MIND, BRAIN, AND EDUCATION

On the Same Wavelength: Exploring Team Neurosynchrony in Undergraduate Dyads Solving a Cyberlearning Problem With Collaborative Scripts

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ABSTRACT— As teammates adjust their cognition and behavior, synchronizations of information can be observed across verbal, postural, and neurophysiological systems. This study explored the synchrony of mutually interacting brains, or team neurosynchrony, during cyber-enabled collaborative problem solving. Mixed-sex dyads defined and solved an authentic problem using either a social script or an epistemic script. Alpha-band phase-locking value, or the absolute value of the sum of the phase differences of electrodes at a particular time and frequency across a number of epochs, was used as a measure of team neurosynchrony. Contrary to our hypotheses, analyses revealed greater alpha-band phase-locking values between the central and parietal electrodes of dyad members in the epistemic script condition. Mean alpha phase-locking values were positively correlated with collaborative problem solving performance and negatively correlated with time spent on the problem solving process, suggesting that epistemic scripts were more effective scaffolds of collaborative problem solving compared to social scripts in this study.

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Effective collaborative learning requires more than simply placing learners in groups (Stahl, Koschmann, & Suthers, 2014). Similar to how scaffolds are used in building construction to extend the reach and support construction workers, instructional scaffolding is used to structure learning and collaboration allowing learners to perform tasks that they would otherwise not be able to accomplish on their own (Reiser & Tabak, 2014). Scaffolding of collaborative learning is frequently approached using collaboration scripts (Dillenbourg, Järvelä, & Fischer, 2009; Kollar, Fischer, & Slotta, 2007). A collaboration script helps learners understand and distribute roles in the collaborative process and provides guidance regarding the specific activities to be undertaken by collaborators (De Wever, Van Keer, Schellens, & Valcke, 2010). Two particular types of scripts have been studied in computer-supported collaborative learning (CSCL) research: epistemic and social. Epistemic scripts focus on pre-structuring the learning task in order to facilitate collaborative knowledge construction. Task pre-structuring is typically accomplished in epistemic scripts by providing learners with a sequence of steps to complete as a team (e.g., analyze contextual information, negotiate a shared definition of the problem, identify existing claims and evidence relevant to solving the problem, discuss the viability of each claim and evidence relative to potential problem solution, etc.) On the other hand, social scripts facilitate collaborative learning by structuring the interactions of learners, rather than the task to be completed. For example, in dyadic problem solving social scripts have been employed to facilitate problem definition, analysis of information resources, and solution negotiation through collaborative interpretation of learning materials as teammates alternate between the roles of a Summarizer and a Questioner (Weinberger, Kollar, Dimitriadis, Mäkitalo-Siegl, & Fischer, 2009). Existing evidence suggests that social scripts are more effective at supporting individual students' knowledge acquisition during CSCL (Noroozi, Weinberger, Biemans, Mulder, & Chizari, 2012; Weinberger et al., 2009; Weinberger, Ertl, Fischer, & Mandl, 2005). The influence of epistemic and social scripting in the more specific context of cyber-enabled collaborative problem solving remains to be explored.

Team Neurosynchrony

Collaboration scripts have the potential to enhance and streamline team interactions as people learn together (Kollar, Fischer, & Hesse, 2006; Weinberger et al., 2005). Teams have been conceptualized as complex dynamic systems that exist in a context, develop as teammates interact over time, and evolve and adapt based on the dynamic task demands and goals (Kozlowski & Ilgen, 2006). Using complexity science as the framework, Stevens and Galloway (2014) defined teams as self-organized flows of information that consolidate periodically around a common goal and change form as the task and environment evolve. As teammates adjust their cognition and behavior, their information exchanges synchronize across different systems including gestural (Ashenfelter, 2007), postural (Shockley, Santana, & Fowler, 2003), verbal (Drew, 2005), physiological (Guastello, Pincus, & Gunderson, 2006), and, more recently, neurophysiological (Mu, Guo, & Han, 2016; Poulsen, Kamronn, Dmochowski, Parra, & Hansen, 2017; Stevens & Galloway, 2014).

Team neurosynchrony has been the focus of several recent studies that employed a brain hyperscanning technique that allows recording neural activity from two or more individuals simultaneously (Montague, 2002) to examine the functional role of across-brain activity in social interactions (Babiloni & Astolfi, 2014; Dikker et al., 2017; Dumas, Nadel, Soussignan, Martinerie, & Garnero, 2010; Konvalinka & Roepstorff, 2012). One such investigation analyzed neurosynchrony between team members during submarine piloting simulations (Stevens, Galloway, Wang, & Berka, 2012). In this study, electroencephalography (EEG) derived measures of cognitive engagement were normalized and pattern classified by self-organizing artificial neural networks. Results demonstrated that neurosynchrony expression for engagement shifted across task segments and task changes. Shannon entropy measures of the neurosynchrony data stream revealed predictable decreases associated with periods when the team was stressed.

Konvalinka et al. (2014) employed a synchronized finger-tapping task while measuring dual-EEG from pairs of individuals who either mutually adjusted to each other (interactive condition) or followed a computer metronome (non-interactive condition). The interactive condition was characterized by a stronger suppression of alpha over frontal areas in contrast to the non-interactive condition. A multivariate analysis of two-brain activity to classify interactive versus non-interactive trials revealed asymmetric patterns of the frontal alpha suppression in each pair. Analysis of behavioral data allowed the authors to conclude that team leaders exhibited stronger frontal alpha suppression in eight out of nine pairs, suggesting that leaders invested more cognitive resources in prospective planning and control.

More recently, across-brain synchrony was explored in a high school biology classroom over an entire semester (Dikker et al., 2017). The researchers recorded brain activity from a group of 12 students as they engaged in natural classroom activities (discussion, lecture, and video viewing) and social interactions. They found that total interdependence (a measure of across-brain synchrony; Wen & Ding, 2012) between students consistently predicted class engagement and social dynamics reported by students for each class. Additionally, confirming prior research on alpha dynamics in relation to task demands (Haegens, Handel, & Jensen, 2011), a reduction in a student's alpha oscillatory activity (8–12 Hz) was accompanied by an increase in student-to-group alpha coherence.

Alpha-band activity has been shown to be a neural marker of across-brain synchrony and inter-individual coordination in a number of hyperscanning studies. For example, Dumas et al. (2010) employed a dual-EEG setup and phase-locking value (PLV), the absolute value of the sum of the phase differences of electrodes at a particular time and frequency across a number of epochs, as an across-brain phase synchrony index and revealed a two-brain synchronizing network in the parietal alpha band, which correlated with behavioral interactional synchrony during an imitation of hand movements task. The alpha-band across-brain synchrony also occurred based on a partial directed coherence multivariate spectral measure of across-brain connectivity when two pilots in a dual-EEG setup coordinated with each other during simulating takeoff and landing (Astolfi et al., 2012). Across-brain synchrony was not observed for theta (4–7 Hz), beta (14–30 Hz), or gamma (30–50 Hz) bands.

Mu et al. (2016) employed a hyperscanning dual-EEG setup and PLV to explore dyadic neurosynchrony during a coordination game in which two participants were asked to synchronize with a partner (coordination task) or with a computer (control task) by counting in mind rhythmically in order to make a button press at the same time after counting. Greater across-brain synchrony of alpha-band neural oscillations was observed during the coordination (vs. control) task in female but not male dyads. Importantly, the increased alpha-band across-brain synchrony predicted better interpersonal behavioral synchrony (response time lags) across all participants.

Taken together, the findings of the recent EEG hyperscanning research suggest that alpha-based across-brain synchrony is a sensitive measure that can reflect dynamic social interactions in laboratory and authentic, in-situ learning tasks. Informed by the emerging empirical literature on team neurosynchrony and the prior work on the effects of collaboration scripts on individual and team learning (Noroozi et al., 2012; Weinberger et al., 2005, 2009), our study explored which collaboration script—epistemic or social—would result in increased alpha-band across-brain synchrony and behavioral manifestations of improved learning during an authentic collaborative problem-solving task. Specifically, this study was designed to test the following hypotheses:

- H1: Use of a social script will result in improved individual learning (individual knowledge acquisition) and team learning (collaborative problem-solving performance and efficiency).
- H2: Dyads using a social script will exhibit higher alpha-band phase-locking values, indicating enhanced team neurosynchrony, compared to epistemic script dyads.

METHOD

Participants

Study participants were 140 undergraduate students at a large public university in the southeastern United States. All participants were native speakers of English. Most participants were sophomore and junior students in biology, nursing, and engineering programs. All participants were between 18 and 24 years old. Guided by educational research on effective team composition (Wentzel & Watkins, 2011), 70 heterogeneous dyads were formed, each consisting of a male and a female participant who did not know each other. A subsample of 80 participants (40 dyads) took part in the team neurosynchrony portion of the study. Prior EEG hyperscanning studies have employed anywhere from 12 participants (Dikker et al., 2017 in a group neurosynchrony study) to 68 participants (Mu et al., 2016 in a dyadic neurosynchrony study). Neurosynchrony study participants were all right-handed, and reported no history of brain trauma and current prescriptions for medications that affect mental activity.

Treatment

Dyads were asked to collaboratively use a cyberlearning environment entitled "Are We Really What We Eat?", define the problem to be solved based on the provided description of societal context, and solve this problem using what they deemed to be relevant resources and solution strategies. Similar to most contemporary cyberlearning environments, each resource page consisted mostly of text with one or two representational images. To simulate real-world cyber-enabled problem solving, some resources (three of the seven resource pages) were not relevant to solving the problem. A test of prior knowledge focusing on recommended dietary allowance and daily energy intake, protein, iron, and vitamin B1 requirements revealed overall low levels of prior knowledge on the topic and no significant differences between individuals in each experimental condition.

Half of the dyads were asked to use an epistemic script as a problem-solving scaffold, while the other half employed a social script. The epistemic script was designed using the work of Weinberger et al. (2005) and prior research on scaffolding the problem-solving process (Kim & Hannafin, 2011). This kind of scaffolding is meant to communicate the process, which involves explicitly providing the students with the stages of an activity (Hmelo-Silver, 2006). The script walked the participants through the steps of defining the problem, exploring learning resources, analyzing the available claims and evidence, and generating and justifying a viable solution. The social script was designed to scaffold learner interactions (Weinberger et al., 2005) by having the students analyze the learning materials as either a summarizer or questioner (cf. Palincsar & Herrenkohl, 2002; Weinberger et al., 2009). Participants were instructed to alternate roles for each information resource they studied as part of the problem-solving process. Social script dyads were also asked to provide their definition of the problem and solution along with solution rationale.

Audio recordings of student interactions were examined to determine whether participants used the scripts as intended. About 75 % of the script prompts were addressed in the intended sense and no significant difference with respect to the use of prompts was found between conditions ($\chi^2 = 1.73$, $p = .62$).

Each dyad shared a desk with two chairs and a computer that displayed the learning materials. Participants could not access any other external resources. Usability testing software Techsmith Morae™ (Techsmith Corporation, Okemo, MI) was used to record the computer screens, keyboard and mouse interactions, and audio and video of all participant interactions. The participants in the 40 dyads in the team neurosynchrony portion of the study each wore a nine-electrode wireless EEG headset (B-Alert X-10™, Advanced Brain Monitoring, Carlsbad, CA) and completed the resting alpha baseline task before working on the problem-solving activity. The B-Alert X-10 acquires nine channels of monopolar EEG recordings with a linked mastoid reference. EEG sensor sites collect electrophysiological activity from the scalp at frontal (Fz, F3, and F4), central (Cz, C3, and C4) and parietal (Pz, P3, and P4) regions. EEG was digitized at a sampling rate of 250 Hz and band-pass filtered online between 0.1 and 100 Hz. Impedances were kept low below 50 kΩ, as recommended by the manufacturer. Subsequently, processing of the recorded data occurred offline, applying a Butterworth band-pass filter (0.1–45 Hz) and re-referenced to a common average reference (Ludwig et al., 2009). Artifacts were removed using independent component analysis in EEGLAB in all time windows of interest. Two experienced EEG researchers collaboratively examined the component properties and labeled vertical and horizontal eye movement components for rejection (e.g., based on strong far-frontal projection). This artifact decontamination procedure also helped us eliminate potential sources of non-cognitive synchrony in the EEG associated with synchronized ocular activity.

Measures

Collaborative problem-solving performance was determined by analyzing teams' problem definition, analysis of learning resources, final solution, and solution justification. Three trained raters used the problem-solving rubric developed and validated by the Association of American Colleges and Universities (2013) specifically to evaluate open-ended problem solving. Intraclass correlation coefficient reached .73, which is considered acceptable in educational research (Griffin & Gonzalez, 1995).

Collaborative problem-solving efficiency was computed by determining how much time each team spent on the entire problem-solving process in general and specifically on each of the three phases: (a) defining the problem, (b) exploring resources, and (c) negotiating solution.

Individual knowledge acquisition was measured using a cued-recall task consisting of 12 fill-in-the-blank items taken verbatim from the learning materials.

Team neurosynchrony was assessed by calculating phase synchrony of continuous alpha-band activity in the participants' EEG using PLV, an established measure of across-brain neurosynchrony (Dumas et al., 2010; Linkenkaer-Hansen, Nikouline, Palva, & Ilmoniemi, 2001; Mu et al., 2016). First, we identified time windows when both participants in each dyad were silent between conversations and computer usage. This was done to eliminate any possible perceptual-motor confounds associated with viewing images, diagrams, text, and tables shown on the computer, variable display luminance on different website screens, talking, using the mouse, keyboard, or writing (Gerjets, Walter, Rosenstiel, Bogdan, & Zander, 2014). Temporal alignment of EEG and screen, video, and audio recording data streams was achieved by placing a marker

$$w(t, f_0) = Ae^{(-t^2/2\sigma_t^2)} \cdot e^{2i\pi f_0 t}$$

Fig. 1. The complex Morlet wavelet $w\,(t, f_0)$ with a Gaussian shape in time (*SD* σ_t) and frequency (*SD* σ_f) domains around its central frequency f_0 with $\sigma_f = 1/2\pi\sigma_t$ used to provide a time frequency (TF) representation of the signal (Kronland-Martinet, Morlet, & Grossmann, 1987).

within each of the two data acquisition programs (Biopac AcqKnowledge™ [Biopac Systems, Inc., Goleta, CA] and Techsmith Morae™) 2 s following the presentation of problem-solving stimulus to the dyad. During data analysis, two experimenters reviewed the time-aligned recordings and identified 30 2-second epochs common to both participants in each dyad. In previously published research using PLV as a measure of across-brain synchrony and Morlet wavelets as a time frequency representation of the signal (e.g., Mu et al., 2016), 10 trials were completed by 17 dyads in each experimental condition, producing good signal-to-noise ratios. After the segmentation and artifact removal, PLVs were quantified based on a wavelet decomposition of the alpha signal (between 8 and 13 Hz) in 1 Hz steps, similar to prior studies (Linkenkaer-Hansen et al., 2001; Mu et al., 2016; Mu, Fan, Mao, & Han, 2008; Mu & Han, 2010, 2013). The signal was then convoluted by the complex Morlet wavelet w (t, f_0) with a Gaussian shape in time (*SD* σ_t) and frequency (*SD* σ_f) domains around its central frequency f_0 with $\sigma_f = 1/2\pi\sigma_t$, as depicted in Figure 1. Wavelets were normalized so that their total energy was 1.

Similar to previous research (Doesburg, Roggeveen, Kitajo, & Ward, 2008; Gross et al., 2004), we used this Morlet wavelet transform to estimate the across-brain phase synchrony in the alpha band. The PLV was defined as the absolute value of the sum of the phase differences of two electrodes (j, k) at time t and frequency f across N epochs (Mu et al., 2016) with the resulting formula shown in Figure 2. PLV is a value between 0 and 1, where 0 indicates randomly dispersed phases among all trials and 1 indicates fully phase-locked oscillations between electrodes j and k in a specific time window. In other words, PLV equates 1 if the two signals are perfectly phase-locked across the whole time window observed, and equates 0 if they are completely unsynchronized. Thus, PLV is equal to one minus the circular variance of phases' differences. Following the approach

$$\mathrm{PL\ V}_{j,k,t} = N^{-1}\, |\sum_N e^{i[\Phi_j(f,t) - \Phi_k(f,t)]}\,|$$

Fig. 2. Calculation of PLV defined as the absolute value of the sum of the phase differences of two electrodes (j, k) at time t and frequency f across N epochs (Mu et al., 2016).

Table 1
Descriptive Statistics for Collaborative Problem-Solving Performance

	Social Script					*Epistemic Script*				
Rubric Criterion	Mdn	M	SD	*Min*	*Max*	Mdn	M	SD	*Min*	*Max*
Define Problem[a]	3	2.57	.50	2	3	3	2.51	.51	2	3
Identify Strategies	3	2.69	.63	2	4	3	3.09	.61	2	4
Propose Solutions	3	2.71	.46	2	3	3	3.17	.62	2	4
Evaluate Solutions	2	2.46	.66	2	4	3	2.83	.66	2	4
Total Rubric Score	10	10.43	.95	9	12	12	11.60	1.36	9	15

[a]Maximum score for each of the four rubric criteria was 4 for a total maximum score of 16.

of Mu et al. (2016), across-brain phase synchrony was estimated in this study by examining two electrodes from the two individuals in each dyad. We used all 9 available electrodes from each individual over the frontal (F3, F4, and Fz), central (C3, C4, and Cz), and parietal (P3, P4, and Pz) regions, resulting in 81 (9×9) electrode pairs.

RESULTS AND DISCUSSION

Collaborative Problem-Solving Performance

Table 1 provides a summary of the descriptive statistics for problem-solving rubric criteria Define Problem, Identify Strategies, Propose Solutions, and Evaluate Potential Solutions, as well as the Total Rubric Score. Because the rubric data were ordinal and the scores were not normally distributed (a common issue with rubric scores), two-tailed Mann–Whitney U tests were performed in SPSS to examine potential differences between 35 teams in the social script condition and 35 teams in the epistemic script condition. Contrary to our hypotheses, dyads in the epistemic script condition outperformed social script dyads on three of the four criteria as well as the total rubric score: Identify Strategies ($U = 809.00$, $n_1 = 35$, $n_2 = 35$, $z = 2.56$, $p = .009$), Propose Solutions ($U = 842.50$, $n_1 = 35$, $n_2 = 35$, $z = 3.22$, $p = .001$), Evaluate Potential Solutions ($U = 801.50$, $n_1 = 35$, $n_2 = 35$, $z = 2.45$, $p = .014$), and Total Score ($U = 917.50$, $n_1 = 35$, $n_2 = 35$, $z = 3.70$, $p < .0001$). Effect sizes were computed based on Rosenthal's (1991) and Rosenthal, Rosnow, and Rubin (2000) effect size correlation procedure by dividing the standardized test statistic z by squared root of the total number of observations: Identify Strategies ($r = .31$), Propose Solutions ($r = .39$), Evaluate Potential Solutions ($r = .29$), and Total Score ($r = .44$). All reported effect sizes are at or above the .3 threshold for a medium effect.

Collaborative Problem-Solving Efficiency

Table 2 provides the descriptive statistics for the time spent by social and epistemic script dyads on each collaborative problem-solving task.

Social script dyads spent significantly more time on the problem-solving process in general ($t_{68} = 3.30$, $p = .002$, $r = .37$) and exploring information resources specifically ($t_{68} = 4.81$, $p < .0001$, $r = .50$). On average, social script dyads spent 767 s of that time exploring irrelevant resources (i.e., 60% of all time spent on resources), compared to the average of 464 s spent on irrelevant information by epistemic script teams (i.e., 50% of total time exploring resources). This difference was significant ($t_{68} = 5.96$, $p < .0001$) and the effect size was large ($r = .59$). Social script teams also tended to spend less time negotiating solutions than the epistemic script dyads ($t_{68} = -4.63$, $p < .0001$) for a large effect size of $r = .49$. Problem-solving performance data reported earlier suggest that the increased time exploring information resources and decreased time negotiating solutions resulted in inferior problem-solving performance compared to the epistemic script dyads.

Individual Knowledge Acquisition

Individual knowledge acquisition was measured using a cued recall task consisting of 12 fill-in-the-blank items

Table 2
Descriptive Statistics for Collaborative Problem-Solving Efficiency

	Social Script Time Spent (seconds)				*Epistemic Script Time Spent (seconds)*			
Problem-Solving Phase	M	SD	*Min*	*Max*	M	SD	*Min*	*Max*
Collab. Problem Solving	1962	442	1128	3141	1679	249	1277	2252
a. Define Problem	305	85	199	602	285	70	112	385
b. Explore Resources	1290	406	580	2452	922	203	628	1691
c. Negotiate Solution	367	70	229	510	472	116	290	754

Table 3
Treatment Effect (Social Script vs. Epistemic Script) on Alpha Across-Brain Phase-Locking Value (PLV)

Electrode Pairs	F	p	*Partial eta-squared*
Cz-Pz	6.74	0.01	0.170
Cz-P3	7.39	0.01	0.183
Cz-P4	4.19	0.04	0.112
P3-Pz	5.75	0.02	0.150
Cz-Cz	5.68	0.02	0.168

taken verbatim from the learning materials. The maximum possible score was 12. Participants from social script dyads outperformed participants in the epistemic script condition with a mean score of 9.07 ($SD = 1.34$) versus the mean score of 8.31 ($SD = 1.25$). This difference was statistically significant ($t_{138} = 3.46$, $p = .001$) and the effect size was medium ($r = .39$). This finding is not surprising given that social script dyads spent significantly more time exploring information resources and discussed resources by both summarizing and questioning the claims and evidence presented in resource pages.

Team Neurosynchrony

The differences in alpha-band across-brain PLV were assessed using analyses of variance (ANOVAs) with Treatment (social script vs. epistemic script) as a between-subjects variable. The analysis focused only on alpha activity because relevant prior work reported increased alpha-band across-brain synchrony during interpersonal coordination (Astolfi et al., 2012; Mu et al., 2016). To avoid multiple comparison issues, all EEG results were corrected using cluster-based correction (Dumas et al., 2010). Clusters were defined by any three adjacent data points (each point covered 100 ms) and any three adjacent electrodes pairs (cf. Mu et al., 2016). Only data from the five electrode pairs in the clusters that exceeded the cluster-level threshold ($p < .05$) were used in ANOVA tests and reported (Table 3). As a reminder, the PLV measure is 1 if the two signals from the two dyad members are perfectly phase-locked across the entire time window observed, and 0 if they are completely unsynchronized.

Contrary to our predictions, our PLV analyses revealed significant differences in the alpha-band PLVs between the central and parietal electrodes of dyad members in the epistemic script condition compared to the social script condition ($F_{1,39} = 4.19–7.39$, ps $< .05$; Table 3; Figure 3).

Figure 4 demonstrates the distribution of alpha-band mean PLVs for the five pairs of electrodes in Table 3 for each dyad in each condition. Interestingly, only 4 of the 20 dyads in the epistemic script condition demonstrated alpha mean PLVs below .3, whereas 14 of the 20 dyads in the social script condition generated alpha-band mean PLVs under .3. Mean PLVs for alpha in the epistemic script condition were significantly higher ($M = .33$, $SD = .09$) than alpha mean PLVs in the social script dyads ($M = .24$, $SD = .07$) and this difference was significant ($t_{38} = 3.34$, $p = .002$, $r = .26$).

To further explore the role of alpha PLV-derived team neurosynchrony in collaborative problem solving, we examined whether alpha-band mean PLV values were associated with either the collaborative problem-solving performance (total rubric score), or the collaborative problem-solving efficiency (total time spent on the problem-solving session). This analysis revealed that mean alpha PLV was positively correlated with collaborative problem-solving performance ($r_{S,38} = .59$, $p < .001$) and negatively correlated with collaborative problem-solving efficiency ($r_{38} = -.51$, $p < .001$). Scatterplots for each condition are provided in Figure 5. Two-tailed Spearman correlation analyses were then performed for each treatment group to explore the relationship between mean alpha PLV and collaborative problem solving performance (the latter was an ordinal variable). For the social script group, mean alpha PLV positively correlated with collaborative problem-solving performance but this

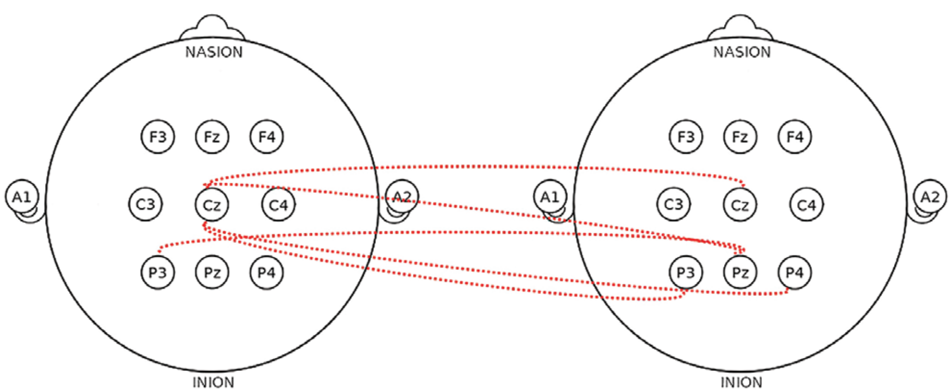

Fig. 3. The electrode pairs that showed enhanced alpha-band PLVs in the epistemic script vs. social script condition.

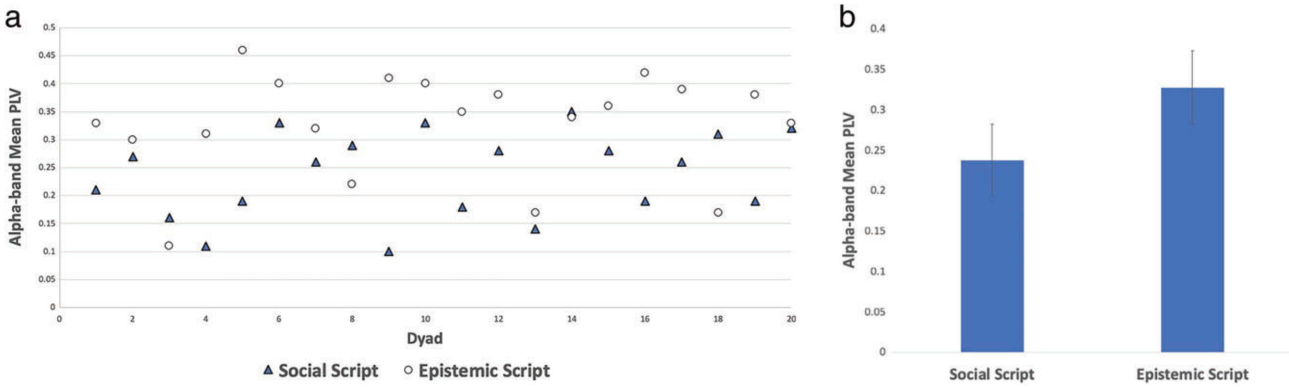

Fig. 4. Distribution of alpha-band mean PLVs for electrode pairs Cz-Pz, Cz-P3, Cz-P4, P3-Pz, and Cz-Cz in the social script and epistemic script conditions.

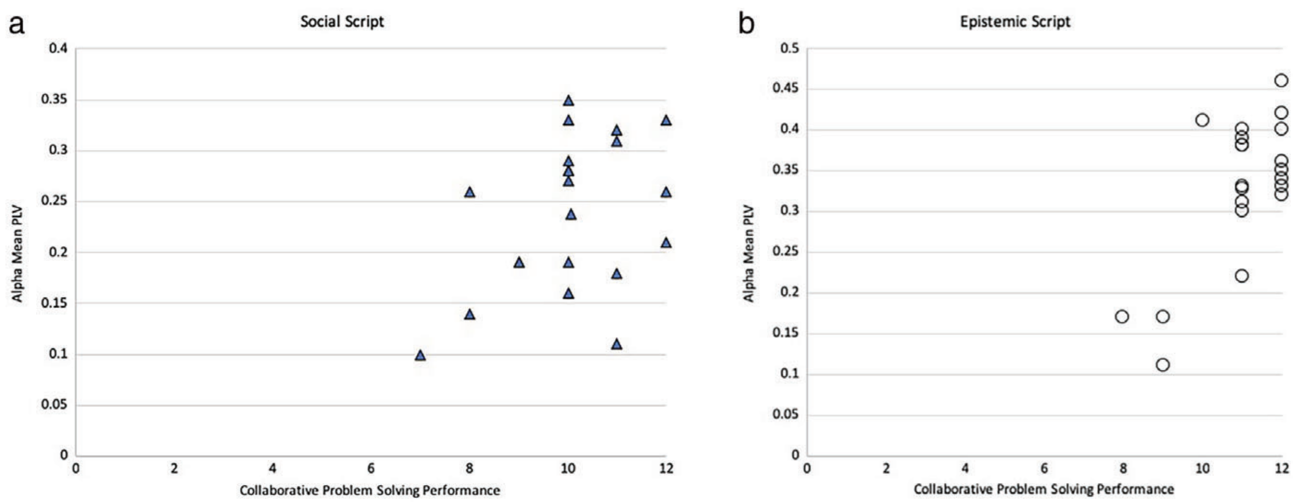

Fig. 5. Scatterplots showing the relationship between mean alpha PLV and collaborative problem-solving performance for the social script group and the epistemic script group.

correlation did not reach significance ($p = .14$). Mean alpha PLV was also positively correlated with problem-solving performance for the epistemic group and this difference was significant ($r_{S,18} = .47$, $p < .04$). Thus, the increased alpha-band across-brain synchrony predicted enhanced behavioral performance on collaborative problem solving and this suggests that, pending additional testing in other team learning contexts, alpha-band PLV may potentially serve as a useful neural marker of team neurosynchrony during collaborative learning.

Enhanced alpha-band across-brain synchrony, such as the phenomenon observed in this study, may be explained as a manifestation of teammates' shared inhibition of processing in task-irrelevant regions. Klimesch, Schack, and Sauseng (2005), Klimesch, Sauseng, and Hanslmayr (2007), and Klimesch (2012) suggested that alpha event-related synchronization plays an active role in the inhibitory control and timing of cortical processing. Similarly, Jensen and Mazaheri (2010) proposed that alpha oscillations are responsible for "gating" information by inhibiting task-irrelevant regions and routing information to task-relevant regions. Such functional inhibition is reflected in decreased oscillatory activity in the alpha band. To explore whether a shared inhibition account is reasonable in the context of this study, we examined the relationship between alpha-band across-brain synchrony and alpha band power—a well-characterized index of inhibition (Haegens et al., 2011; Klimesch, 2012; Palva & Palva, 2007). Alpha power change indices were computed for each of the 30 epochs for each individual participant using the Pfurtscheller and Lopes da Silva (2005) approach shown in Figure 6. Then, the alpha power change values for each individual participant were averaged and the resulting means were averaged for each pair of participants in a dyad. As expected, a reduction in dyad members' alpha oscillatory activity was accompanied by an increase in mean alpha PLV ($r_{38} = -.51$, $p = .007$).

$$ERD / ERS\% = \frac{\text{baseline interval band power} - \text{test interval band power}}{\text{baseline interval band power}} * 100$$

Fig. 6. Computation of event-related desynchronization/synchronization percentage (Pfurtscheller & Lopes da Silva, 2005). During the baseline task teammates sat facing each other, eyes open, for 30 s.

CONCLUSIONS AND IMPLICATIONS

The results produced by this study contribute useful insights regarding our understanding of team function and scaffolds that support collaborative problem solving. This study confirms the finding that social scripts can improve individual knowledge acquisition for learners during collaborative learning (Weinberger et al., 2005). In addition to individual knowledge acquisition, this study focused on measures of group cognition, such as collaborative problem-solving performance and efficiency, and team neurosynchrony. Contrary to our predictions, data from these measures suggest that epistemic scripts may in fact be a better scaffold for collaborative problem solving. Epistemic scripts that focus on scaffolding the problem-solving process appear to be more effective in collaborative learning situations where the goal of learning is to define and solve a specific problem, rather than simply retain information. It is reasonable to conclude that the additional effort epistemic script participants invested in coordinating their cognitive activities (evidenced by increased shared inhibition in the alpha band; Jensen & Mazaheri, 2010) resulted in both enhanced across-brain neurosynchrony and better outcomes on collaborative problem-solving task. On the other hand, dyads following the social script engaged in pre-coordinated interpretation of information resources, which resulted in enhanced individual knowledge retention; but because the script did not specifically scaffold negotiating a shared problem definition or possible pathways to a viable problem solution, they underperformed on the measure of problem-solving performance and exhibited decreased neurosynchrony compared to their epistemic script counterparts. Given the unique affordances of epistemic and social scripts, future research should test the effects of integrated social and epistemic scripting on collaborative problem solving.

More conceptual and empirical research is needed to investigate the potential of team neurosynchrony measures and models to inform our understanding of team function. To date, methodologies for assessing the learning benefits of collaboration have relied on learning tests for individual learners or time-consuming discourse analysis prone to interrater variability. It is still very difficult for learning scientists to disentangle the role of the individual from the overall functioning of the team (Puntambekar, Erkens, & Hmelo-Silver, 2011). Research on collaborative problem solving is only beginning to acknowledge the expanding neurodynamic understanding of how brain-to-brain coupling within groups may drive complex cooperative behaviors (Stevens & Galloway, 2014). Compared with other teamwork modeling approaches like shared mental models (Maynard & Gilson, 2014), team cognition (Cooke, 2015), and macrocognition (Warner, Smith, & Letsky, 2017), a team neurosynchrony approach offers multiple advantages. Neuroimaging measures can be recorded, modeled and reported within seconds. Also, neural signatures of various cognitive processes are distinct and can be modeled independently (Jensen, Gelfand, Kounios, & Lisman, 2002; Klimesch, 2012). This speed of processing and level of specificity allow just-in-time information to be used for adapting the learning environment to the cognitive patterns of both teams and individuals.

While much of our cognitive activity is not available for conscious introspection, neuroscientific evidence has made it clear that nonconscious neural activity, such as fluctuations in teammates' alpha-band oscillatory activity, is essential for controlling our behavior (Kringelbach, 2009). Team neurosynchrony afforded by examining changes in alpha phase locking appears to be a useful measure of team coherence. Recent research suggests that across-brain synchrony is beneficial for learning and group cohesion (e.g., Dikker et al., 2017; Mu et al., 2016; Poulsen et al., 2017; Stevens & Galloway, 2014). Future studies should explore whether or not the role of across-brain synchrony in general, and alpha-band PLV specifically, is confirmed in different learning tasks and different learning environments. More conceptual and empirical work is needed to explore how individual and team neurosynchrony can be assessed and modeled in real time using the emerging low-cost non-invasive brain imaging systems such as the one used by Dikker et al. (2017). Combining a high-temporal resolution technology such as EEG with a high-spatial resolution technology like functional near infrared spectroscopy can provide further insights regarding not only when important changes in neurodynamics occur but also where in the brain this activity is reflected.

Quantitative expertise is also developing to devise robust and rigorous neuroimaging based metrics and analytical approaches. Promising methods for analyzing neuroimaging data in social neuroscience include multidimensional scaling (Gorman, Martin, Dunbar, Stevens, & Galloway, 2013), classification methods using artificial neural networks (Stevens & Galloway, 2014) and least partial squares (McDonald & Soussou, 2011), multilevel modeling (Dikker et al., 2017), and correlated component analysis (Poulsen et al., 2017). Research on team neurosynchrony offers the potential to inform design of adaptive and personalized cyberlearning environments that are sensitive to individual and collaborative learning dynamics. Neurosynchrony-informed systems can provide just-in-time scaffolds customized for each individual learner and each team, enhancing team cohesion and function for 21st-century learning and problem solving.

REFERENCES

Ashenfelter, K. (2007). *Simultaneous analysis of verbal and nonverbal data during conversation: symmetry and turn-taking* (Unpublished thesis). University of Notre Dame, Notre Dame, IN.

Association of American Colleges and Universities. (2013). *Assessing learning outcomes: Lessons from AAC&U's VALUE project*. Washington, DC: AACU.

Astolfi L., Toppi J., Borghini G., Vecchiato, G., He, E. J., Roy, A., … Babiloni, F. (2012). Cortical activity and functional hyperconnectivity by simultaneous EEG recordings from interacting couples of professional pilots. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE* (pp. 4752–4755).

Babiloni, F., & Astolfi, L. (2014). Social neuroscience and hyperscanning techniques: Past, present and future. *Neuroscience and Biobehavioral Reviews*, *44*, 76–93.

Cooke, N. J. (2015). Team cognition as interaction. *Current Directions in Psychological Science*, *24*, 415–419.

De Wever, B., Van Keer, H., Schellens, T., & Valcke, M. (2010). Roles as a structuring tool in online discussion groups: The differential impact of different roles on social knowledge construction. *Computers in Human Behavior*, *26*, 516–523.

Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., … Poeppel, D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology*, *27*, 1375–1380.

Dillenbourg, P., Järvelä, S., & Fischer, F. (2009). The evolution of research on computer-supported collaborative learning. *Technology-Enhanced Learning*, *1*, 3–19.

Doesburg, S. M., Roggeveen, A. B., Kitajo, K., & Ward, L. M. (2008). Large-scale gamma-band phase synchronization and selective attention. *Cerebral Cortex*, *18*, 386–396.

Drew, P. (2005). Conversation analysis. In K. L. Fitch & R. E. Sanders (Eds.), *Handbook of language and social interaction* (pp. 71–102). Mahwah, NJ: Lawrence Erlbaum.

Dumas, G., Nadel, J., Soussignan, R., Martinerie, J., & Garnero, L. (2010). Inter-brain synchronization during social interaction. *PLoS One*, *5*(8), e12166. http://doi.org/10.1371/journal.pone.0012166

Gerjets, P., Walter, C., Rosenstiel, W., Bogdan, M., & Zander, T. O. (2014). Cognitive state monitoring and the design of adaptive instruction in digital environments: Lessons learned from cognitive workload assessment using a passive brain-computer interface approach. *Frontiers in Neuroscience*, *8*, 385.

Gorman, J. C., Martin, M. J., Dunbar, T. A., Stevens, R. H., & Galloway, T. (2013). Analysis of semantic content and its relation to team neurophysiology during submarine crew training. In D. D. Schmorrow & C. M. Fidopiastis (Eds.), *Foundations of augmented cognition* (pp. 143–152). Berlin, Germany: Springer.

Griffin, D., & Gonzalez, R. (1995). The correlational analysis of dyad-level data: Models for the exchangeable case. *Psychological Bulletin*, *118*, 430–439.

Gross, J., Schmitz, F., Schnitzler, I., Kessler, K., Shapiro, K., Hommel, B., & Schnitzler, A. (2004). Modulation of long-range neural synchrony reflects temporal limitations of visual attention in humans. *Proceedings of the National Academy of Sciences*, *101*, 13050–13055.

Guastello, S. J., Pincus, D., & Gunderson, P. R. (2006). Electrodermal arousal between participants in a conversation: Nonlinear dynamics for linkage effects. *Nonlinear Dynamics, Psychology, and Life Sciences*, *10*, 365–399.

Haegens, S., Handel, B. F., & Jensen, O. (2011). Top-down controlled alpha band activity in somatosensory areas determines behavioral performance in a discrimination task. *Journal of Neuroscience*, *31*, 5197–5204.

Hmelo-Silver, C. E. (2006). Design principles for scaffolding technology based inquiry. In A. M. O'Donnell, C. E. Hmelo-Silver, & G. Erkens (Eds.), *Collaborative reasoning, learning and technology* (pp. 147–170). Mahwah, NJ: Lawrence Erlbaum.

Jensen, O., Gelfand, J., Kounios, J., & Lisman, J. E. (2002). Oscillations in the alpha band (9–12 Hz) increase with memory load during retention in a short-term memory task. *Cerebral Cortex*, *12*, 877–882.

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience*, *4*, 186. http://doi.org/10.3389/fnhum.2010.00186

Kim, M. C., & Hannafin, M. J. (2011). Scaffolding problem solving in technology-enhanced learning environments (TELEs): Bridging research and theory with practice. *Computers and Education*, *56*, 403–417.

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*, 606–617.

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition-timing hypothesis. *Brain Research Reviews*, *53*, 63–88.

Klimesch, W., Schack, B., & Sauseng, P. (2005). The functional significance of theta and upper alpha oscillations for working memory: A review. *Experimental Psychology*, *52*, 99–108.

Kollar, I., Fischer, F., & Hesse, F. W. (2006). Collaboration scripts: A conceptual analysis. *Educational Psychology Review*, *18*(2), 159–185.

Kollar, I., Fischer, F., & Slotta, J. D. (2007). Internal and external scripts in computer-supported collaborative learning. *Learning and Instruction*, *17*, 708–721.

Konvalinka, I., Bauer, M., Stahlhut, C., Hansen, L. K., Roepstorff, A., & Frith, C. D. (2014). Frontal alpha oscillations distinguish leaders from followers: Multivariate decoding of mutually interacting brains. *NeuroImage*, *94*, 79–88.

Konvalinka, I., & Roepstorff, A. (2012). The two-brain approach: How can mutually interacting brains teach us something about social interaction? *Frontiers in Human Neuroscience*, *6*, 215.

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest*, *7*, 77–124.

Kringelbach, M. L. (2009). Neural basis of mental representations of motivation, emotion and pleasure. In G. G. Berntson & J. T. Cacioppo (Eds.), *Handbook of neuroscience for the behavioral sciences* (pp. 807–828). New York, NY: John Wiley.

Kronland-Martinet, R., Morlet, J., & Grossmann, A. (1987). Analysis of sound patterns through wavelet transforms.

International Journal of Pattern Recognition and Artificial Intelligence, *1*, 273–302.

Linkenkaer-Hansen, K., Nikouline, V. V., Palva, J. M., & Ilmoniemi, R. J. (2001). Long-range temporal correlations and scaling behavior in human brain oscillations. *Journal of Neuroscience*, *21*, 1370–1377.

Ludwig, K. A., Miriani, R. M., Langhals, N. B., Joseph, M. D., Anderson, D. J., & Kipke, D. R. (2009). Using a common average reference to improve cortical neuron recordings from microelectrode arrays. *Journal of Neurophysiology*, *101*(3), 1679–1689.

Maynard, M. T., & Gilson, L. L. (2014). The role of shared mental model development in understanding virtual team effectiveness. *Group and Organization Management*, *39*(1), 3–32.

McDonald, N. J., & Soussou, W. (2011). Quasar's Qstates cognitive gauge performance in the cognitive state assessment competition 2011. In *Proceedings of the 2011 International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 6542–6546). Red Hook, NY: Curran Associates.

Montague, P. (2002). Hyperscanning: Simultaneous fMRI during Linked Social Interactions. *NeuroImage*, *16*, 1159–1164.

Mu, Y., Fan, Y., Mao, L., & Han, S. (2008). Event-related theta and alpha oscillations mediate empathy for pain. *Brain Research*, *1234*, 128–136.

Mu, Y., Guo, C., & Han, S. (2016). Oxytocin enhances inter-brain synchrony during social coordination in male adults. *Social Cognitive and Affective Neuroscience*, *11*, 1882–1893.

Mu, Y., & Han, S. (2010). Neural oscillations involved in self-referential processing. *NeuroImage*, *53*, 757–768.

Mu, Y., & Han, S. (2013). Neural oscillations dissociate between self-related attentional orientation versus evaluation. *NeuroImage*, *67*, 247–256.

Noroozi, O., Weinberger, A., Biemans, H. J., Mulder, M., & Chizari, M. (2012). Argumentation-Based Computer Supported Collaborative Learning (ABCSCL): A synthesis of 15 years of research. *Educational Research Review*, *7*(2), 79–106.

Palincsar, A. S., & Herrenkohl, L. R. (2002). Designing collaborative learning contexts. *Theory Into Practice*, *41*(1), 26–32.

Palva, S., & Palva, J. M. (2007). New vistas for alpha-frequency band oscillations. *Trends in Neurosciences*, *30*, 150–158.

Pfurtscheller, G., & Lopes da Silva, F. H. (2005). Event-related desynchronization (ERD) and event-related synchronization (ERS). In E. Niedermeyer & F. H. Lopes da Silva (Eds.), *Electroencephalography: Basic principles, clinical applications and related fields* (5th ed., pp. 1003–1016). Philadelphia, PA: Lippincott, Williams & Wilkins.

Poulsen, A. T., Kamronn, S., Dmochowski, J., Parra, L. C., & Hansen, L. K. (2017). EEG in the classroom: Synchronised neural recordings during video presentation. *Scientific Reports*, *7*, 43916. http://doi.org/10.1038/srep43916

Puntambekar, S., Erkens, G., & Hmelo-Silver, C. E. (2011). *Analyzing interactions in CSCL: Methods, approaches and issues*. New York, NY: Springer.

Reiser, B., & Tabak, I. (2014). Scaffolding. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (2nd ed., 44–62). New York, NY: Cambridge University Press.

Rosenthal, R. (1991). *Meta-analytic procedures for social research* (2nd ed.). Newbury Park, CA: Sage.

Rosenthal, R., Rosnow, R., & Rubin, D. B. (2000), *Contrasts and effect sizes in behavioral research: A correlational approach*. Cambridge, England: Cambridge University Press.

Shockley, K., Santana, M.-V., & Fowler, C. A. (2003). Mutual interpersonal postural constraints are involved in cooperative conversation. *Journal of Experimental Psychology: Human Perception and Performance*, *29*, 326–332.

Stahl, G., Koschmann, T., & Suthers, D. (2014). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences*. (2nd ed., 479–500) New York, NY: Cambridge University Press.

Stevens, R., & Galloway, T. (2014). Towards a quantitative description of the neurodynamic organizations of teams. *Social Neuroscience*, *9*(2), 160–173.

Stevens, R. H., Galloway, T. L., Wang, P., & Berka, C. (2012). Cognitive neurophysiologic synchronies: What can they contribute to the study of teamwork? *Human Factors*, *54*, 489–502.

Warner, N., Smith, C. A. P., & Letsky, M. (2017) *Macrocognition in teams: Theories and methodologies*. London, England: CRC Press.

Weinberger, A., Ertl, B., Fischer, F., & Mandl, H. (2005). Epistemic and social scripts in computer-supported collaborative learning. *Instructional Science*, *33*(1), 1–30.

Weinberger, A., Kollar, I., Dimitriadis, Y., Mäkitalo-Siegl, K., & Fischer, F. (2009). Computer-supported collaboration scripts: Perspectives from educational psychology and computer science. In N. Balacheff, S. R. Ludvigsen, T. de Jong, S. Barnes, & A. W. Lazonder (Eds.), *Technology-enhanced learning: Principles and products* (pp. 155–173). Berlin, Germany: Springer.

Wen, X., Mo, J., & Ding, M. (2012). Exploring resting-state functional connectivity with total interdependence. *NeuroImage*, *60*, 1587–1595.

Wentzel, K. R., & Watkins, D. E. (2011). Peer relationships and learning: Implications for instruction. In R. Mayer & P. Alexander (Eds.), *Handbook of research on learning and instruction* (pp. 322–343). New York, NY: Routledge.