Translating Driving Research from Simulation to Interstate Driving with Realistic Traffic and Passenger Interactions

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Abstract. In this driving study, participants were assigned to a driver-passenger dyad and performed two drives along Interstate-95 in normal traffic conditions. During the driving session, the driver had to safely navigate the route while listening and discussing news stories that were relayed by the passenger. The driver then performed a set of memory tasks to evaluate how well they retained information from the discussion in a multitask context. We report preliminary analyses that examined subjective factors which may influence success in social communication, including trait and state similarity derived from questionnaires as well as physiological synchrony from implicit state measurements derived from brain activity data. Although this dataset is still in collection, these initial findings suggest potential metrics that capture the contextual complexity in naturalistic, multitask environments, providing a rich opportunity to study how successful communication reflects shared social and emotional experiences.

Keywords: Interstate driving · Social network structure · State questionnaires EEG · Neural synchrony · Communication · Individual differences

1 Introduction

For the majority of Americans, driving serves as an essential component of life activities, providing a means for commuting to work, attending social gatherings, and transporting goods from stores to home [1, 2]. Thus, driving has become a task that consumes a large amount of time for many, and the automotive industry has sought technological innovations that improve both the comfort and safety of driving. An impressive suite of technologies have parameterized core components of driving,

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including collision-avoidance sensors, lane-keeping technology, adaptive cruise control, and voice-activated controls [3–5]. As these assistive features have improved, several self-driving cars have been approved for on-road testing. Waymo and Uber have autonomous vehicles driving along normal commute routes in Silicon Valley, Pittsburgh, and Austin (to name a few). While the timeframe for a full conversion from human drivers to automated drivers is unknown (for an in-depth prediction, see [6]), the success of self-driving cars amidst human-driven cars suggest that the nature of driving may rapidly evolve [7, 8]. Soon, drivers may need to spend less effort safely navigating their vehicle; instead, drivers may need to balance the basic oversight of autonomous driving while they engage in other tasks, such as social communication.

In our driving study, we still rely on human drivers for controlling the vehicle, but driving along Interstate-95 is concurrent with a communication task between a driver and passenger. This route was chosen for minimal risk driving conditions with clear lane markings, minimal navigation decisions, and calm traffic patterns. These conditions approximate the level of engagement that drivers may need to oversee the performance of near-term self-driving cars [9], so here, we use it as a proxy for studying how communication dynamics may be influenced in a naturalistic, multitask context. Navigating the interstate with real traffic dynamics carries risk for injury if the driver does not maintain sufficient engagement with the primary driving task [10]. This task hierarchy provides a context to study how a multitask environment influences performance on a secondary task, namely communication with an in-car passenger.

Our experimental design, however, investigates additional layers of contextual complexity that may modulate performance on the communication task. Successful communication inherently involves implicit and explicit processing of information between two or more individuals, and previous research has shown that increased synchrony between people correlates with successful transfer of information [11–13]. Furthermore, recent extensions suggest that concurrent activity between brains may represent abstract cooperative efforts (i.e. hyperscanning: [14]), including rhythmic tapping [15] and musicians performing [16]. Complementary results have been observed in social domains where individuals with similar neural activity during social exclusion demonstrate similar susceptibility to peer influence [17] and have similar real-life social network structures [18].

Our core hypothesis posits that successful communication depends upon shared social experiences and similar emotional states that facilitate joint understanding of information and interest in comprehending another's perspective on a topic. In our driving study, we collected several metrics about a participant's social interactions, including their real-life social network structure as well as their interactions with their dyad partner outside of the study. Similarly, a participant's communication performance will likely be heavily influenced by their current state, e.g., emotional, physiological, and cognitive states. We collected both explicit estimates of state, indexed by self-report questionnaires, as well as implicit estimates from physiological data from brain (EEG) and body (HRV, GSR). Consequently, our experimental design allows us to examine how these various contextual factors influence a driver's performance on a communication task that is embedded in a multitask, driving context. Here, we present a set of preliminary analyses on only a small subset of these individual difference measures. Although this data is still in collection, our initial findings indicate the promise of similarity and synchrony metrics to capture trait and state influences on performance in a naturalistic, multitask context.

2 Methods

Participants. The present study used data from twenty-eight adults (68% male) between the ages of 21 and 55 (M = 38.02; SD = 11.44) who participated as part of an ongoing longitudinal experiment aimed at investigating the communication dynamics between driver-passenger dyads during interstate driving under naturalistic conditions. All study volunteers provided informed consent in accordance with study approval from the accredited Institutional Review Board at U.S. Army Research Laboratory and in accordance with the U.S. Army Research Laboratory Human Research Protection Program (32 CFR 219 and DoDI 3216.01). Participants were recruited either from the U.S. Army Research Laboratory (Aberdeen Proving Ground) or DCS Corporation (Alexandria, VA and Abingdon, MD locations) to ensure that they received liability insurance in the event of a car accident (none occurred). Inclusion criteria consisted of being at least 21 years of age, having normal or corrected to normal visual acuity, and possession of an unrestricted driver's license for a minimum of two years. Participants were excluded if they had medical conditions that prevented normal driving (e.g., seizures) or motion sickness in cars. All criteria were assessed through self-report.

Experimental Design. An overview of the experimental design for the 9–15 week longitudinal study is depicted in Fig. 1. During a 40-min intake session, participants received an actigraphy watch (Readiband Actigraph SBV2; Fatigue Science, Vancouver, BC) to monitor sleep and physical activity throughout the course of the study, provided a cell phone number to receive daily text messages during the study, and completed a one-time set of trait assessments. In these preliminary analyses, we only report trait data from the Social Network Information questionnaire.

Participants were then assigned to driver-passenger dyads based on their schedule availability for drives. Each dyad completed two driving sessions: one where they were the passenger and one as the driver. Each driving session took approximately 2.5 to 3 h to complete. Traffic, weather, and vehicle conditions were assessed prior to each session, and drives were only conducted when both participants and the experimenters agreed that conditions met minimal risk criteria.

The driving session occurred in an all-wheel drive, 2016 Ford Fusion Titanium instrumented with an Ergoneers D-Lab data acquisition system. As depicted in Fig. 1B–D, each driving session consisted of three segments: pre-drive, on-drive, and post-drive. The D-Lab recorded time-synchronized multi-sensor vehicle environment data for all three segments, including MobilEye and On-Board Diagnostics (OBD) data, audio, and four channels of video. One camera recorded the external environment out the front windshield, one out the back windshield, one angled at the driver seat in the car, and one angled at the passenger seat. The MobilEye provided driving performance data by monitoring the vehicle position and elements of the external environment, such as lane markings and other traffic. Additional driving performance can be ascertained from OBD data, including steer angle, speed, acceleration, and braking. None of these data are reported in these preliminary analyses, but the recorded dialogue in the audio file and facial/body gestures in the videos serve as the basis for planned analyses about successful communication during the driving session.

During the pre-drive segment, each participant separately completed a series of state assessments while they were outfitted with a set of multimodal physiological sensors to measure brain activity, respiration, heart rate, and galvanic skin responses. Each participant then completed pre-drive tasks based on their role for the driving session. The driver reviewed the route and safety procedures outside the vehicle, while the passenger sat in the vehicle and watched 16 videos of unique news stories on a tablet. The passenger was asked to remember as many news stories as possible to share them with the driver in conversation during the on-drive segment. The dyad then jointly watched an instructional video about their responsibilities for the drive and provided 3 min of baseline physiological data. Once in the vehicle, the physiological sensors were paired to recording devices and synchronized with the D-Lab system data through the use of a common reference signal (engine RPM) recorded to all data logs using OBD splitters; this common reference ensured time synchronization across participants and vehicle/task events during the driving session. In these preliminary analyses, we only report physiological data from the brain sensors as well as state data from three questionnaires, the Perceived Stress Scale (PSS), the Motivation Visual Analog Scale (MVAS), and the Driver-Passenger Social Interaction questionnaire (DPSI).

The on-drive segment consisted of three subcomponents. During the first 10 min, the dyad jointly listened to a 2-min podcast about the importance of sleep or physical activity for healthy living (one topic was assigned to each drive; counterbalanced between dyads) and then discussed their opinions about the health information. Next, they drove 40 miles on Interstate-95, turning around at 20 miles, and the passenger communicated details about the news stories with the driver in two sequential memory tasks. The first was an open recall task where the passenger had 5 min to share as many news stories as they could remember and engage the driver in a discussion about their opinions on the topics. The second memory task was a cued recall where the passenger saw a visual cue for each of the 16 unique news stories, and the dyad discussed the topic for 1 min each. After the dyad exited the interstate, they spent the final 10 min jointly listening to a second podcast on the same health topic as the start of the drive, and they freely discussed their opinions on the additional health information.

Finally, in the post-drive segment, each participant separately completed a series of survey assessments as well as a 32-item recognition memory task about fine-grained details from the news stories (e.g., change tax burden to 25% or to 32%, where one is accurate and the other is a lure). However, the driver completed two additional memory tasks without the passenger present. The first was a 3-min open recall to recount as many news stories and conversation details as possible, and the second was a cued recall task where they had 40 s to talk aloud about each of the 16 cued news clips, including details about the opinions discussed with their dyad partner during the drive. In short, across these two additional tasks, the driver reported details that captured how successfully the passenger communicated the news stories as well as the success of the dyad's information exchange in the discussion itself.

After all of the tasks in the driving session were completed, the experimenters removed physiological sensors and debriefed the participants. The participants then completed the daily text tasks while wearing the actigraphy watch for 2–3 weeks before returning for their second drive. The flow of drive 2 mirrored drive 1, except that the participants changed roles (i.e., driver in drive 1 is passenger in drive 2) and they discussed a different, unique set of the 16 news clips.

2.1 Trait Similarity Metric

Social Network Analysis. During the intake session, participants completed a web-based application [19] to characterize their real-life social networks. In this task, participants identified up to 10 people with whom they have communicated in the past week in each of four communication types: face-to-face conversation, voice call, text messaging, and online social media. The maximum number of unique individuals possible to include was 40, but many participants had communicated with the same subset of people across the media or had communicated with fewer than 10 people through at least one medium in the past week, so all social networks consisted of fewer than 40 individuals. For each unique individual listed, the participant then indicated the strength of their relationship ("closeness"), subjective estimates of their friend's preferences ("driving riskiness" and "political interest"), and which of their friends knew each other. From the latter responses, an undirected graph of their most recent contacts was computed, where each node corresponds to a friend and an edge connects every pair of people who know each other. The size of the social networks ranged from 13 to 33 people (Mean = 21.0; SD = 5.0).

We calculated the density of each social network by taking the number edges and dividing by the number of possible edges (i.e., the number of edges in a fully connected graph where every friend of the participant is also a friend with each other). Thus, a higher density corresponds to a social network in which more of the participant's friends know each other, while a lower density indicates that a participant has more distinct groups of friends.

2.2 State Similarity Metrics

Perceived Stress Scale (PSS). During the pre-drive segment, participants provided self-report responses on a 10-item Perceived Stress Scale [20], capturing subjective perceptions of stress. Responses were scored on a 5-point Likert scale (0 = never to 4 = very often) regarding thoughts and feelings experienced within the last month. Sample items included, "In the last month, how often have you been able to control irritations in your life?" and "In the last month, how often have you felt nervous and stressed?" A total score was calculated by summing scores on all items, where higher total scores indicated higher levels of perceived stress.

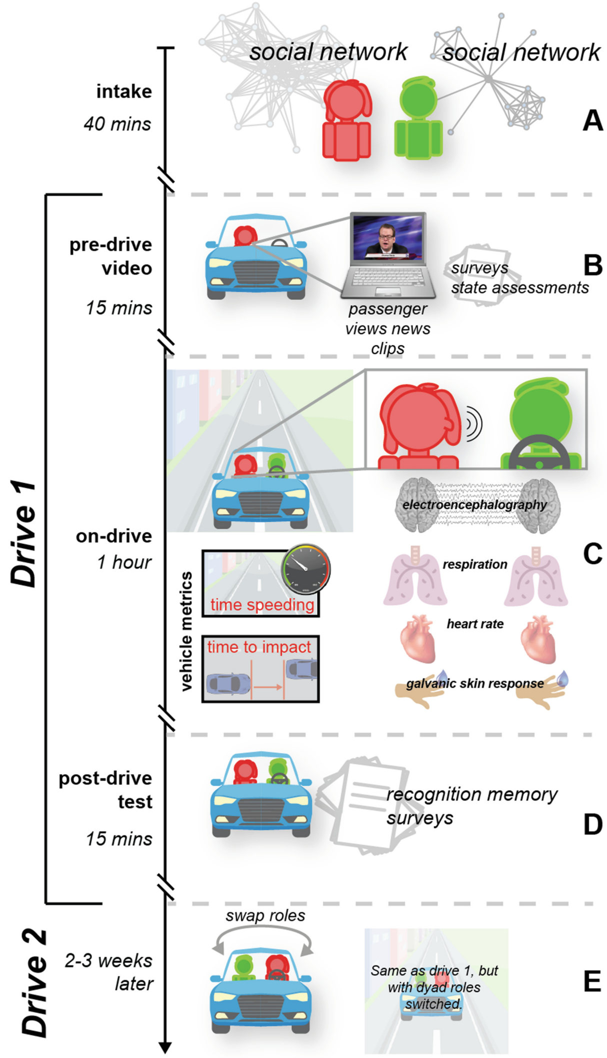

Fig. 1. *Experimental Design Overview.* (A) During an intake session, participants provided social network information as a trait variable. (B) Both driver and passenger completed pre-drive state surveys (e.g., PSS, MVAS, DPSI) and tasks specific to their role in the drive. In particular, the passenger separately watched 16 video news clips that served as discussion topics during the drive. (C) During the on-drive segment, the passenger communicated the news topics and led a discussion with the driver. All vehicle CAN bus data (speed, time to contact, steering, lane position, etc.) and multimodal physiological data (EEG, respiration, heart rate, and galvanic skin responses) were measured and synchronized continually throughout the driving session. (D) In the post-drive segment, participants independently completed memory tasks and post-drive surveys. (E) Several weeks later, the dyad returned for a second drive, but they swapped roles (driver in drive 1 is passenger in drive 2) and discussed a different set of news clips.

Motivation Visual Analog Scale (MVAS). During the pre-drive segment, participants were asked to provide subjective ratings of general motivation on a scale from 0 ("I am not motivated") to 100 ("I am very motivated"). The scale was represented as a horizontal line with an initial position of the slider at 50 in the middle. Visual analog scales are typically used to provide a visual guide for participants to rate their perception of subjective feelings or states on a continuous scale by choosing a location between two extremes [21–24].

Driver-Passenger Social Interaction Questionnaire (DPSI). In order to assess the existing relationship between dyad partners prior to the study session, participants answered 5 items regarding the frequency of interaction as well as the likelihood of accepting advice from their partner for general and work-related concerns. For the present study, we focused on the frequency of casual interaction prior to the study session. During the pre-drive segment, participants indicated frequency using the following scale: 0 = Never, 1 = Past 12 Months, 2 = Past 6 Months, 3 = Past Month, 4 = Past Week, and 5 = Last Day.

2.3 Physiological Synchrony Metric

Electroencephalography (EEG). For this study, we used the ABM B-Alert X24 Electroencephalography (EEG) system (Advanced Brain Monitoring, Inc, Carlsbad, CA) sampled at 256 Hz. The flexible electrode strip consisted of a set of flat electrodes in standard 10–20 scalp locations, and conductive paste was placed on cylindrical foam pads on each electrode to serve as the conductive medium between the scalp and sensor. The electrode strip was then affixed to a headband that was adjusted to fit the head of the participant, and a wireless transmitter that attached to the headband sent EEG signals to a separate device for data capture. The B-Alert system is relatively light, weighing less than 200 g, allowing the participant to freely move during the driving session.

The EEG data were preprocessed to remove nuisance and non-brain signals, such as muscle activity, electrical noise in the car, and vehicle movement, using the PREP approach implemented in EEGlab [25]. The steps included are: (1) line noise removal via a frequency-domain (multi-taper) regression technique to remove 60 Hz and harmonics present in the signal, (2) a robust average reference with a Huber mean, (3) artifact subspace reconstruction to remove residual artifact with the standard deviation cutoff parameter set to 5, (4) band-pass filtering using a Butterworth filter with 2-dB attenuation at 2 and 50 Hz, and (5) an automated independent component analysis-based component removal to specifically target residual muscle and eye-related artifacts that may influence our physiological synchrony metric [26]. This artifact removal procedure has been shown to be robust to high artifact environments [27, 28].

EEG Synchrony. Across the entire duration of the on-drive segment, we estimated EEG synchrony in the alpha band (8–12 Hz) between dyad partners using Matlab (Mathworks, Inc.). For each channel pair, the phase-locking value (PLV) was computed using a Hilbert transform across 2 s EEG epochs in 62 ms steps. PLV estimates the similarity in phase between the two signals [12], where 1 equates with perfect phase locking and 0 with no phase locking. In this preliminary analysis, we focused on alpha since this frequency band has been proposed as a gating mechanism for perceptual information [29] or access controller for semantic knowledge [13], both of which may underlie successful communication via physiological synchrony.

3 Results

Our preliminary analyses focused on identifying and describing variability of subjective factors that may influence social communication between and within driver-passenger dyads. Here, we utilized data from intake and drive 1 sessions from a dataset still in collection, and we examined similarity among both trait and state metrics as well as synchrony for a physiological metric derived from scalp EEG data.

3.1 Real-Life Social Networks Capture Trait Similarity Among Dyads

We first used social network analysis to examine individual differences in trait metrics derived from the participant's real life social interactions. Using an online tool [19], participants reported their most recent interactions and indicated which friends knew one another. From these relationships, we computed the density of the participant's social network. A social structure with high density denotes a network where a large proportion of a participant's friends know one another, while a low density indicates that the participant may have distinct clusters of friends who know one another but little crossover among subgroups of friends.

The social network density for each dyad collected thus far is plotted in Fig. 2: individual participants are indicated by a circle connected to their dyad partner by a line, so that their adjoining line reflects their similarity (short line = high similarity, long line = low similarity). Across dyads, we observe variability in density, including dyad 4 where the participants' network densities are 0.61 and 0.68 and dyad 3 where each participant's density is 0.32. In contrast, we also have dyads where the participants have dissimilar network density scores, such as dyads 8 and 12.

Next, we illustrate the social network structures for several dyad partners as a graph. In each graph, the participant is represented as the red node, friends are black nodes, and edges between nodes represent a direct connection. For participants in dyads 2 and 3, their social network reflects clusters of friends with interconnections, but often the only connection between clusters is through the participant. In contrast, dyad 8 includes one participant who has a similar cluster structure, while the other mostly interacts with friends who also know one another. Thus, within the current participant sample, we observe variability both within and between dyad participants, indicating that this trait measure can be examined as a covariate to account for variablity in communication success in future analyses.

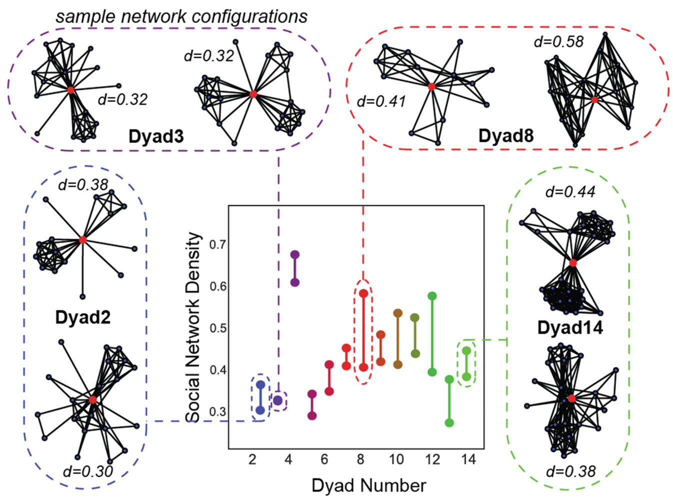

Fig. 2. *Trait Similarity Metric.* Participants' social network information was extracted using Friendly Ocean [19]. Examples from several dyads are depicted. For each subject's social network, density or the number edges divided by the number of possible edges was calculated. Higher density reflected social networks in which participants' friends were acquainted (see dyad 8, right), while lower density within the network is indicative of distinct groups of friends (see Dyad 2).

3.2 Dyad Interaction Outside of the Experiment Relate to State Effects at Drive 1

We next examined intra- and inter-dyad variability in subjective reports of motivation and stress at the start of their first driving session. Variability in intra-dyad scores was observed for metrics (Fig. 3 top). Absolute difference scores were calculated to determine the level of intra-dyad similarity for subjective state measures. Specifically, dyads 1, 2, 5, 6, 8, and 10–12 exhibited relatively high levels of intra-dyad similarity for motivation as indicated by lower absolute difference score values (short adjoining lines). In contrast, dyads 3, 4, 7, 9, 13 and 14 displayed relatively low levels of intra-dyad similarity for motivation (long adjoining lines). Across dyads, there was high inter-dyad variability in general motivation (range = 0–40; SD = 15.10).

For perceived stress, dyads 1, 5, 10–12, and 14 exhibited relatively high levels of intra-dyad similarity (short adjoining lines), whereas dyads 2–4, 6–9, and 13 showed relatively low levels of intra-dyad similarity (long adjoining lines). Across dyads, results demonstrated high inter-dyad variability in perceived stress at the start of their first drive session (range: 1–14; SD: 4.04). Interestingly, we observed consistency for the intra-dyad similarity between these two state metrics. Dyads 1, 5, and 10–12 had low absolute difference values for both the motivation and stress state metrics. Notably, dyads 2, 5, and 6 also displayed high levels of similarity for both density of social networks (trait) and general motivation (state).

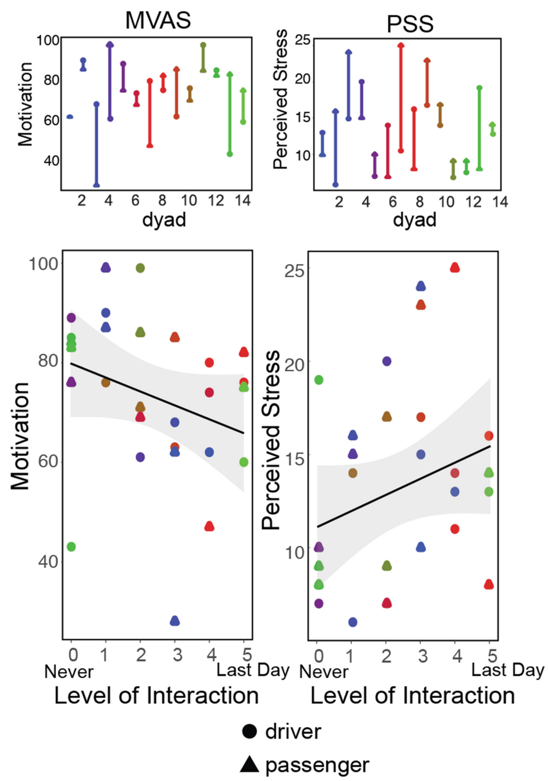

Fig. 3. *State Similarity Metrics.* Top row: state estimates for each participant, organized by dyads, for MVAS and PSS pre-drive surveys are depicted. Lines connecting driver and passenger scores reflect their level of similarity. Bottom row: self-report scores on the MVAS and PSS are plotted as a function of the self-reported level of interaction outside the experiment, where 0 = never, 1 = last 12 months, 2 = last 6 months, 3 = last month, 4 = last week, and 5 = last day.

Finally, we capitalized on the fact that our participants were recruited from two cohesive work environments, and most had interacted with each other prior to the experiment. This analysis examined whether intra-dyad similarity in state metrics related to the frequency of the dyad's real-life interactions. In Fig. 3 (bottom row), the scatter plots relate the two state metrics (motivation left and stress right) with the participant's reported frequency of casual interaction in the DPSI questionnaire done during the pre-drive segment of the driving session. Preliminary results demonstrate a negative trend between general motivation scores and frequency of interaction, such that participants with relatively higher motivation scores are those that interact less frequently ($r = -.28$). In contrast, there appears to be a positive trend between perceived stress and frequency of interaction in the real-world demonstrating that those who interact more frequently reported higher levels of perceived stress ($r = .29$). These trends suggest that frequency of interaction with a dyad partner may produce differential effects in subjective state metrics. Individuals may be more highly motivated to make a strong first impression with new colleagues, while they simultaneously experience heightened performance-related stress with partners with whom they interact frequently. However, we acknowledge that these emerging trends are preliminary and may change as we collect additional data.

3.3 Neural Synchrony Captures Time-Evolving Relationships Between Dyad Partners

While the first two analyses investigated similarity in state and trait variables, our final preliminary analysis examined the amount of synchrony between physiological measurements during the drive. In Fig. 4, the PLV synchrony metric is shown for a single dyad for the initial task of the on-drive segment of drive 1. The first time segment (labeled −60 to 0) is the joint listening task to a health podcast, while the second time segment (labeled 0 to 60) is the open discussion about the health information. The heat map at the bottom of Fig. 4 displays the range of PLV across the time interval with a maximum synchrony of PLV = 0.64. The purple line located above the heat map averages the synchrony across channels and displays a complex temporal profile of intervals of synchrony and asynchrony within and across both time segments. Finally, the two topographic plots on the head models at the top of Fig. 4 reveal that the spatial pattern of this physiological synchrony metric is maximal in the back of the scalp, which likely reflects visual processing. This might indicate a jointly perceived change in the environment (e.g., traffic), but future research will relate these metrics and spatial patterns to successful communication to investigate whether neural synchrony can account for moment-to-moment fluctuations in successful communication.

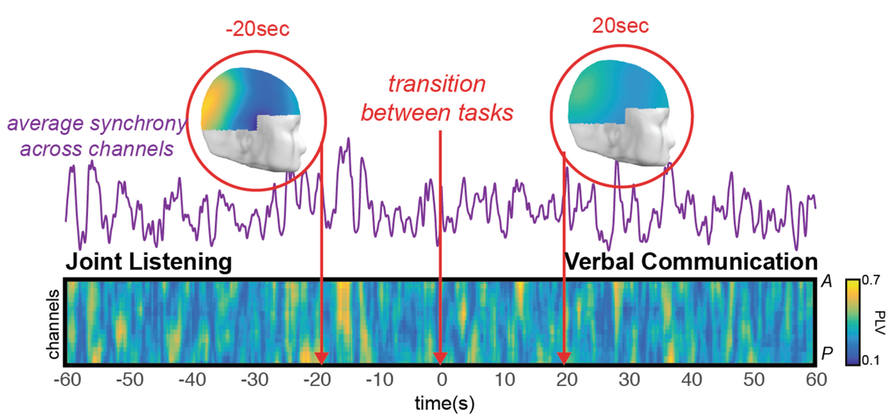

Fig. 4. *Inter-subject Synchrony.* Sample time segment of the PLV synchrony metric for a single dyad during the initial task of the on-drive segment of drive 1. The topographic plots on the head models at the top show the spatial distribution of the PLV across the scalp 20 s before and after the task transition. The purple line plot displays the average synchrony across channels shown in the heat map at the bottom of the figure.

4 Discussion

The present study provides a framework for understanding the subjective factors that may influence social communication variability within a multitask, driving context. Our core hypothesis asserts that successful communication between driver-passenger dyads will likely occur when similarity in shared social experiences or emotional states arise, providing a foundation for engagement and interest in understanding another's perspective [30, 31]. In this paper, we conducted preliminary analysis on a set of subjective factors that operationalized these trait and state relationships. These results demonstrated strong intra- and inter-dyad variability among social network structure in the trait similarity metric. Furthermore, we also observed a trending relation showing that real life interactions between dyad partners accounted for variability in motivation and stress states at the beginning of their first driving session. Finally, we investigated implicit measures of state captured in the physiological synchrony from scalp EEG sensors. Preliminary results identified that alpha activity captures dynamic fluctuations in neural synchrony which can be used as a covariate in future analyses of communication success. Collectively, these explicit and implicit metrics of similarity and synchrony may play critical roles in shaping successful communication between dyad partners.

Our future analyses will examine both the audio and video files collected during the drive to characterize and quantify dyad communication [32]. From the transcript of the driver's post-drive memory tasks, we can determine the number of news stories remembered as well as recall of idiosyncratic details from the conversation, reflecting driver engagement when communicating with their partner. Furthermore, natural language processing [33, 34] will be applied in order to extract sentiment information and quantify attitudes expressed by individuals within and across dyads. We expect that the passenger's valence while communicating the news stories may influence memory and recall of the driver [35]. Similarly, analysis of the videos will focus on extracting gestures and facial expressions that may also capture implicit metrics of connection that drive successful communication [36–38]. Lastly, we plan to investigate how these metrics of social communication are related to driving performance, including how social interactions and bonding can positively impact not only performance in the vehicle but health and well-being more generally.

In summary, our initial results demonstrate promising metrics that can quantify how social and emotional experiences influence performance in naturalistic, multitask environments. By identifying ways to quantify contextual complexity, this translational research can augment our understanding about how to enhance human performance within contexts with increasingly sophisticated technology automation.

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