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Previous research indicates that measures of joint attention provide unique insight into team cognition and performance. In this study, we examined the effects of practice and joint attention on team performance improvement using multivariate mixed models, with an emphasis on exploring the correlation structure between the variances in growth trajectories of team performance and joint attention around estimated means. Observed patterns in team performance showed time dependent trends well known in a variety of learning contexts, including non-linear growth, performance retention, and performance retention loss between multiple practice sessions. Joint attention was found to decrease non-linearly over time, starting out comparatively high and decreasing as a function of time on task. Additionally, we found evidence of negative relationships between joint attention and team performance in our task environment, and we established that joint attention was significantly higher than the chance levels that would be expected by task-constraints alone.

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EVALUATING THE RELATIONSHIP BETWEEN TEAM PERFORMANCE AND JOINT ATTENTION WITH LONGITUDINAL MULTIVARIATE MIXED MODELS

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Previous research indicates that measures of joint attention provide unique insight into team cognition and performance. In this study, we examined the effects of practice and joint attention on team performance improvement using multivariate mixed models, with an emphasis on exploring the correlation structure between the variances in growth trajectories of team performance and joint attention around estimated means. Observed patterns in team performance showed time dependent trends well known in a variety of learning contexts, including non-linear growth, performance retention, and performance retention loss between multiple practice sessions. Joint attention was found to decrease non-linearly over time, starting out comparatively high and decreasing as a function of time on task. Additionally, we found evidence of negative relationships between joint attention and team performance in our task environment, and we established that joint attention was significantly higher than the chance levels that would be expected by task-constraints alone.

Visual gaze patterns, both within individuals and pairs, offer unique insight into the cognitive processes that help shape behavior. For instance, there is evidence that measures of joint attention capture underlying similarities in the cognitive processes of interacting pairs (Richardson, Dale, & Tomlinson, 2009), and may also index the establishment of a common ground understanding that helps support successful interpersonal coordination and communication (Vinson, Dale, Tabatabaeian, & Duran, 2015). In applied settings, gaze patterns have been shown to be indicative of control room operators' readiness and capability to respond to abnormal situations (Kodappully, Srinivasan, & Srinivasan, 2016), and are related to the expertise level of surgeons (Hermens, Flin, & Ahmed, 2013). These results suggest that the use of eye tracking, as a means to record gaze patterns that serve as proxies for attention, may provide a uniquely sensitive and non-invasive method for indexing the evolution of team states, readiness, and performance. As such, understanding the relationship between team gaze coordination and team performance over an interval in which learning and adaptation occur in a complex task environment can provide guidance for the development of team diagnostic procedures and training applications (Hermens et al., 2013). However, evaluating the evolution of these relationships is a complicated problem that is compounded by the multiple variables associated with complex learning (Van Merrienboer & Sweller, 2005). Multivariate analyses using mixed models offers a way to approach this problem.

Mixed models are flexible tools for analyzing longitudinal relationships between variables, as they are well suited to handle correlations between observations. Multivariate mixed models are an extension of these well-known procedures and can be approached using several methods. For example, a conditional approach models one outcome variable as a function of a time-varying covariate. This method has several limitations, including the possibility of misspecification (Curran, Obeidat, & Losardo, 2010) and the fact that parameters estimated by the model will be a function of which covariate is entered as the dependent variable – the latter of which may confuse interpretation of the marginal growth of the two covariates (Codd, 2014). Another approach is to model multiple dependent variables simultaneously, and evaluate their dependence by allowing within participant variations around estimated mean values to be correlated. This yields the advantage of providing estimations of the changes within each variable, as well as their mutual relationships.

The goal for this study was to employ a multivariate mixed models approach to identify changes in patterns of joint attention associated with task performance in a longitudinal design. We employed a multivariate-modeling framework to investigate the temporal evolution of team performance in a medium-fidelity simulated task environment and the associated changes in joint attention that are posited to capture similar or shared cognitive states. In as much as the task requires coordinated activity and shared understanding of task constraints, we predicted that higher magnitudes of joint attention would be positively related to successful task outcomes. Additionally, we sought to investigate the influence of pre-existing social ties on joint attention and performance by evaluating differences between teams comprised of friends and teams with no prior relationship.

METHODS

Participants

Forty-eight participants took part in this study. Due to incomplete data, three teams were omitted from analyses. Ages in the remaining 21 same-sex dyads (16 women and 26 men) ranged from 18 to 35 (M = 23.98, SD = 4.33). Of these, ten were comprised of self-identified friends, while the other 11 were composed of pairs who had not met before.

Design

The experiment was a 2 (friends) × 3 (session) × 12 (trial) × 2 (task difficulty) mixed design, where friends was a between-groups factor, and session, trial, and task-difficulty were within-groups factors. For this report, we focused on the changes in joint attention and performance during the first two sessions, where task difficulty remained constant, yielding a 2 (friend) × 2 (session) × 12 (trial) mixed design.

Materials and Apparatus

Gaze data were collected using two desk-mounted Seeing Machines Inc., faceLAB eye trackers recording at 60 Hz. Participants sat at desks in padded chairs 95 cm from separate Samsung Syncmaster 2443 60.96 cm LCD monitors with 1280×1024 displays.

Team Task. Participants engaged in the Experimental Research Environment for Supervisory Control of Heterogeneous Unmanned (RESCHU) Vehicles synthetic task environment (see Figure 1). In RESCHU, participants work together to control several unmanned aerial vehicles (UAVs) with the ultimate goal of locating specific objects of interest in urban coastal and inland settings. Participants had distinct roles in the simulation. The *navigator* was able to see the entire map, including all UAVs, all targets, and all threats; the *pilot* controlled the UAVs via a point and click interface, but was only able to see targets and threats in the sectors populated by UAVs. Thus, for the team to approach a target successfully with a UAV, the navigator would use the chat interface to indicate to the pilot the location of the target and any threats along the path from a chosen UAV to the specified target. After a UAV arrived at an area of interest, either participant could engage in a visual search task. This secondary task consisted of looking for a particular target in an image by panning and zooming a simulated camera feed. Visual search and control of UAVs could be conducted in parallel. The goal of the RESCHU task was for participants to maximize their performance by 1) reaching as many areas of interest as possible, 2) correctly completing as many of the target detection tasks as possible, and 3) avoiding threat areas. Performance on this task was measured by the total number of arrivals at targets plus the total number of successful search tasks, minus the number of threat areas encountered in each trial.

Procedure

Written informed consents were obtained from all participants upon arrival for the first session. Participants were then given instructions regarding the RESCHU task and one participant from each dyad was assigned at random to the role of navigator, while the other was assigned to be the pilot. Participants maintained their assigned roles throughout the experiment. During the study, participants sat at separate desks situated along a common wall with 3.05 m between them. Participants were equipped with physiological monitoring sensors, including heart rate, electroencephalography (data from these sensors will be reported elsewhere), and the eye-tracking equipment described earlier (calibrated to less than 2 degrees of error in measured visual angle). To prevent interference with physiological monitoring equipment, participants were asked not to talk to one another, and to communicate only via the RESCHU chat interface. Teams took part in 12 ten-minute trials during each session. Teams received a ten-minute break every three trials, with an optional half-hour break between the sixth and seventh trials. Each session lasted approximately eight hours, with the two sessions separated by three to five days, dictated by participant scheduling constraints.

Analyses and Models

Gaze. Gaze data were pre-processed by removing samples for which an eye tracking system lost track of both the pupils and irises of either participant. Gaze locations greater than 100 pixels outside of the calibration area were also removed. Sections of data in which there were greater than 250 ms of contiguously missing data for either participant in a pair were deemed bad, and files that contained greater than 10% bad data were removed from subsequent analyses (resulting in the removal of two files). A cubic spline interpolation was used to replace removed samples, and data were then down-sampled to 20 Hz.

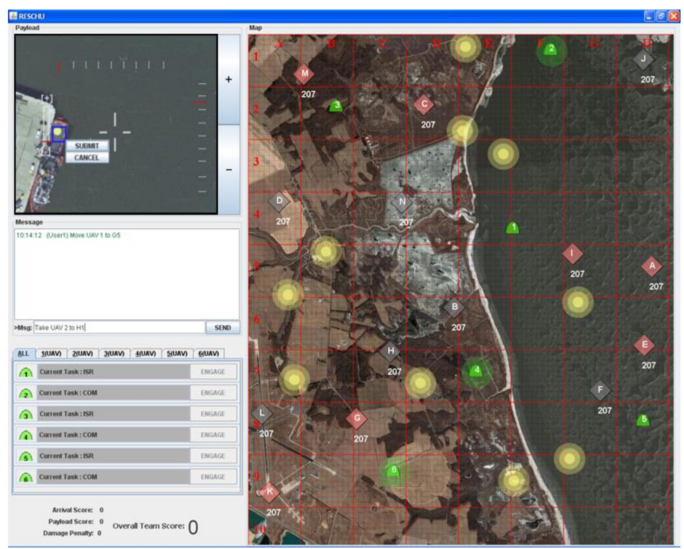

Figure 1. The RESCHU interface. Participants worked together to navigate UAVs (green icons) to targets (diamonds) while avoiding threat areas (yellow circles). A visual search task appeared in the upper left corner upon UAV arrival at a target. The left center window is a chat interface, and the left bottom window contains indicators of UAV engagement.

Joint attention was estimated from the separate two-dimensional time series of screen coordinates (in pixels) of team gaze data using Cross Recurrence Quantification Analysis (CRQA) (Marwan, Carmen Romano, Thiel, & Kurths, 2007; Richardson, Dale, & Kirkham, 2007; Richardson et al., 2009). This technique quantifies the degree of similarity between two different sets of time series. With respect to the parameters, no delay embedding was used, the radius was set to 250 pixels, and data were analyzed within a 30-second window from the diagonal. This means that when participants were looking at locations of their screens within 250 pixels of each other, and within the 30 s window, that sample was identified as recurrent. Percent recurrence (%REC) was then calculated as the number of observed recurrences to the total number of possible recurrences for each 10 minute trial. Simply put, %REC with these parameter settings gives the percentage of time participants spent looking at the same areas of their displays within 30 s of each other. It should be noted that prior work has used smaller windows to evaluate joint attention (e.g., 3 s in Richardson et. al, 2009). However, in our preliminary analyses, we found qualitatively similar results for %REC between 3 s (M = 16.64, SD = 1.19) and 30 s (M = 16.03, SD =0.97) windows over the 10 minute trial. We used the larger 30 s window so that in a future publication we might be able to compare joint attention with other measures that require larger amounts of data. As a test of joint attention versus task-constrained gaze patterns, team %REC was compared against surrogate %REC values that were calculated from virtual pairings of navigators and pilots from 30 different groups (Shockley, Baker, Richardson, & Fowler, 2007; Strang, Funke, Sheldon, Dukes, & Middendorf., 2014).

Models. Linear mixed model analyses were conducted in R (R Core Team, 2015) using the package *nlme* (Pinheiro, Bates, Sarkar, & R Core Team, 2015). To prevent spurious correlations between slopes and intercepts, the time variable was centered, meaning that all intercepts are to be interpreted as projected average values for the time between trials 12 and 13. To allow comparison of nested models, the Maximum Likelihood estimator was used. A sequential analysis method was used in which the best univariate model was found for the individual variables, which were then combined in a multivariate model to test for relationships between random effects (MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997). The following terms were entered sequentially, first as fixed effects and then as random effects, starting from the null model fitting only the intercept with a random term added for group: trial (time), trial^2, session, and friends. For clarification, the trial^2 allows the slope to vary as the second order function of trial, which captures quadratic trends in the data. Each term was also tested for group level random effects. The most parsimonious, best fitting model for each variable was determined from likelihood ratio tests of nested models. Visual inspection of the normalized Quartile-Quartile plots of the model residuals versus observed values revealed three points that were identified as possible outliers. Removal of these values did not significantly alter the fit of either model. Reported results are for the multivariate model estimated with these data points removed.

The univariate models were combined and analyzed using the techniques specified in MacCallum et al. (1997), in which each of the dependent variables are stacked into a single column vector with two dummy column vectors specifying the contribution of each in the model. The random effects variance-covariance matrix for the null model had a mean of zero, with full specification of covariances within performance and %REC, and with zero covariances between random effects estimated for performance and %REC. As the two variables were measured on different scales, separate residual variables were required in the multivariate model. We thus specified zero mean residuals with independent variance components for both performance and %REC. The multivariate model was specified as:

$$y_{itk*} = \delta_{Score}[\beta_{0i(score)} + \beta_{1i(score)}x_{it} + \beta_{2i(score)}x_{it}^2 + \beta_{3i(score)}x_{ij} + e_{i(score)}] + \delta_{\%REC}[\beta_{0i(\%REC)} + \beta_{1i(\%REC)}x_{it} + \beta_{2i(\%REC)}x_{it}^2 + e_{i(\%REC)}], \qquad (1)$$

where y_{itk*} is a measure for team i at time t for variable $k*$; δ_{score} and $\delta_{\%REC}$ are dummy variables for team performance (score) and %REC. Time for team i at trial t is captured by x_{it}, while the quadratic effect of time is captured by x_{it}^2. The effect the j^{th} session for team i is captured by x_{ij}. The β coefficients were specified to capture fixed means for all variables, random effects for the intercepts of performance and %REC, the first and second order effects of trial on performance, the first order effect of trial on %REC, and random effects for these later components. As a final test for dependency between growth trajectories of %REC and performance, an alternative model with the same form as (1) was constructed, but the constraints forcing non-interacting variances and covariances of random effects between performance and %REC were relaxed.

RESULTS

Plots for performance, %REC, and %REC surrogate analyses as a function of trial can be seen in Figure 2. There is an obvious upward trend for performance, with a decreasing slope as a function of trial. Similar observations can be made of %REC, though the trends are in the opposite directions. A single sample t-test comparing the average %REC for each team against the average surrogate %REC shows that %REC for actual teams was higher than what would be expected by chance alone, $t(20) = 4.88$, $p < .001$, though this difference lessens over time.

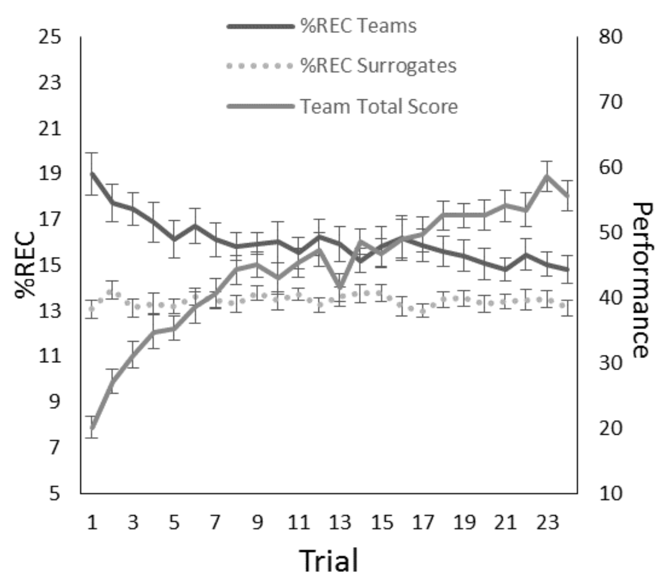

Figure 2. Mean values of %REC of team gaze data, %REC of surrogate gaze data, and team performance plotted against trial. Error bars represent ±1 standard error of the mean.

The final multivariate model allowing covariances between random effects estimated for %REC and performance resulted in a significantly better fit compared to the null model, -2LLχ^2 (6) = 17.48, p = .001, meaning that there were significant relationships between the growth trajectories of %REC and performance not accounted for by the intravariable fixed and random effects. Parameter estimates from the final multivariate model can be seen in Tables 1 and 2, while plots of the estimated trajectories for each pair can be seen in Figure 3. The significant intercepts for performance and %REC represent the projected average values for the time between trials 12 and 13. The significant linear slope for performance shows that, as trials progressed, teams became better at the task, though the quadratic change in slope in the negative direction indicates that this trend was decreasing over time, likley capturing an asymptotic approach to some ceiling or plateau in peformance. The fixed effect of session on performance means that the observed values in session two were lower than they would have been if the trends from session one continued without interruption. The significant negative slope for %REC shows that, as trials progressed, the joint attention within pairs decreased, though the positive second order change in slope shows that the magnitude of this negative trend decreased over time. In Figure 1, it can be seen that the mean value of %REC was approaching chance levels, possibly indicating that participants were adopting increasingly independent gaze behaviors as time progressed.

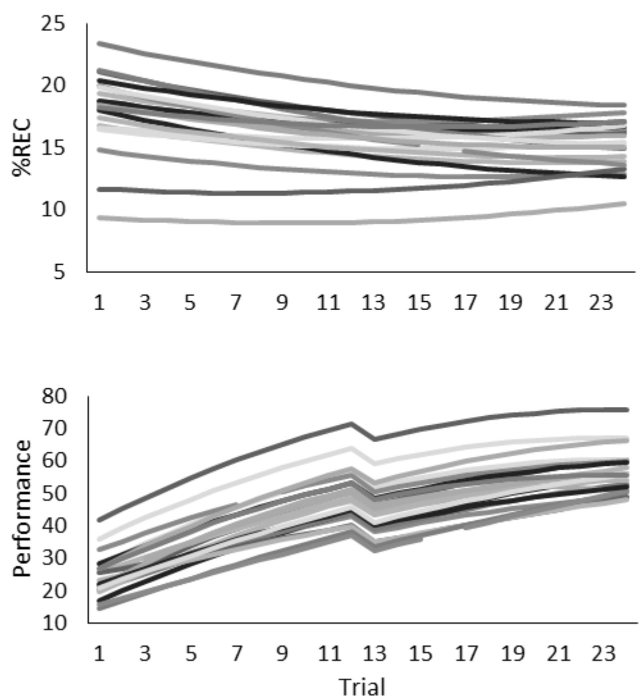

Figure 3. Estimated values of %REC and performance for individual teams, demonstrating the overall growth trajectories captured by the fixed effects, as well as the within group variability modeled by the random effects. Broken lines correspond to the trials that were removed from analysis (either due to missing data or from being flagged as possible outliers).

We were particularly interested in the variation and covariation of random effects of the individual pairs around estimated mean intercepts and slopes. The negative correlation between the intercept of performance and %REC indicates that an increased amount of joint attention above the overall mean was associated with poorer performance, while the positive relation between the slope of %REC and performance indicates that groups with higher %REC slopes tended to have better performance by the end of session one than groups that had lower slopes of %REC. This seems to somewhat contradict the finding that associates higher %REC with lower performance, though it may be explained by positing that groups who started out with relatively low %REC, and thus were likely to have had smaller negative slopes, peformed better than groups that started with high %REC, and thus were likely to have had larger negative slopes. This is supported by the negative relationship between the %REC intercept and slope.

Table 1.
Estimates of Fixed Effects for Multivariate Model

Coefficient	Estimate	SE	*t*	*p*
Performance Intercept	56.435	2.538	22.238	<.001
%REC Intercept	15.654	0.532	29.422	<.001
Performance × Trial	1.672	0.094	17.852	<.001
Performance × Trial ^{2}	-0.049	0.009	-5.402	<.001
Performance × Session	-6.307	1.109	5.686	<.001
%REC × Trial	-0.117	0.026	-4.445	<.001
%REC × Trial ^{2}	0.007	0.002	3.206	0.001

Note. The fixed effects of Performance and %REC intercepts indicate the projected intercepts between sessions 12 and 13

Table 2.
Estimates of Random Effects for Multivariate Model of Change in %REC and Performance

	Variances, Covariances, and Intracorrelations of Random Effects				
	Perf. Intercept	%REC Intercept	Perf. × Trial	Perf. × Trial^2	%REC × Trial
Perf.	47.641	-8.660	0.428	-0.040	0.523
%REC	-0.326	9.657	-0.965	0.048	-0.243
Perf. × Trial	0.138	-0.005	0.577	-0.022	0.025
Perf. × Trial^2	-0.684	0.404	-0.224	0.001	-0.002
%REC × Trial	0.680	-0.521	-0.537	-0.545	0.010
Residual Variances:					
Performance	38.025				
%REC	4.592				

Note. The numbers in the upper right triangle and along the diagonal are variances and covariances, while the numbers in the lower left triangle are correlations. Perf. = Performance.

DISCUSSION

In this study, we evaluated the growth curves of team task performance and joint attention in a complex team-task environment, with special emphasis on the multivariate analysis of the relationship between variations in individual group performance and joint attention around estimated means. We found well-known characteristics of task learning in the performance variable, which increased over time with a decreasingly positive slope, meaning that teams performed asymptotically better as trials progressed. There was also a negative estimated fixed effect of session, indicating a performance retention loss between sessions, but the small magnitude of the decrement indicated an overall net retention of learned behavior. We found a similar curve in joint attention, though in the opposite direction, and without the effect of session. On average, teams started out with a higher degree of joint attention, and this value decreased asymptotically over time. With respect to the relationship between performance and joint attention, we found that lower overall levels of joint attention were positively correlated with better performance, while the slope of joint attention was positively correlated with better performance. These latter findings indicate that teams who started out with lower magnitudes of joint attention decreased less in this measure over time, which is borne out in the negative correlation between %REC intercept and its slope. Finally, we found no effects of friendship on either joint attention or team performance, which indicates that pre-established social ties do not necessarily lead to better performance in a cooperative task.

Our findings with respect to the qualitative change in performance are consistent with prior studies of learning, retention, and retention loss (Adams, 1987). In that our task required coordination and communication between teammates, we expected a positive relationship between task performance and %REC, but found instead a negative relation. We note, however, that our present findings are in line with those of Strang and colleagues (2014), who reported a negative relationship between physio-behavioral coupling and task performance in teams playing a cooperative video game. The authors hypothesized that efficient team strategies might emphasize unique contributions of each individual, which would decrease the overall amount of similar physio-behavioral states. It is possible that the larger magnitudes of joint attention observed in the earlier stage of our present experiment indicated a learning phase, in which participants established a common ground understanding of the task constraints. However, as the task progressed and this common understanding helped establish effective and efficient communication patterns, participants were increasingly free to perform independent roles, possibly with the navigator spending less time looking at the UAV map, and more time engaging in the visual search task. Further investigations into these hypotheses are ongoing.

We did not expect the lack of influence of friendship on performance or joint attention, as prior work has demonstrated that friendship can facilitate performance in decision-making and motor tasks (e.g., Shah & Jehn, 1993). However, a recent meta-analytic review of the effect of friendship on team performance indicates that the positive relationship is mediated by the degree of task interdependence (Chung, 2015). This reinforces our interpretation that role differentiation played a key part in the development of team performance over time.

Limitations of this study include that the task specific constraints likely limit the generalization of our findings across team tasks that demand continuous, uninterrupted collaboration. In this task, once directions are given to the pilot by the navigator, the navigator is free to engage in the visual search task while the pilot controls the UAVs. Tasks in which such behavioral independence is not possible are likely to show relationships between joint attention and performance different from those observed in the present study.

Overall, the results of this experiment provide evidence supporting the use of joint attention and multivariate mixed models in understanding the evolution of team performance in complex, coordinative task environments.

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