 'bookstore', 'fairbanks', 'coop', 'lemon_gift', 'Jcrew', 'talbots'
Medical Facilities	'CVS', 'DHMC', 'hitchcock', 'ropeferry'
Religious Places	'StDenisCatholicChurch', 'StThomasEpiscopalChurch', 'aquinas', 'christian_reading', 'church', 'rollins-chapel'
Miscellaneous*	'blunt_alumni_center', 'dartmouth_hall', 'den', 'dewey', 'mcnuttt', 'ovis', 'parkhurst', 'payroll', 'reed', 'remote_offices_HREAP'

We used the location types (clusters) as a categorical variable to test if conversation variables at certain locations show any significant relation to the brain function. First, we removed the ‘miscellaneous’ locations and the ones where subjects did not frequent (locations with population size $N < 40$), leaving us with 8 locations. Then, we extracted the four conversation features (duration, number, average, and variance) for each remaining location. Results relating the brain functional connectivity to conversation features were also compared.

Personality Questionnaires

On the day of the scan, all subjects filled out a series of personality and mental health questionnaires. These self-reported scores include the 8-item Patient Health

Questionnaire which assesses depressive symptoms (PHQ-8; Kroenke et al., 2009), 7-item General Anxiety Disorder (GAD-7; Spitzer et al., 2006), Janis-Field Feelings of Inadequacy scale (Janis & Field, 1956), 14-item Perceived Stress Scale (PSS-14; Cohen, Kamarck, & Mermelstein, 1983), and the State Self Esteem scale (SSES; Heatherton & Polivy, 1991). The SSES is further divided into 3 sub-scales: (1) Performance (SSE-Per) subscale reports a score for how an individual may think they are performing in their everyday life, (2) Social (SSE-Soc) subscale reports what the person thinks others may perceive of them, and (3) Appearance (SSE-App) subscale reports how one perceives of their physical self. Since the thesis primarily aims at exploring connections between the brain and conversation behaviour, we did not use personality and mental health scores as primary variables. However, we explored the interaction of mental state in terms of personality trait or mental health with conversation trait-features or location-categorised conversation behaviours.

Results

A high-level look at the main data is summarised below, with the complete set of statistics available in *Appendix A*. For each variable, we present the mean, standard deviation (std), 1-sample, 2-tailed t-score against the null of zero-mean ($\mu = 0$), the degrees of freedom associated with the t-test, and the corresponding p-value . All our data have distributions that are significantly different from null.

Table 03: Statistics of the data and features used: *the ‘Features’ column contains the name of the data feature recorded in the results. ‘Avg. Conversation’ is the average duration of conversations over a span of 8 weeks and is recorded in the unit of minutes (min), ‘Conversation Var.’ is variance in unique conversation durations over the same time and is recorded in the unit of minutes-squared (min²), and the two resting state functional connectivity (‘RSFC’) variables are BOLD-activity derived network features. The statistics reported for each feature are presented in their respective rows under the columns of ‘mean’, standard deviation (‘std’), 1-sample 2-tailed t-score (‘t’), the degree of freedom (‘df’), and t-tested p-value (‘p’). Note that the categorical variable of ‘Gender’ is not reported in this table.*

Feature	mean	std	t	df	p
Avg. Conversation (min)	9.594	4.017	21.628	81	2.13×10^{-35}
Avg. Conversation at Eateries (min)	11.574	5.223	19.821	79	2.14×10^{-32}
Conversation Var. (min ²)	319.302	546.408	5.292	81	1.01×10^{-6}
Conversation Var. at Eateries (min ²)	193.065	163.814	10.541	79	9.98×10^{-17}
LIFG-dMPFC RSFC	0.456	0.110	38.684	86	3.61×10^{-56}
LIFG-DMN RSFC	0.181	0.102	16.541	86	1.88×10^{-28}
SSE-Performance	19.765	2.308	78.966	84	1.35×10^{-80}
SSE-Social	18.435	6.288	27.032	84	3.31×10^{-43}
PSS-14	31.729	7.680	38.089	84	9.04×10^{-55}

To test whether there is a categorical gender difference in these features, we run independent 2-tailed t-tests with unequal variance for each category. We find that average disposition to conversations do not show any gender-based differences, regardless of if the conversations occur in their vicinity generally ($t(78) = 0.186, p = 0.85$) or specifically at eateries ($t(78) = 1.356, p = 0.18$). We find the same result for the variance in unique conversations, in that they do not show significant gender-based differences, regardless of the conversations across all locations ($t(77) = 1.56, p = 0.12$), though it is noteworthy that there is a marginal effect at eateries ($t(77) = 1.95, p = 0.06$), with females spending more time around conversations at eateries. When categorically distributed according to the participants' gender, we do not find differences in the self-reported mental health scores from perceived stress scale ($t(82) = 0.35, p = 0.73$) or the social-subscale of the self-esteem ($t(83) = 0.54, p = 0.59$). However, we see a significant gender-difference in the performance-subscale of the state self-esteem ($t(83) = -2.069, p = 0.045$), with females having lower self-esteem than males, on average. The LIFG-dMPFC subsystem RSFC shows no significant relation to or differences within gender ($\beta = -0.015, t(85) = 0.626, p = 0.53$), and neither does the LIFG average connectivity within the DMN ($t(84) = -0.408, p = 0.69$). Although we only find gender-differences in state self esteem (SSE) performance subscale, the following sections report interactions with the variable to rule out gender differences.

LIFG-dMPFC connectivity relates to average time spent around conversations

LIFG RSFC is related to the average duration

To test our hypothesis of the role of Left IFG-dorsomedial subsystem function in conversations, we ran a correlation analysis between average LIFG-dorsomedial subsystem functional connectivity and conversation-based features. We observe that Left IFG functional connectivity within the dorsomedial subsystem tracks the average duration that the individual is exposed to conversations (*pearson's r* = 0.26, $p = 0.024$). However, the functional connectivity does not significantly correlate to the total duration of exposure to conversations

($r = 0.18$, $p = 0.13$), number of times an individual may be exposed to conversations over the 8-week period ($r = 0.12$, $p = 0.32$), nor to the variance in individual conversations ($r = 0.09$, $p = 0.42$). We do not see gender differences interacting with this relationship ($\beta = -0.0128$, $t(77) = 1.00$, $p = 0.32$).

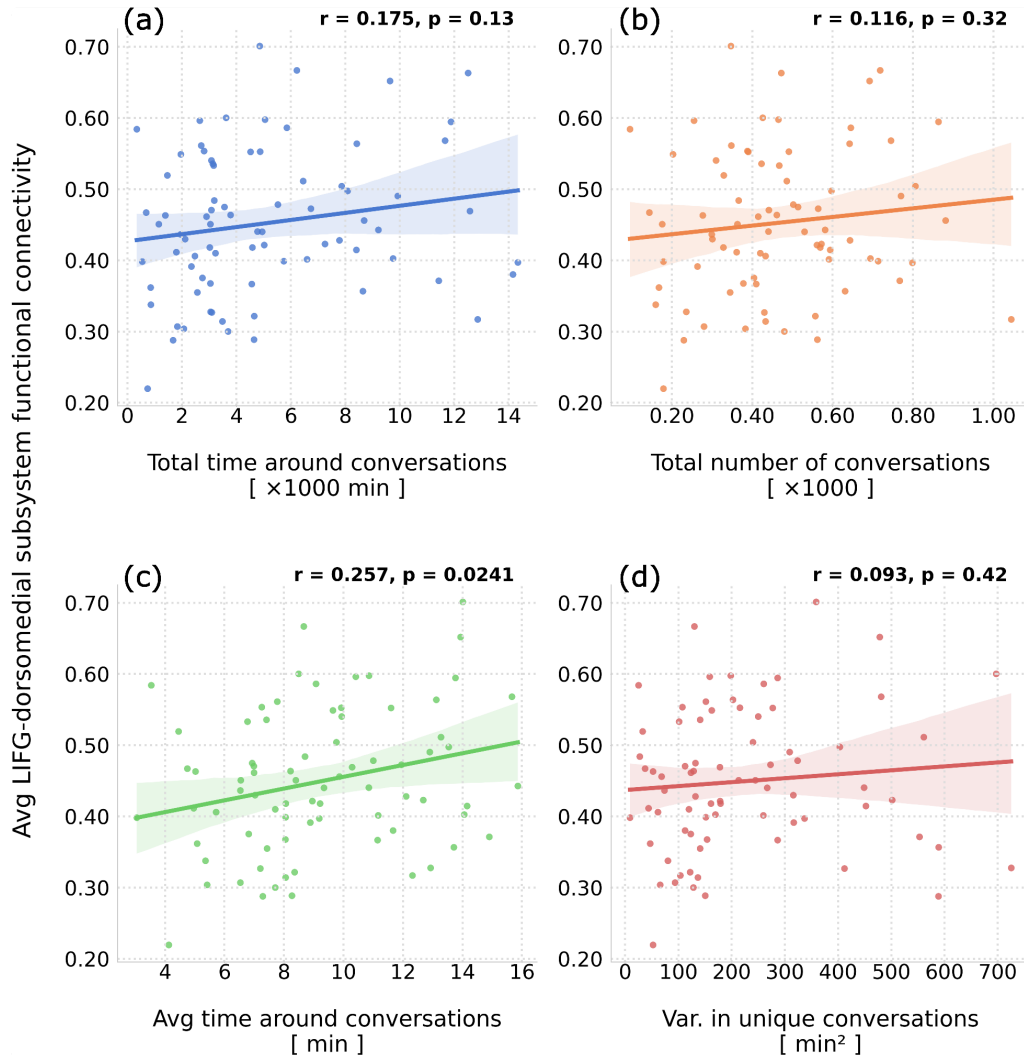


Figure 02: Correlations between LIFG-dMPFC subsystem fc and behavioural conversation features: The four plots presented above include the correlations between the average Left IFG-dorsomedial subsystem functional connectivity on the Y-axis and the behavioural feature on X-axis. The behaviours reported in the figure include: (a) total time spent around conversations (measured in min; blue), (b) HMM-sensed total number of conversations (unitless; orange), (c) average time spent around a given conversation (measured in min; green), and (d) variance in time spent around unique conversations (measured in min^2 ; red).

Numerous factors may affect one's average disposition to conversations. One such variable may be the mental state of the individual indulging in conversations, such as their mental health (daSilva et al., 2021). To test if there are any interactions between the mental health, functional connectivity, and conversation, we ran a generalised linear model with an interaction term between conversation and mental health self-reports. Although the functional connectivity of L-IFG within the dorsomedial subsystem at rest is marginally correlated with the self-reported perceived stress scores (PSS-14; $r = -0.191$, $p = 0.089$) and the performance subscale of state self esteem (SSE-Per; $r = -0.187$, $p = 0.095$), we do not see an interaction with either the PSS-14 scores ($\beta = 0.016$, $t(69) = 1.208$, $p = 0.231$) or with the SSE-Performance subscale scores ($\beta = 0.013$, $t(69) = 1.18$, $p = 0.242$). In other words, participants' mental health on the day of the scan does not influence the relationship between LIFG-dorsomedial subsystem connectivity and average time spent in conversation over the eight weeks.

Only LIFG RSFC is related to the average duration

Although we focus on average LIFG functional connectivity in the dMPFC subsystem of DMN, there are other regions that make up the subsystem. So, we first ran a correlation analysis with within-subsystem connectivity and average conversation duration, given that within-dMPFC connectivity is significantly and positively correlated with average LIFG RSFC in the subsystem (*pearson's* $r = 0.76$, $p = 5.19 \times 10^{-17}$). However, we do not observe any significant correlation for within-dorsomedial subsystem functional connectivity and average conversation duration ($r = 0.103$, $p = 0.37$). The strongly significant correlation between within-subsystem connectivity and LIFG-dMPFC RSFC may be because of other regions' contribution to the functional connectivity in the dorsomedial subsystem. To test if these regions show similar relationships with conversation as the average LIFG RSFC, we run correlations with average functional connectivities of other ROIs with average conversation duration. However, using other dorsomedial subsystem ROIs as seeds in the dorsomedial subsystem connectivity did not show significant relationships with average conversation duration (r 's < 0.16 , p 's > 0.1). Next, we checked to see if the correlation between

LIFG-dorsomedial subsystem functional connectivity and average duration was itself significantly different from the (non-significant) correlations examining the same relations but with the other dorsomedial subsystem seeds. None of these comparisons were significant ($t(74) < 3.03$, $p > 0.7$). Thus, while only the LIFG-dorsomedial subsystem shows a meaningful relationship with average conversation duration, this relationship may not be systematically different from other regions in the same subsystem.

These results suggest that among other ROIs and among the possible features that we were able to extract from the participants' real-world social interaction behaviour, the functional connectivity of Left IFG within the dorsomedial subsystem of the DMN is significantly related to the average duration an individual may spend in or around a conversation. Since available mental health scores do not interact with these results, we may assume that depressive symptoms, perceived stress, or state self-esteem does not mediate the relationship between the given brain function and conversation behaviour. We also do not observe any interactions with gender, suggesting that males and females similarly demonstrate the observed relationships.

LIFG-dMPFC RSFC relates to average time spent around conversations at eateries

Literature in social psychology suggests that there may be situational dependency on interaction behaviour, with a particular focus on the role of conversing over meals for social bonding (Dunbar, Marriott, & Duncan, 1997; Dunbar, 2017). We extract the conversation features from before per location and run correlations for average conversations at each location. Consistent with the social psychology literature and building on the previous results, we found that the LIFG connectivity within the dorsomedial subsystem relates to average duration of conversations at eateries (*pearson's* $r = 0.286$, $p = 0.012$). We also find that such a relation does not exist for other locations with one marginal result (conversations at athletic facilities; $r = 0.232$, $p = 0.075$) or not significant ($|r| \leq 0.2$, $p > 0.1$). The behaviour in itself does not depend on gender ($t(78) = 1.356$, $p = 0.18$), or show an interaction with gender to explain LIFG average functional connectivity

($\beta = 0.019$, $t(78) = 1.625$, $p = 0.108$). We also do not see an interaction with either the stress scores (PSS-14; $\beta = 0.016$, $t(66) = 1.39$, $p = 0.168$) or with SSE performance subscale scores ($\beta = 0.005$, $t(66) = 0.518$, $p = 0.606$).

LIFG-dMPFC RSFC relates to variance and total duration in conversations at eateries

Unlike general conversation behaviour, we find average LIFG functional connectivity is significantly correlated to variance in duration of conversations one may be exposed to at eateries (*pearson's* $r = 0.286$, $p = 0.028$). Variance of conversation durations at other locations are marginally ($r = 0.2$, $p = 0.076$, $df = 72$ for conversations at libraries) or not correlated ($|r| < 0.07$, $p \geq 0.4$, $df > 53$) with average LIFG RSFC within the dorsomedial subsystem. It is noteworthy that the correlation between LIFG-RSFC within the dorsomedial subsystem and conversation at eateries is not significantly different from the other seed-based correlations with average time spent around conversations ($t(74) < 2.66$, $p > 0.7$) or with conversation variance ($t(70) \leq 3.45$, $p > 0.7$). We may observe these results because the variance of conversation duration in the case of eateries is more significantly correlated with the average duration of exposure to conversations at the location ($r = 0.64$, $p < 0.0001$), but we do not see any interaction between the variance and average of conversation durations ($\beta = -0.0007$, $t(66) = -0.06$, $p = 0.952$) to explain average LIFG functional connectivity. This may imply that it is not the trait-level exposure to average conversations that this LIFG-dorsomedial subsystem connectivity may be predicting, but the overall conversation exposure at eateries, a location where individuals tend to share highly salient social information. To test this idea, we correlate average LIFG-dMPFC RSFC with total duration of exposure to conversations at eateries and find significant correlation ($r = 0.284$, $p = 0.013$). However, the total number of such unique exposures to conversations at eateries is not significantly correlated with the neural metric ($r = 0.089$, $p = 0.45$), suggesting that the app's classification of audio into unique conversations may not be subjectively meaningful.

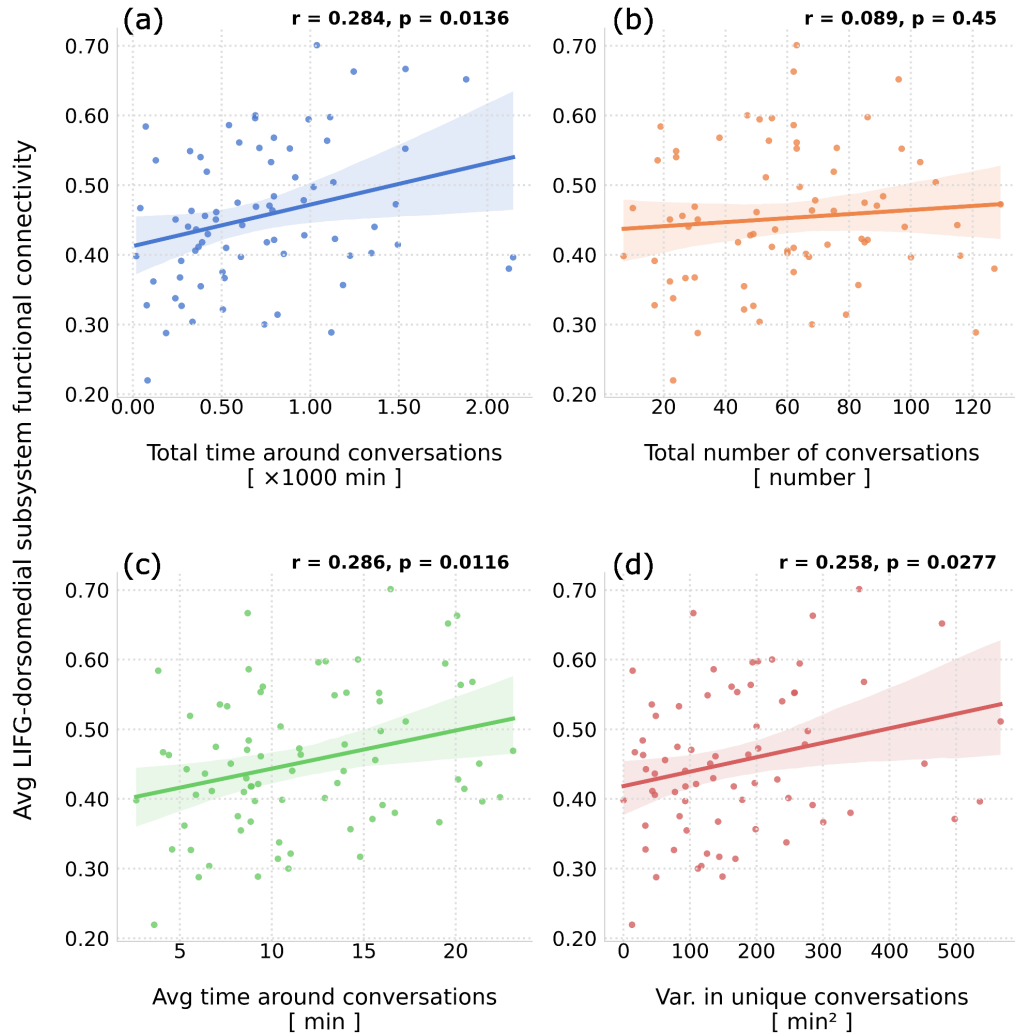


Figure 03: Correlations between LIFG-dMPFC subsystem fc and behavioural features for conversations at eateries: *The four plots presented above include the correlations between the average Left IFG-dorsomedial subsystem functional connectivity on the Y-axis and the behavioural feature for conversations occurring only at eateries¹ on X-axis. The behaviours reported in the figure include: (a) total time spent around conversations (measured in min; blue), (b) HMM-sensed total number of conversations (unitless; orange), (c) average time spent around a given conversation (measured in min; green), and (d) variance in time spent around unique conversations (measured in min²; red).*

¹ Similar plots for all the locations with larger sample sizes ($n > 40$) are reported in *Appendix B*.

Other locations also show non-significant relationships between total duration and LIFG average functional connectivity in dMPFC subsystem ($|r|$'s < 0.12 , p 's > 0.3), with an exception for 'culture and arts' ($r = 0.27$, $p = 0.038$). It is noteworthy here too that the correlation between LIFG-RSFC within the dorsomedial subsystem and total duration of exposure to conversations at eateries is not significantly different from the other locations ($t(72) \leq 2.13$, $p > 0.8$). As with variance in duration, we do not observe gender differences in total duration spent around conversations ($t(61) = 0.47$, $p = 0.64$) at eateries. We don't see any interactions of the duration-variance in unique conversations with perceived stress (PSS-14 scores; $\beta = 0.012$, $t(66) = 1.017$, $p = 0.313$), or with the performance-subscale scores of the state self esteem inventory (SSE-Per subscale scores; $\beta = 0.013$, $t(66) = 0.992$, $p = 0.32$), to explain average LIFG-dMPFC functional connectivity. The total duration around conversations also do not show interactions with perceived stress ($\beta = 0.019$, $t(66) = 1.494$, $p = 0.14$) or the performance-scores of self esteem scale ($\beta = 0.0085$, $t(66) = 0.715$, $p = 0.477$), to predict the average LIFG-dorsomedial subsystem RSFC. Moreover, correlations between the RSFC and average duration does not seem to be significantly different from variance ($t(71) = 1.188$, $p = 0.88$) or total duration ($t(73) = 0.289$, $p = 0.61$), and neither do the latter two correlations seem significantly different from one-another ($t(69) = 0.183$, $p = 0.57$).

These results suggest that conversations occurring over meals (at eateries) may be important to brain function in regions associated with social cognition and language comprehension. Since the variance, total, and average statistics show significant correlations, there may be a more general feature that the LIFG may track. As with previous results observed for conversations across-locations, we don't see interactions between mental states of depression, anxiety, stress, or self-esteem. The present results suggest that the LIFG-dMPFC subsystem RSFC may indicate not only everyday real-world conversations, but those that occur around socially salient situations.

Discussion

From behavioural studies ([Holt-Lunstad, Robles, & Sbarra, 2017](#); [Dunbar, 2018](#); [Templeton et al., 2022](#)) to those involving neuroimaging ([Dikker et al., 2017](#); [Burns & Lieberman, 2020](#)), recent social scientific research aims to understand the brain and behavioural bases of real-world social interactions. Our method of combining passive mobile sensing to track everyday behaviour with neuroimaging using BOLD-fMRI provides an avenue to study the brain activities that may reflect these behaviours. Earlier work with mobile-sensing applications have implicated brain activity associated with frequent phone-access (or screen-time; [Huckins et al., 2019a-2019b](#)) and studies using the StudentLife app have also shown that elements of social interactions may show dependency on one's state of mental health ([daSilva et al., 2021](#)). Adding to this literature, we showed that one can utilise mobile sensing measures to link a person's conversation behaviour to their brain function. Specifically, we observe that the resting state functional connectivity of Left IFG, a region implicated in language ([Turken & Dronkers, 2011](#); [Uddén & Bahlmann, 2012](#); [Klaus & Hartwigsen, 2019](#)) and social processes ([Mori & Haruno, 2022](#); [Kim et al., 2023](#)), within the social-cognitive processing region of the dorsomedial (dMPFC) subsystem of DMN ([Saxe & Kanwisher, 2003](#); [Behrens et al., 2008](#); [Collier & Meyer, 2020](#); [Sippel et al., 2021](#)) can predict an individual's close exposure to conversations.

We began by examining the behaviour of an individual across a period of 8 weeks. Our observations suggested that the functional connectivity of Left IFG within the dMPFC subsystem may relate to the average duration an individual is around conversations, a behavioural metric that describes how long that individual was exposed to conversations in their close vicinity. One possible implication for this relationship may hint at the quality of conversations occurring around the participants. Studies on loneliness often express that these subjective feelings of isolation may occur due either to the lack of quantity or quality in the social interactions ([Perlman & Peplau, 1981](#); [Baek & Parkinson, 2022](#)). That is to say, individuals indulging in shorter conversations may also report feeling lonelier. However, to answer questions pertaining to loneliness and

real-world interactions will require further work focussed on feelings of isolation, quality of such conversations, and individual differences observed in brain function.

We also observed that self-reported mental health scores described the brain function with marginal level of significance. Past studies have reported that individuals' mental state may control the conversations of that individual in the near future (daSilva et al., 2021), however, we do not see an effect of the participants' self-reported mental health (stress, depression, or self-esteem) to explain the relationship between brain function and our conversation variable. This inconsistency between the literature and our results may be attributed to the fact that past work linked daily mental health (i.e., stress levels) to daily conversation behaviour, whereas the present results look at mental health at a single time point (the day of the scan). Future work that densely samples resting state functional connectivity may be better suited to identify links between brain function, mental health, and conversation. Then again, interactions are not all the same. Literature has shown that certain types of interactions (Dunbar, 2018; Jolly & Chang, 2021) and conversations occurring in places of high social importance (Dunbar, Marriott, & Duncan, 1997; Dunbar, 2017) may further social connections. So, we looked at the subjects' conversation behaviours across various locations to find that the same brain function – connectivity of Left IFG within the dorsomedial subsystem – is related to social interactions occurring at eateries. Consistent with the results mentioned earlier, we find that an individual's brain function is related to the average duration they spend around conversations. We also find that this brain function is related to the variance in conversation durations at eateries across the 8-week period, such that higher resting state functional connectivity of L-IFG within the dMPFC subsystem may be linked to more varied conversations an individual may indulge in. Literature in social sciences often discusses patterns of interaction during 'social eating' (Giddens, 1982; Delormier, Frohlich, & Potvin, 2009; Dunbar, 2017). Given that conversations over meals are generally socially transactive, informative, or support-seeking (Delormier, Frohlich, & Potvin, 2009; Dunbar, 2017), one can argue that such interactions tend to be more reflective of an individual's gain and exchange of meaningful social knowledge, leading to variance in one's behaviour over time. Perhaps, this variable (variance in duration of conversations) may additionally reflect a personality variable of 'brokerage' in their

social networks (Burt, Kilduff, & Tasselli, 2013; Parkinson, Kleinbaum, & Wheatley, 2017). That is, an individual may choose to partake in different lengths of conversations when having meals with different, otherwise unconnected groups (or social sub-networks). Like the previous result, further research is required to understand the individual differences in variance and a deeper investigation into the social networks of individuals indulging in such ‘social eating.’

The third relation we find is that a sum of all the time spent around conversations at eateries is related to the functional connectivity of Left IFG within the dorsomedial subsystem of DMN, but not the total number of unique conversations. One possibility for not observing a significant relationship between the number of conversations and the brain function may be due to the inconsistency between what the mobile application defines as a ‘unique conversation’ and what an individual may classify as a conversation. For example, perhaps humans would not subjectively count a brief exchange as a meaningful conversation. Alternatively, the time spent around conversations may be more meaningful in qualifying an interaction as a conversation than merely exposure to unique conversations. Perhaps, the brain prefers tracking unique points of information rather than conversation in general. Much like literature linked to episodic memories (Johnson et al., 1988; Spaniol et al., 2009; Baldassano, Hasson, & Norman, 2018), recordings of conversations in such scenarios may be useful to determine if event-boundaries are more reflective of the brain function (Marsh, Richardson, & Schmidt, 2009; Sievers et al., 2020). Combining these findings, one may posit that the functional connectivity of Left IFG within the dorsomedial subsystem of the default mode might track a more complex variable of conversation occurring in socially impactful environments and that these conversations may be reflected in our everyday interactions happening elsewhere.

Limitations

Although we show that one can use mobile-sensing combined with BOLD-fMRI to study real-world conversations, limits are imposed in the data that one may collect. In our case, this limitation was observed in the absence of textual data or vocal transcripts that may have been helpful in studying active-participation in conversations, participation

ratio, turn-taking, topics of conversation, dominance, and possibly, the social network information related to each interaction. We were also limited in neuroimaging with only the resting state scans available to study. With our methods, we were able to explore the importance of Left IFG as a hub within the dorsomedial subsystem of the default network using linear models. Even though we found significant relationships of the region with conversation variables, we were not able to establish a clear uniqueness of this association to L-IFG among other regions of the dorsomedial subsystem. Another methodical limitation might show that the brain function is non-linearly related to behaviour, a theory that may be explored in future studies.

Conclusion

Conversations are a complex and important medium of social interaction. This multifaceted behaviour may be reflected in different and multiple parts of the brain. We have shown that the functional connectivity of Left IFG within the dorsomedial subsystem of the default network may be related to our everyday conversations. Moreover, the same region might specifically track social interactions happening over meals. From the literature, we posit that such interactions are socially important (Delormier, Frohlich, & Potvin, 2009; Dunbar, 2017). Moreover, our method of combining resting state fMRI with passively sensed real-world conversations support studies that explore brain-basis of our everyday behaviours (Huckins et al., 2019a-2019b; daSilva et al., 2021). We end with a discussion on the topics of enquiry that may further the understanding of brain-behaviour relationship of our real-world social interactions and thus, open more avenues of research.

Appendix A

Table A1: Statistics of all the variables mentioned in the thesis: *This table lists the variables used under the ‘Feature’ column. ‘Avg. Conversation’ is the average duration of conversations over a span of 8 weeks and is recorded in the unit of minutes (min), ‘Conversation Var.’ is variance in unique conversation durations over the same time and is recorded in the unit of minutes-squared (min²), ‘Number of Conversation’ is a count of unique conversations (the value is unitless), and ‘Sum of Conversations’ is the total duration of conversations over the period (minutes; min). The four rest-state functional connectivity (‘RSFC’) variables are BOLD-derived network features. The statistics for each feature are presented under ‘mean’, standard deviation (‘std’), 1-sample 2-tailed t-score (‘t’), the degree of freedom (‘df’), and the p-value (‘p’).²*

Feature	mean	std	t	df	p
Avg. Conversation across all locations (min)	9.59	4.017	21.628	81	2.13×10^{-35}
Avg. Conversation at Athletic Facilities (min)	10.686	18.563	4.533	61	2.77×10^{-05}
Avg. Conversation at Classrooms (min)	7.386	3.46	19.095	79	2.47×10^{-31}
Avg. Conversation at Culture and Arts (min)	9.525	7.544	10.335	66	1.97×10^{-15}
Avg. Conversation at Eateries (min)	11.574	5.223	19.821	79	2.14×10^{-32}
Avg. Conversation at Greek Housing (min)	16.022	16.098	8.207	67	1.02×10^{-11}
Avg. Conversation at Libraries (min)	6.908	3.611	16.786	76	2.79×10^{-27}
Avg. Conversation at Marketplace (min)	12.361	11.34	8.23	56	3.24×10^{-11}
Avg. Conversation at Student Housing (min)	9.4	9.459	8.833	78	2.28×10^{-13}
Conversation Var. across all locations (min ²)	319.302	546.408	5.292	81	1.01×10^{-06}
Conversation Var. at Athletic Facilities (min ²)	120.528	209.943	4.52	61	2.90×10^{-05}
Conversation Var. at Classrooms (min ²)	123.080	173.138	6.358	79	1.22×10^{-08}
Conversation Var. at Culture and Arts (min ²)	166.965	282.193	4.843	66	8.07×10^{-06}
Conversation Var. at Eateries (min ²)	193.065	163.814	10.541	79	9.98×10^{-17}
Conversation Var. at Greek Housing (min ²)	237.359	320.395	6.109	67	5.73×10^{-08}
Conversation Var. at Libraries (min ²)	118.498	231.735	4.487	76	2.52×10^{-05}
Conversation Var. at Marketplace (min ²)	255.314	673.245	2.863	56	0.0059
Conversation Var. at Student Housing (min ²)	475.534	1701.237	2.484	78	0.0151
Number of Conversations across all locations	498.939	251.616	17.956	81	5.67×10^{-30}

² Also see: *Table 03, “Statistics of the data and features used.”*

Feature	mean	std	t	df	p
Number of Conversations at Athletic Facilities	18.613	25.967	5.644	61	4.59×10^{-07}
Number of Conversations at Classrooms	66.063	75.027	7.876	79	1.52×10^{-11}
Number of Conversations at Culture and Arts	16.731	18.593	7.366	66	3.61×10^{-10}
Number of Conversations at Eateries	66.225	40.476	14.634	79	3.34×10^{-24}
Number of Conversations at Greek Housing	15.074	17.537	7.088	67	1.06×10^{-09}
Number of Conversations at Libraries	40.831	41.111	8.715	76	4.69×10^{-13}
Number of Conversations at Marketplace	7.439	8.588	6.54	56	1.99×10^{-08}
Number of Conversations at Student Housing	82.443	74.942	9.778	78	3.38×10^{-15}
Sum of Conversations across all locations (min)	5218.492	3893.787	12.136	81	6.52×10^{-20}
Sum of Conversations at Athletic Facilities (min)	203.363	359.341	4.456	61	3.63×10^{-05}
Sum of Conversations at Classrooms (min)	594.791	810.366	6.565	79	5.01×10^{-09}
Sum of Conversations at Culture and Arts (min)	173.839	210.195	6.77	66	4.15×10^{-09}
Sum of Conversations at Eateries (min)	789.864	624.863	11.306	79	3.49×10^{-18}
Sum of Conversations at Greek Housing (min)	207.063	261.078	6.54	67	9.99×10^{-09}
Sum of Conversations at Libraries (min)	334.536	383.299	7.659	76	4.94×10^{-11}
Sum of Conversations at Marketplace (min)	86.313	102.893	6.333	56	4.34×10^{-08}
Sum of Conversations at Student Housing (min)	1008.791	1863.221	4.812	78	7.16×10^{-06}
GAD-7	3.988	3.202	11.485	84	6.65×10^{-19}
Janis-Field Score	111.976	25.004	41.289	84	1.45×10^{-57}
PHQ-8	5.235	4.067	11.868	84	1.19×10^{-19}
PSS-14	31.729	7.681	38.089	84	9.04×10^{-55}
SSE Total	56.0	7.064	73.085	84	8.23×10^{-78}
SSE Appearance	17.8	2.444	67.157	84	8.91×10^{-75}
SSE Performance	19.765	2.308	78.966	84	1.35×10^{-80}
SSE Social	18.435	6.288	27.032	84	3.31×10^{-43}
LIFG-Core subsystem RSFC	0.125	0.145	8.053	86	4.14×10^{-12}
LIFG-MTL subsystem RSFC	-0.121	0.131	-8.624	86	2.86×10^{-13}
LIFG-dMPFC subsystem RSFC	0.456	0.11	38.684	86	3.61×10^{-56}
LIFG-DMN RSFC	0.181	0.102	16.541	86	1.88×10^{-28}

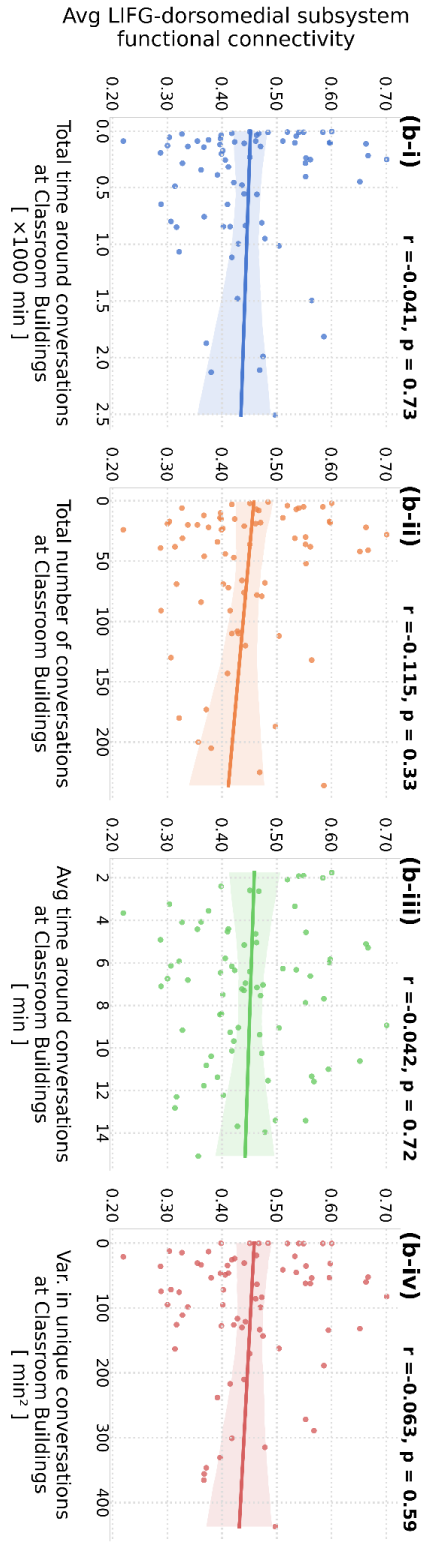
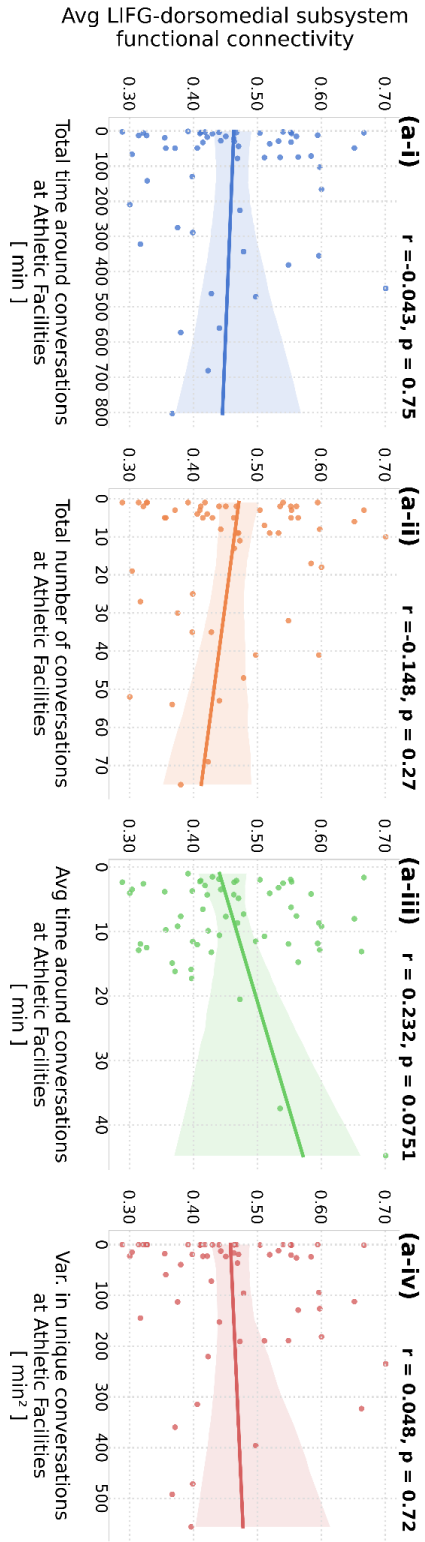
Appendix B

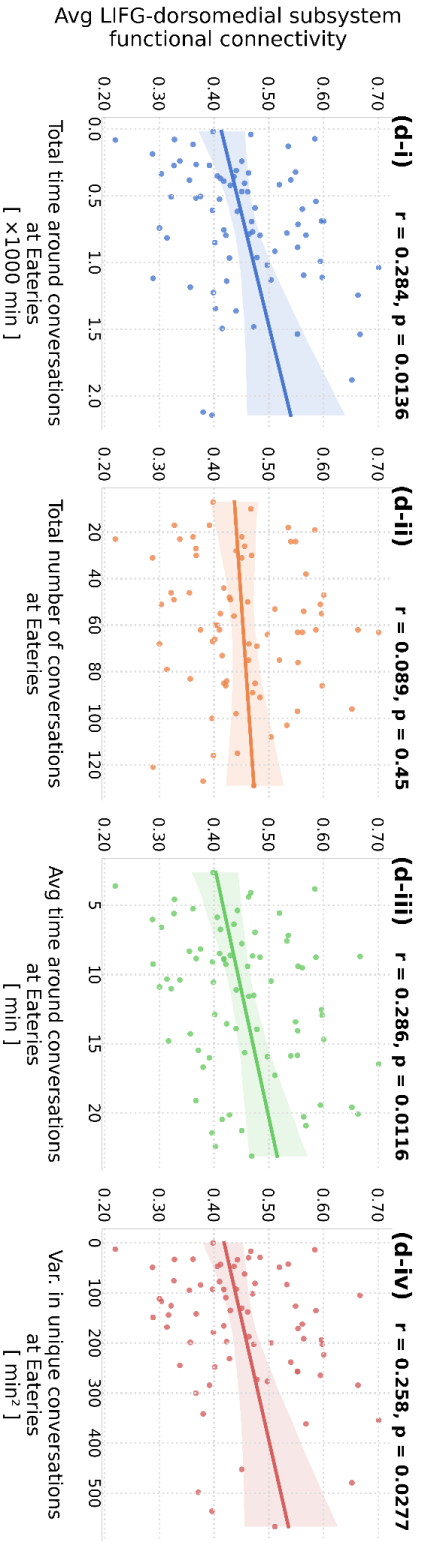
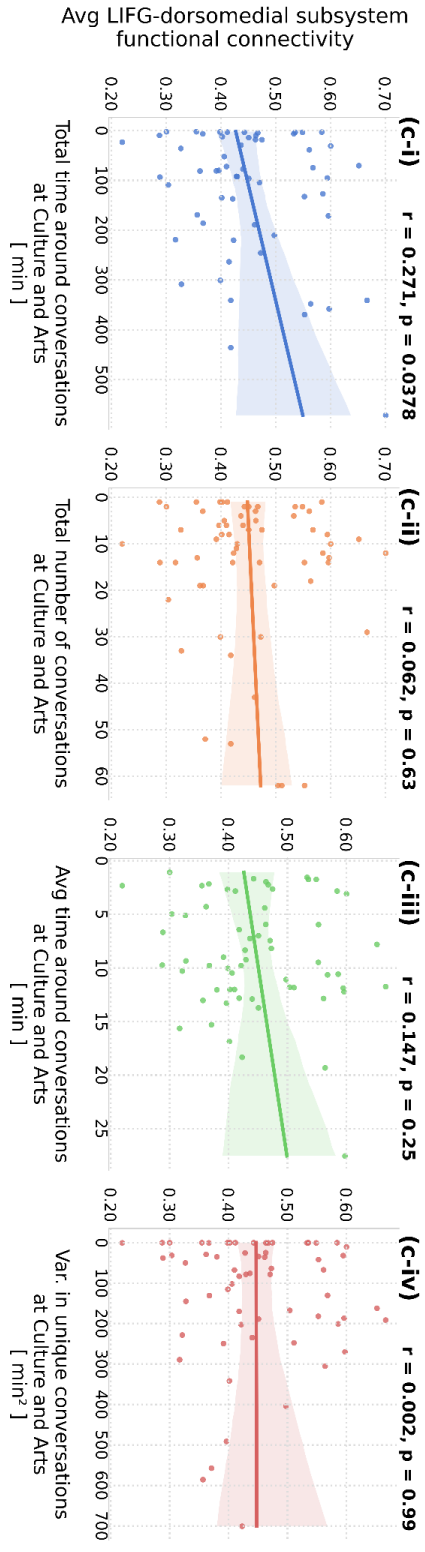
The following figures are supplemental to the main material of the thesis. Only the locations with a larger sample size ($n > 40$) are included in all the results. A complete list of such locations is provided in the *Tracking Location* subsection of the *Data and Methods* section in the thesis³.

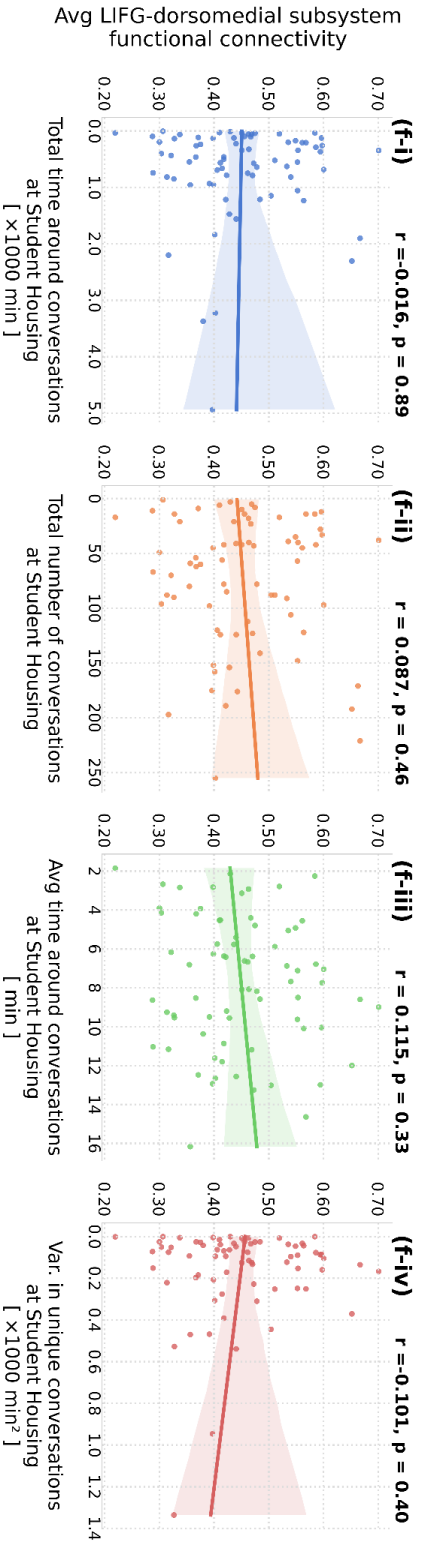
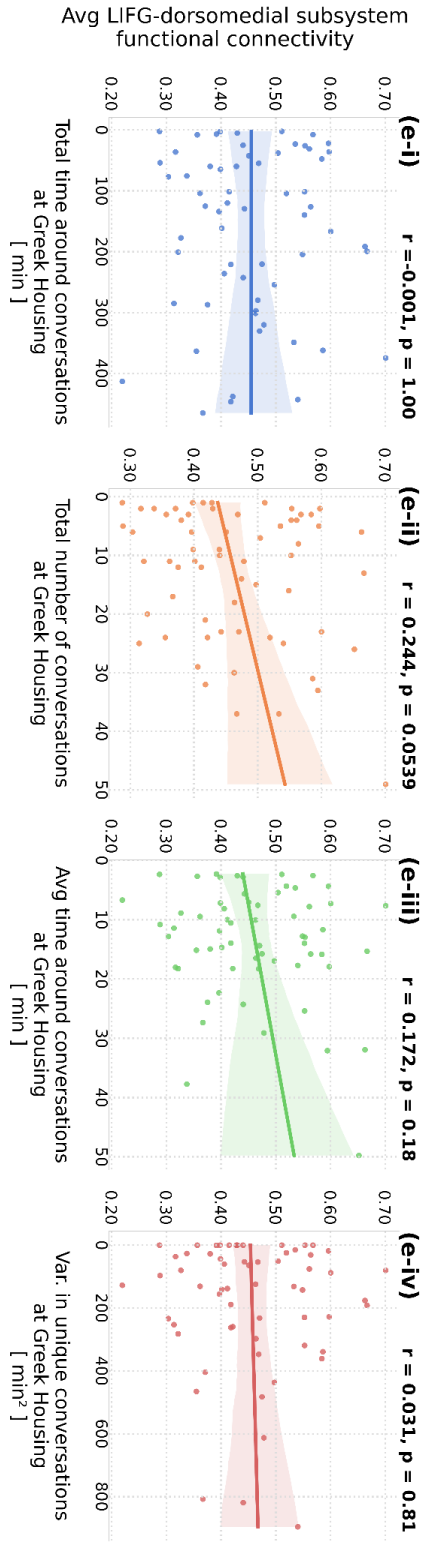
Figure B1: Correlations between L-IFG resting state functional connectivity within the dorsomedial subsystem and behavioural features for conversations at various locations: *The following plots presented below show the correlations between the average Left IFG-dorsomedial subsystem functional connectivity on the Y-axis and the behavioural features for conversations occurring at locations belonging to (a) athletic facilities, (b) classroom buildings, (c) cultural and art venues, (d) eateries⁴, (e) greek housing, (f) student housing, (g) libraries, and (h) marketplace on their respective X-axes. The behaviours reported in the figure include: (i) total time spent around conversations (measured in min; blue), (ii) HMM-sensed total number of conversations (unitless; orange), (iii) average time spent around a given conversation (measured in min; green), and (iv) variance in time spent around unique conversations (measured in min^2 ; red).*

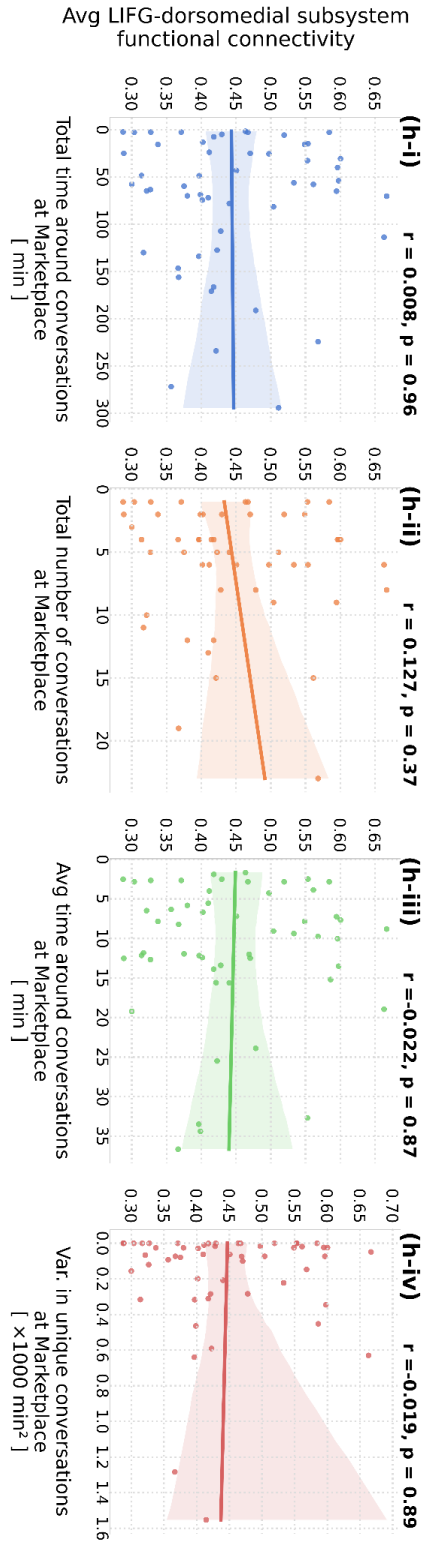
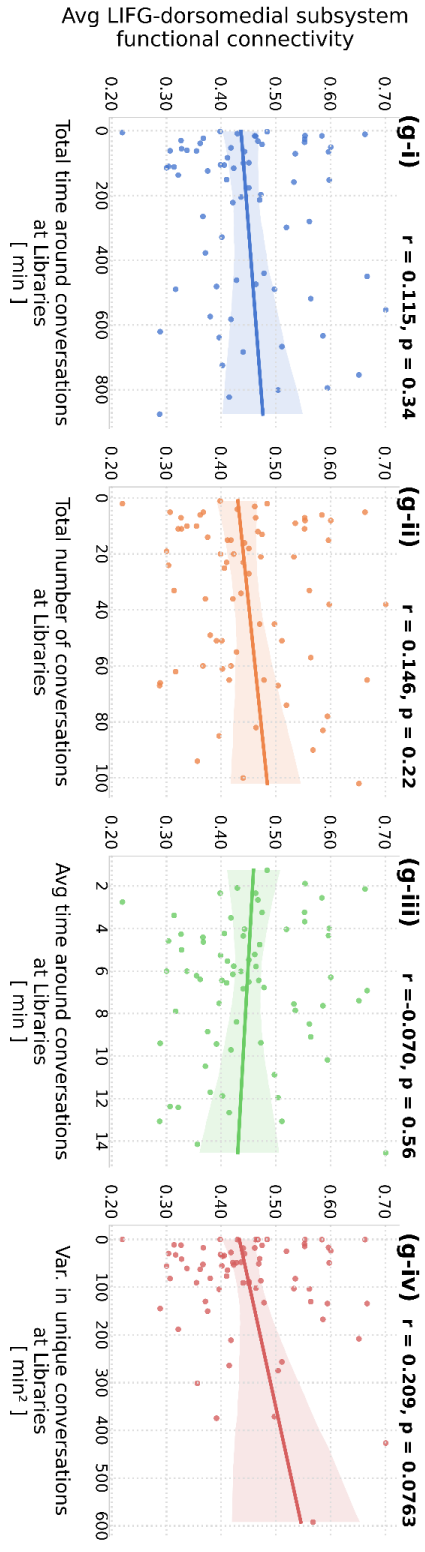
³ See: Table 02, “Spatial clustering of tracked locations.”

⁴ The plots (d-i to d-iv; conversation behaviours tracked at Eateries) are also presented as Figure 03, “Correlations between LIFG-dMPFC subsystem *fc* and behavioural features for conversations at eateries” in the Results section of the thesis.









References

1. Åkerlind, I., & Hörnquist, J. O. (1992). Loneliness and alcohol abuse: A review of evidences of an interplay. *Social Science and Medicine*, 34(4). [https://doi.org/10.1016/0277-9536\(92\)90300-F](https://doi.org/10.1016/0277-9536(92)90300-F)
2. Amodio, D. M., & Frith, C. D. (2006). Meeting of minds: The medial frontal cortex and social cognition. In *Nature Reviews Neuroscience* (Vol. 7, Issue 4). <https://doi.org/10.1038/nrn1884>
3. Andrews-Hanna, J. R., Reidler, J. S., Sepulcre, J., Poulin, R., & Buckner, R. L. (2010). Functional-Anatomic Fractionation of the Brain's Default Network. *Neuron*, 65(4). <https://doi.org/10.1016/j.neuron.2010.02.005>
4. Baek, E. C., & Parkinson, C. (2022). Shared understanding and social connection: Integrating approaches from social psychology, social network analysis, and neuroscience. In *Social and Personality Psychology Compass* (Vol. 16, Issue 11). <https://doi.org/10.1111/spc3.12710>
5. Baek, E. C., Hyon, R., López, K., Finn, E. S., Porter, M. A., & Parkinson, C. (2022). In-degree centrality in a social network is linked to coordinated neural activity. *Nature Communications*, 13(1). <https://doi.org/10.1038/s41467-022-28432-3>
6. Baldassano, C., Hasson, U., & Norman, K. A. (2018). Representation of real-world event schemas during narrative perception. *Journal of Neuroscience*, 38(45). <https://doi.org/10.1523/JNEUROSCI.0251-18.2018>
7. Barnett, P. A., & Gotlib, I. H. (1988). Psychosocial Functioning and Depression: Distinguishing Among Antecedents, Concomitants, and Consequences. *Psychological Bulletin*, 104(1). <https://doi.org/10.1037/0033-2909.104.1.97>
8. Baumeister, R. F., & Leary, M. R. (1995). The Need to Belong: Desire for Interpersonal Attachments as a Fundamental Human Motivation. *Psychological Bulletin*, 117(3). <https://doi.org/10.1037/0033-2909.117.3.497>

9. Behrens, T. E. J., Hunt, L. T., Woolrich, M. W., & Rushworth, M. F. S. (2008). Associative learning of social value. *Nature*, *456*(7219). <https://doi.org/10.1038/nature07538>
10. Bögels, S., & Levinson, S. C. (2017). The Brain Behind the Response: Insights Into Turn-taking in Conversation From Neuroimaging. *Research on Language and Social Interaction*, *50*(1). <https://doi.org/10.1080/08351813.2017.1262118>
11. Burns, S. M., & Lieberman, M. D. (2020). The use of functional near infrared spectroscopy (fNIRS) for unique contributions to social and affective neuroscience. *Preprint*. <https://www.doi.org/10.31234/osf.io/kygbm>
12. Burt, R. S., Kilduff, M., & Tasselli, S. (2013). Social network analysis: Foundations and frontiers on advantage. In *Annual Review of Psychology* (Vol. 64). <https://doi.org/10.1146/annurev-psych-113011-143828>
13. Cacioppo, J. T., Hughes, M. E., Waite, L. J., Hawkley, L. C., & Thisted, R. A. (2006). Loneliness as a specific risk factor for depressive symptoms: Cross-sectional and longitudinal analyses. *Psychology and Aging*, *21*(1). <https://doi.org/10.1037/0882-7974.21.1.140>
14. Chang, L., Manning, J., Baldassano, C., Vega, A. de la, Fleetwood, G., Geerligs, L., Haxby, J., Lahnakoski, J., Parkinson, C., Shappell, H., Shim, W. M., Wager, T., Yarkoni, T., Yeshurun, Y., & Finn, E. (2020). Neuroimaging Analysis Methods For Naturalistic Data. *Annual Meeting of the Organization for Human Brain Mapping 2020*, N/A. <https://doi.org/DOI:10.5281/ZENODO.3937849>
15. Chen, Z., Lin, M., Chen, F., Lane, N. D., Cardone, G., Wang, R., Li, T., Chen, Y., Choudhury, T., & Campbell, A. T. (2013). Unobtrusive sleep monitoring using smartphones BT - 2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2013, May 5, 2013 - May 8, 2013. *2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops*. <https://www.doi.org/10.4108/icst.pervasivehealth.2013.252148>
16. Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, *24*(4). <https://doi.org/10.2307/2136404>

17. Collier, E., & Meyer, M. L. (2020). Memory of others' disclosures is consolidated during rest and associated with providing support: Neural and linguistic evidence. *Journal of Cognitive Neuroscience*, 32(9). https://doi.org/10.1162/jocn_a_01573
18. Czeszumski, A., Liang, S. H. Y., Dikker, S., König, P., Lee, C. P., Koole, S. L., & Kelsen, B. (2022). Cooperative Behavior Evokes Interbrain Synchrony in the Prefrontal and Temporoparietal Cortex: A Systematic Review and Meta-Analysis of fNIRS Hyperscanning Studies. *ENeuro*, 9(2). <https://doi.org/10.1523/ENEURO.0268-21.2022>
19. daSilva, A. W., Huckins, J. F., Wang, W., Wang, R., Campbell, A. T., & Meyer, M. L. (2021). Daily Perceived Stress Predicts Less Next Day Social Interaction: Evidence From a Naturalistic Mobile Sensing Study. *Emotion*, 21(8). <https://doi.org/10.1037/emo0000994>
20. Delormier, T., Frohlich, K. L., & Potvin, L. (2009). Food and eating as social practice - Understanding eating patterns as social phenomena and implications for public health. *Sociology of Health and Illness*, 31(2). <https://doi.org/10.1111/j.1467-9566.2008.01128.x>
21. Denny, B. T., Kober, H., Wager, T. D., & Ochsner, K. N. (2012). A meta-analysis of functional neuroimaging studies of self- and other judgments reveals a spatial gradient for mentalizing in medial prefrontal cortex. *Journal of Cognitive Neuroscience*, 24(8). https://doi.org/10.1162/jocn_a_00233
22. Diener, E., & Seligman, M. E. P. (2002). Very happy people. *Psychological Science*, 13(1). <https://doi.org/10.1111/1467-9280.00415>
23. Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., Rowland, J., Michalareas, G., van Bavel, J. J., Ding, M., & Poeppel, D. (2017). Brain-to-Brain Synchrony Tracks Real-World Dynamic Group Interactions in the Classroom. *Current Biology*, 27(9). <https://doi.org/10.1016/j.cub.2017.04.002>
24. Dunbar, R. I. M. (1998). The social brain hypothesis. *Evolutionary Anthropology*, 6(5). [https://doi.org/10.1002/\(SICI\)1520-6505\(1998\)6:5<178::AID-EVAN5>3.0.CO;2-8](https://doi.org/10.1002/(SICI)1520-6505(1998)6:5<178::AID-EVAN5>3.0.CO;2-8)
25. Dunbar, R. I. M. (2017). Breaking Bread: the Functions of Social Eating. *Adaptive Human Behavior and Physiology*, 3(3). <https://doi.org/10.1007/s40750-017-0061-4>

26. Dunbar, R. I. M. (2018). The Anatomy of Friendship. In *Trends in Cognitive Sciences* (Vol. 22, Issue 1). <https://doi.org/10.1016/j.tics.2017.10.004>
27. Dunbar, R. I. M., Marriott, A., & Duncan, N. D. C. (1997). Human conversational behavior. *Human Nature*, 8(3). <https://doi.org/10.1007/BF02912493>
28. Giddens, A. (1982). Profiles and Critiques in Social Theory. In *Profiles and Critiques in Social Theory*. <https://doi.org/10.1007/978-1-349-86056-2>
29. Hawkley, L. C., & Cacioppo, J. T. (2003). Loneliness and pathways to disease. *Brain, Behavior, and Immunity*, 17(1 SUPPL.). [https://doi.org/10.1016/S0889-1591\(02\)00073-9](https://doi.org/10.1016/S0889-1591(02)00073-9)
30. Heatherton, T. F., & Polivy, J. (1991). Development and validation of a scale for measuring state self-esteem. *Journal of Personality and Social Psychology*, 60(6). <https://doi.org/10.1037//0022-3514.60.6.895>
31. Heatherton, T. F., Wyland, C. L., Macrae, C. N., Demos, K. E., Denny, B. T., & Kelley, W. M. (2006). Medial prefrontal activity differentiates self from close others. *Social Cognitive and Affective Neuroscience*, 1(1). <https://doi.org/10.1093/scan/nsi001>
32. Hirsch, J., Tiede, M., Zhang, X., Noah, J. A., Salama-Manteau, A., & Biriotti, M. (2021). Interpersonal Agreement and Disagreement During Face-to-Face Dialogue: An fNIRS Investigation. *Frontiers in Human Neuroscience*, 14. <https://doi.org/10.3389/fnhum.2020.606397>
33. Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. In *PLoS Medicine* (Vol. 7, Issue 7). <https://doi.org/10.1371/journal.pmed.1000316>
34. Holt-Lunstad, J., Robles, T. F., & Sbarra, D. A. (2017). Advancing social connection as a public health priority in the United States. *American Psychologist*, 72(6). <https://doi.org/10.1037/amp0000103>
35. Huckins, J. F., Adeyemo, B., Miezin, F. M., Power, J. D., Gordon, E. M., Laumann, T. O., Heatherton, T. F., Petersen, S. E., & Kelley, W. M. (2019a). Reward-related regions form a

- preferentially coupled system at rest. *Human Brain Mapping*, 40(2). <https://doi.org/10.1002/hbm.24377>
36. Huckins, J. F., daSilva, A. W., Wang, R., Wang, W., Hedlund, E. L., Murphy, E. I., Lopez, R. B., Rogers, C., Holtzheimer, P. E., Kelley, W. M., Heatherton, T. F., Wagner, D. D., Haxby, J. v., & Campbell, A. T. (2019b). Fusing Mobile Phone Sensing and Brain Imaging to Assess Depression in College Students. *Frontiers in Neuroscience*, 13. <https://doi.org/10.3389/fnins.2019.00248>
37. Hyon, R., Youm, Y., Kim, J., Chey, J., Kwak, S., & Parkinson, C. (2020). Similarity in functional brain connectivity at rest predicts interpersonal closeness in the social network of an entire village. *Proceedings of the National Academy of Sciences of the United States of America*, 117(52). <https://doi.org/10.1073/PNAS.2013606117>
38. Inagaki, T. K., & Meyer, M. L. (2020). Individual differences in resting-state connectivity and giving social support: Implications for health. *Social Cognitive and Affective Neuroscience*, 15(10). <https://doi.org/10.1093/scan/nsz052>
39. Janis, I. L., & Field, P. B. (1956). A Behavioral Assessment of Persuasibility: Consistency of Individual Differences. *Sociometry*, 19(4). <https://doi.org/10.2307/2785766>
40. Johnson, M. K., Foley, M. A., Suengas, A. G., & Raye, C. L. (1988). Phenomenal Characteristics of Memories for Perceived and Imagined Autobiographical Events. *Journal of Experimental Psychology: General*, 117(4). <https://doi.org/10.1037/0096-3445.117.4.371>
41. Jolly, E., & Chang, L. J. (2021). Gossip drives vicarious learning and facilitates social connection. *Current Biology*, 31(12). <https://doi.org/10.1016/j.cub.2021.03.090>
42. Kable, J. W., & Glimcher, P. W. (2007). The neural correlates of subjective value during intertemporal choice. *Nature Neuroscience*, 10(12). <https://doi.org/10.1038/nn2007>
43. Kim, J., Andrews-Hanna, J. R., Eisenbarth, H., Lux, B. K., Kim, H. J., Lee, E., Lindquist, M. A., Losin, E. A. R., Wager, T. D., & Woo, C.-W. (2023). A dorsomedial prefrontal cortex-based dynamic functional connectivity model of rumination. *Nature Communications*, 14(1), 3540. <https://doi.org/10.1038/s41467-023-39142-9>

44. Klaus, J., & Hartwigsen, G. (2019). Dissociating semantic and phonological contributions of the left inferior frontal gyrus to language production. *Human Brain Mapping, 40*(11). <https://doi.org/10.1002/hbm.24597>
45. Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B. W., Berry, J. T., & Mokdad, A. H. (2009). The PHQ-8 as a measure of current depression in the general population. *Journal of Affective Disorders, 114*(1–3). <https://doi.org/10.1016/j.jad.2008.06.026>
46. Lakey, B., & Orehek, E. (2011). Relational Regulation Theory: A New Approach to Explain the Link Between Perceived Social Support and Mental Health. *Psychological Review, 118*(3). <https://doi.org/10.1037/a0023477>
47. Lane, N. D., Lin, M., Mohammad, M., Yang, X., Lu, H., Cardone, G., Ali, S., Doryab, A., Berke, E., Campbell, A. T., & Choudhury, T. (2014). BeWell: Sensing sleep, physical activities and social interactions to promote wellbeing. *Mobile Networks and Applications, 19*(3). <https://doi.org/10.1007/s11036-013-0484-5>
48. Lane, N., Mohammad, M., Lin, M., Yang, X., Lu, H., Ali, S., Doryab, A., Berke, E., Choudhury, T., & Campbell, A. (2012). *BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing*. <https://doi.org/10.4108/icst.pervasivehealth.2011.246161>
49. Mars, R. B., Neubert, F. X., Noonan, M. A. P., Sallet, J., Toni, I., & Rushworth, M. F. S. (2012). On the relationship between the “default mode network” and the “social brain.” *Frontiers in Human Neuroscience, JUNE 2012*. <https://doi.org/10.3389/fnhum.2012.00189>
50. Marsh, K. L., Richardson, M. J., & Schmidt, R. C. (2009). Social Connection Through Joint Action and Interpersonal Coordination. *Topics in Cognitive Science, 1*(2). <https://doi.org/10.1111/j.1756-8765.2009.01022.x>
51. Meyer, M. L. (2019). Social by Default: Characterizing the Social Functions of the Resting Brain. *Current Directions in Psychological Science, 28*(4). <https://doi.org/10.1177/0963721419857759>
52. Meyer, M. L., Davachi, L., Ochsner, K. N., & Lieberman, M. D. (2019). Evidence that default network connectivity during rest consolidates social information. *Cerebral Cortex, 29*(5). <https://doi.org/10.1093/cercor/bhy071>

53. Momennejad, I., Duker, A., & Coman, A. (2019). Bridge ties bind collective memories. *Nature Communications*, 10(1). <https://doi.org/10.1038/s41467-019-09452-y>
54. Mori, K., & Haruno, M. (2022). Resting functional connectivity of the left inferior frontal gyrus with the dorsomedial prefrontal cortex and temporoparietal junction reflects the social network size for active interactions. *Human Brain Mapping*, 43(9). <https://doi.org/10.1002/hbm.25822>
55. Parkinson, C., Kleinbaum, A. M., & Wheatley, T. (2017). Spontaneous neural encoding of social network position. *Nature Human Behaviour*, 1(5). <https://doi.org/10.1038/s41562-017-0072>
56. Perlman, D., & Peplau, L. (1981). Toward a social psychology of loneliness. *Personal Relationships*, 3(May).
57. Piva, M., Velnoskey, K., Jia, R., Nair, A., Levy, I., & Chang, S. W. C. (2019). The dorsomedial prefrontal cortex computes task-invariant relative subjective value for self and other. *ELife*, 8. <https://doi.org/10.7554/elife.44939>
58. Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *NeuroImage*, 59(3). <https://doi.org/10.1016/j.neuroimage.2011.10.018>
59. Rabbi, M., Ali, S., Choudhury, T., & Berke, E. (2011). Passive and in-situ assessment of mental and physical well-being using mobile sensors. *UbiComp'11 - Proceedings of the 2011 ACM Conference on Ubiquitous Computing*. <https://doi.org/10.1145/2030112.2030164>
60. Sallet, J., Mars, R. B., Noonan, M. P., Andersson, J. L., O'Reilly, J. X., Jbabdi, S., Crosson, P. L., Jenkinson, M., Miller, K. L., & Rushworth, M. F. S. (2011). Social network size affects neural circuits in Macaques. *Science*, 334(6056). <https://doi.org/10.1126/science.1210027>
61. Saxe, R., & Kanwisher, N. (2003). People thinking about thinking people: The role of the temporo-parietal junction in "theory of mind." *NeuroImage*, 19(4). [https://doi.org/10.1016/S1053-8119\(03\)00230-1](https://doi.org/10.1016/S1053-8119(03)00230-1)

62. Sievers, B., Welker, C., Hasson, U., Kleinbaum, A. M., & Wheatley, T. (2020). How consensus-building conversation changes our minds and aligns our brains. <https://doi.org/10.31234/osf.io/562z7>
63. Sippel, L. M., Holtzheimer, P. E., Huckins, J. F., Collier, E., Feilong, M., Wheatley, T., & Meyer, M. L. (2021). Neurocognitive mechanisms of poor social connection in posttraumatic stress disorder: Evidence for abnormalities in social working memory. *Depression and Anxiety*, 38(6). <https://doi.org/10.1002/da.23139>
64. Spaniol, J., Davidson, P. S. R., Kim, A. S. N., Han, H., Moscovitch, M., & Grady, C. L. (2009). Event-related fMRI studies of episodic encoding and retrieval: Meta-analyses using activation likelihood estimation. In *Neuropsychologia* (Vol. 47, Issues 8–9). <https://doi.org/10.1016/j.neuropsychologia.2009.02.028>
65. Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, 166(10). <https://doi.org/10.1001/archinte.166.10.1092>
66. Templer, V. L., Wise, T. B., Dayaw, K. I. T., & Dayaw, J. N. T. (2018). Nonsocially housed rats (*Ratus norvegicus*) seek social interactions and social novelty more than socially housed counterparts. *Journal of Comparative Psychology*, 132(3). <https://doi.org/10.1037/com0000112>
67. Templeton, E. M., Chang, L. J., Reynolds, E. A., LeBeaumont, M. D. C., & Wheatley, T. (2022). Fast response times signal social connection in conversation. *Proceedings of the National Academy of Sciences of the United States of America*, 119(4). <https://doi.org/10.1073/pnas.2116915119>
68. Testard, C., Larson, S. M., Watowich, M. M., Kaplinsky, C. H., Bernau, A., Faulder, M., Marshall, H. H., Lehmann, J., Ruiz-Lambides, A., Higham, J. P., Montague, M. J., Snyder-Mackler, N., Platt, M. L., & Brent, L. J. N. (2021). Rhesus macaques build new social connections after a natural disaster. *Current Biology*, 31(11). <https://doi.org/10.1016/j.cub.2021.03.029>

69. Thomas Yeo, B. T., Krienen, F. M., Sepulcre, J., Sabuncu, M. R., Lashkari, D., Hollinshead, M., Roffman, J. L., Smoller, J. W., Zöllei, L., Polimeni, J. R., Fisch, B., Liu, H., & Buckner, R. L. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of Neurophysiology*, *106*(3). <https://doi.org/10.1152/jn.00338.2011>
70. Turken, A. U., & Dronkers, N. F. (2011). The neural architecture of the language comprehension network: Converging evidence from lesion and connectivity analyses. *Frontiers in Systems Neuroscience*, FEBRUARY 2011. <https://doi.org/10.3389/fnsys.2011.00001>
71. Uddén, J., & Bahlmann, J. (2012). A rostro-caudal gradient of structured sequence processing in the left inferior frontal gyrus. In *Philosophical Transactions of the Royal Society B: Biological Sciences* (Vol. 367, Issue 1598). <https://doi.org/10.1098/rstb.2012.0009>
72. Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A. T. (2014). Studentlife: Assessing mental health, academic performance and behavioral trends of college students using smartphones. *UbiComp 2014 - Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. <https://doi.org/10.1145/2632048.2632054>