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COGNITIVE & PHYSIOLOGIC PERFORMANCE (CPP): PHYSIO BEHAVIORAL COUPLING

Supplementary Analysis

Hana Ulman & Kaleb Embaugh
Mile Two, LLC

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Date: 2024.02.12 13:42:09 -05'00'

ANTONINO DEL ROSSA, 1 Lt, USAF
Program Manager
Applied Cognitive Neuroscience Research Area
Performance Optimization Branch
Air and Space Biosciences Division

WILLIAMS.LOGAN.ANDREW.1273597634

Digitally signed by WILLIAMS.LOGAN.ANDREW.1273597634
Date: 2024.02.12 16:13:50 -05'00'

LOGAN A. WILLIAMS, DR-III, PhD
Human Performance Product Area Lead
Operational Product Section
Product Development Branch
Air and Space Biosciences Division

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14. ABSTRACT
This Supplemental Technical Report summarizes additional analyses on the physiological measurement of individuals in teams, conducted as part of the Cognitive & Physiologic Performance (CPP) research program. These analyses examined whether individuals in a team condition developed physiological concordance, termed “physiobehavioral coupling (PBC),” while working conjointly on a task and if this PBC was related to differential task performance outcomes. The primary objective of the CPP research program is to explore the feasibility of using real time physiological measures to gauge the state of operators working in Distributed Common Ground Systems (DCGS). This is motivated by reports of high levels of stress as well as physical and emotional fatigue, and concerns that these may impact operational readiness and performance.

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1.0 INTRODUCTION

1.1 Motivation for Understanding Team Dynamics

Realizing the importance of human performance to achieving the operational functions of Distributed Common Ground System (DCGS) sites, the goal of the Cognitive & Physiological Performance (CPP) research program is to develop methods appropriate for assessing and monitoring the health and performance capacity of Intel operators. Over the last decade there has been increasing awareness and concerns about the psychological health of the Air Force's 'remote warriors.' These remote warriors are typically stationed safely outside the theater of operation, and are actively engaged in combat (e.g., drone pilots) or Intelligence activities (e.g., full motion video analysts). Though these remote warriors are not under direct threat from an enemy, they are often involved in making and observing the consequences of potentially life and death decisions.

Understanding team dynamics was motivated by the changes within the DCGS from a platform-centric "Process, Exploitation, and Dissemination" structure to an Analysis & Exploitation Team (AET) organization. The shift from Intelligence work in permissive environments to contested or near-peer engagements motivated the DCGS to evolve into the current AET model which is platform agnostic and asks for teams of analysts from different backgrounds to solve increasingly complex problems. In the AET structure each analyst is trained "to think holistically and historically, leveraging, cumulative knowledge, experience, and context to comprehensively and creatively address problems" (Borukhovich & Morton, 2020). The expectation is that the AET format will encourage a "swarm mindset" with increased synergy within the DCGS towards collaborative problem solving. However, there is also the potential that the need for real-time collaboration may introduce other stresses on operators.

Team cognition describes the mental state of team members that enables effective anticipation and coordination to productively complete a task (Niler et al., 2021). At the macro level, team cognition is dependent on a multitude of characteristics that affect the success of the collaborative process, including, but not limited to, decision making, communication, and interpersonal interactions. Prior research examining teamwork and team dynamics has indicated that productive teaming is not necessarily driven by average or maximum individual intelligence, but rather the social sensitivity, distributed turn taking, and gender composition of the group (Wooley et al., 2010).

Design efforts for productive teaming lack an objective and non-invasive means to assess the social dynamics of teamwork (Henning et al., 2009). However, interpersonal coordination dynamics - the way in which behavior, physiology, and emotional state covary between teamed individuals over time – may provide a promising solution. Namely, actions of mimicry that occur as a result of interpersonal coordination dynamics are not deliberate and reflect a spontaneous and unintended response when two individuals perform a cooperative task. Further research has suggested that this phenomenon of mimicry can be extended to team members' physiology (Strang et al., 2014; Henning et al., 2009; Elkins et al., 2009; Henning et al., 2001). Capture of psychophysiological measures (such as, but not limited, to cardiac activity), provides an unobtrusive and objective means to gain insight into a team's social dynamics, readiness, and operational efficiency.

1.2 Physio Behavioral Coupling

Physio-behavioral coupling (PBC) or 'physiological compliance' has been used to describe the phenomena wherein two or more members of a team engaged in a cooperative behavior exhibit similar cortical, autonomic, or behavioral responses. Feasibility of using psychophysiological measures to understand social dynamics has been demonstrated and proposed as an index of collaborative performance (Ahonen et al., 2016). Although PBC is not a novel construct, it is somewhat understudied. Generally, during periods of social interaction more congruent physiological response patterns between teammates is thought to be an index of higher team proficiency (Henning et al., 2001; Henning & Korbelak, 2005). However, some studies have suggested that in the case of differential roles, reduced PBC is related to better performance, as teammates complete their separate, but inter-related tasks (Strang et al., 2014).

Researchers contend that if the physiological signals have a proven relationship to cognitive activity, then the degree of synchronicity may provide a means to identify effective collaboration. Elkins et al., 2009 reported that PBC of inter-beat interval (IBI) data was significantly different in low vs. high performing groups in a "room clearing" task; with higher PBC coupling being indicative of higher performance. Henning and Korbelak, 2005 found that higher cardiac PBC predicted lower error tracking in teams, suggesting that PBC could serve as a predictor for team's performance and ability to manage the unanticipated.

Although the aforementioned studies have suggested that highly synchronized physiological signals may result in a more congruent or productive interaction, it is important to note that the tasks the subjects performed were largely physical in nature. Therefore, it is unsurprising that higher levels of PBC would be associated with better performance when the task inherently requires synchronized physical and cognitive demands between teammates. In military settings, it is not uncommon for individuals within a team to assume differentiated, yet inter-related roles to solve a shared goal. Namely, within the context of Intel operators, a 1N1 (geospatial intelligence analyst) and 1N2 (signals specialization) may analyze intelligence data concurrently, yet independently, and then report their findings to a 1N0 (all source). Hence, it is presumptuous to assume that in the case of differentiated roles, PBC will be highly correlated with performance. We find the possibility of both outcomes to be meaningful contributions to the understanding of physiological indicators of successful collaboration.

To our best knowledge, this is the first study that has examined the feasibility and relevance of PBC to predict the performance of dyads while completing a naturalistic task in the DCGS population.

1.3 Objectives

To this end 4 subgoals have been identified and are outlined below. The first objective aims to implement various methodological practices used in PBC analysis. The next two objectives serve as a validation check on whether PBC exists as a result of collaboration and coordination or are simply due to the inherent nature of the biological signal or experimental task. Lastly, the fourth objective evaluates PBC within the context of the experimental design and paradigm.

(1) Explore various techniques for PBC measurement on IBI time series.

To date there is not a specific gold-standard methodology used to implement PBC analysis. Prior studies have demonstrated success with Cross Correlation (Henning et al., 2005), Cross – Recurrence Quantification Analysis (Konvalinka et al., 2011), Cross-Fuzzy Entropy (Strang et al., 2014), and Magnitude Squared Coherence (Singh, et al., 2018) techniques. The overall goal of this objective was to determine which methodological practice best suits PBC within the context of the present study design. Previous studies have found that these techniques do not always converge on the same pattern of relationships (Strang et al., 2014). Therefore, the impetus for inclusion of these three techniques was largely driven by prior success, with the caveat that success may be contingent on the nature of the task itself. PBC performance will be characterized based off the mean inherent PBC (objective 2), mean PBC from experimental teams, and mean difference scores, in addition to, mean PBC for randomized individual teams (objective 3) and corresponding mean difference scores.

(2) Determine whether PBC between team members is greater than what is expected by chance.

The first objective is to determine whether PBC was a chance occurrence or was influenced by the task environment. It is likely that at some level, PBC will exist due to inherent biological constraints; for example, heart rate values often exist within a range of 50-200 beats per minute (BPM). Therefore, it is not unreasonable to expect a degree of similarity between two disparate time series just by chance alone, regardless of whether the data recorded were from pairs performing a cooperative task.

(3) Determine whether PBC was influenced by interpersonal coordination dynamics.

Examine whether the observed PBC reflected physiological and behavioral responses at the individual level related to the nature of the experimental task or rather, were attributed to interpersonal coordination dynamics. Specifically, if PBC was influenced by the task constraints alone, then it would be expected that the PBC between two individuals completing the task concurrently, yet independently (not working collaboratively) would have high PBC. On the other hand, if PBC was primarily driven by the effects of interpersonal coordination dynamics, it would be expected that team members completing the tasks collaboratively would have a greater PBC than their individual counterparts.

(4) Understand the relationship of PBC as a function of fatigue, task difficulty, and team performance.

Although prior studies have examined PBC in relation to team coordination and performance, to our best knowledge, there are no existing studies that have examined the impact of fatigue state and task demand on PBC. Namely, we aim to characterize how PBC varies across performance levels (top, middle, and bottom performers) related to the experimental manipulations of difficulty and fatigue.

2.0 METHODOLOGY

2.1 Study Design Background

The study followed a 2 x 2 x 2 design with two levels of Difficulty (Hard vs. Easy), Fatigue (High vs. Low), and Team (Individual vs. Pair). Table 1 provides a breakdown of each independent variable. As mentioned previously, the main objective of this report is to explore the relationships associated with team performance. Therefore, only data from the Paired Team condition were included in this writeup.

Table 1. The independent variables and brief descriptions of their manipulations

Independent Variable	Manipulation
Fatigue level	Participants participated in both a Low Fatigue state (i.e., had an 8+ hour break since their last shift) and in a High Fatigue state (i.e., within an hour of ending a shift).
Task Difficulty	The Hard scenario required participants to read more Intelligence documents (total of 12), consider more alternatives, and combine two pieces of a clue spread across two documents to interpret properly. The Easy scenario required less reading (total of 6), fewer options, and did not divide clues amongst the documents.
Teaming level	Participants were either assigned to complete the task working as an Individual or in a Paired Team.

Twenty-four Airmen (9 females; 15 males) between the ages of 18 and 44 years (mean [M]= 26, standard deviation [SD] = 6) completed two experimental sessions. The participants were paired into 12 dyadic teams; teams were self-selected. The following sections explore the manipulations of task Difficulty and Fatigue State in further detail.

2.1.1. Limitations

It is important to note that the current scenarios (described in the following section) were not explicitly designed to examine team coordination and functionality. Perhaps, the cost benefit ratio of coordination and communication were skewed, where the cost of collaboration did not appropriately match the demand for additional individuals working on the task. Furthermore, dyads were composed of a variety of specialties (1N0's, 1N1's, 1N2's, etc.) and ranks, where combinations of backgrounds were not randomized or controlled. Our limitations related to sample composition were related to sample recruitment constraints; to achieve our desired N and meet the requirements for fatigue states, dyads were self-selected and largely comprised of individuals that worked on the same shift together. Future studies would require more challenging scenarios with more explicitly defined team structures.

2.2 Task Difficulty

Scenarios were generated in collaboration with a former USAF commander with over 25 years of experience in the ISR space. The Easy scenario challenged participants to determine the most likely port of origin from which surface-to-air-missile components were being illicitly shipped between two fictitious nation-states. The Hard scenario required analysts to assess the most likely site to which a notional adversary had relocated a surface-to-air-missile weapon system to fill a gap in their air defense coverage.

Both scenarios contained several background documents that outlined the scenario and the task instructions. Specifically, the scenarios included the following: (1) Threat to Joint Operations or Target Systems Analysis; (2) Air Operations Directive or Fragmentary Order; and (3) Request for Information. Each scenario also included operationally relevant Intelligence products that replicated a variety of Intelligence report types from a range of Intelligence specialties, such as human Intelligence, imagery Intelligence, open-source Intelligence, and signals Intelligence. Michigan vs. Ohio (MvO), the Easy scenario, had fewer options to consider, fewer additional reports (allowing more reading time), and treated the information in each document as a complete whole. The Hard scenario, on the other hand, split an important clue across two documents requiring participants to properly interpret the information available (e.g., Clue 1 and Clue 2 were meaningless on their own, but became important in conjunction). It also had more options to consider and more Intelligence documents to act as 'distractors or noise' to decrease the amount of time participants could spend per document. All dyads experienced both levels of Task Difficulty.

2.3 Fatigue State

Fatigue was manipulated using two different testing periods based on participant work schedule. All participants experience both levels of Fatigue over the course of two separate research sessions. The High Fatigue condition was administered at the end of a work shift when fatigue level was expected to be highest due to the time and effort expended during a shift. The Low Fatigue condition was administered prior to a work shift or on a non-working day, with the expectation that the analysts would have been relatively more rested. Specifically, a minimum of eight hours were required to have elapsed since the end of their most recent shift. This manipulation was coordinated with the DCGS leadership to ensure that participation in the study would have minimal impact to readiness and operational performance.

2.4 Physiological Measurement

Wearable, electrocardiography, (H10 Polar Electro, Kempele, Finland) devices were used to collect IBI data at 1000 hertz (Hz). Data were streamed wirelessly to a Microsoft Windows-based laptop via custom software developed by Mile Two, LLC.

2.5 Methods for Measurement of PBC

There is no gold-standard technique used to implement PBC analysis and success is largely dependent on the context in which the data were collected. In response to this we have reviewed various potential methods for measurement. Table 2 details the advantages and disadvantages of using cross correlation, cross recurrence quantification analysis, cross fuzzy entropy, and magnitude squared coherence analysis. The impetus for inclusion of these techniques is motivated largely by previous investigations of PBC where these methodologies were employed (Strang et al., 2014; Henning et al., 2001; Henning and Korbelak, 2005; Konvalinka et al., 2011; Richardson et al., 2005; Xie et al., 2010).

Table 2. Statistical methodologies for PBC implementation on IBI signal

Method	Brief Description	Advantages	Disadvantages
Cross Correlation	Indexes degree of synchronicity between two time series	Associated with a long history to examine bivariate coupling strength	Assumptions of linearity and stationarity
Cross – Recurrence Quantification Analysis	Describes the degree of shared nonlinear temporal structure	No assumption of linearity and stationarity; outputs multiple features of nonlinear coupling	No standard recommendation for the minimum length of time series
Cross Fuzzy Entropy	Quantifies the degree of regularity between two time series	No assumption of periodicity.	Assumption of data stationarity
Magnitude Squared Coherence Analysis	Quantifies the degree of coherence between two signals in the frequency domain	Provides insight into the spectral component of a signal.	Assumption of data stationarity. Compares timepoint to timepoint, potential information loss if there is any lag.

The procedures used to evaluate the first three techniques were taken from Strang et al., 2014. In this study, researchers evaluated the methods of Cross Correlation, Cross Recurrence Quantification Analysis, and Cross Fuzzy Entropy in IBI time series. They found that the Cross Fuzzy Entropy technique demonstrated the greatest success. Other studies have employed the Magnitude Squared Coherence Analysis technique, which motivated its inclusion in this present analysis.

2.6 Parsing the Data

Data were parsed across the duration of the scenario and time aligned across pairs of participants; namely, from when participants started the scenario until they submitted their final report. Participants submitted a joint report, to this end, the submission timestamp for the team member who submitted the final report was used as the end timestamp for both participants.

2.7 Assessing and Correcting for IBI Nonstationary

Nonstationary (data whose statistical properties change across time) was assessed via the Kwiatkowski-Phillips-Schmidt-Shin test (alpha [α] = 0.05) to eαch IBI time-series. All the IBI data included significant nonstationary. To implement Cross Correlation, Cross Fuzzy Entropy and Magnitude Squared Coherence Analysis the data must be stationary; therefore, the data were filtered using a second-order Butterworth filter with a 0.1 Hz high frequency cutoff, where it then met assumption for stationarity.

2.8 Data Processing & Windowing

The filtered IBI time series were then normalized to unit variance for each pair. The resultant array of data for each participant was then windowed into 300 second segments with a 150 second windowed overlap. In total, each participant had a total of 19 data segments.

3.0 RESULTS

3.1 Results for Objective 1: Explore various techniques for PBC measurement on IBI time series.

Each of these techniques provide the means to assess the synchronization of complex systems. This section provides a brief description of each PBC technique and Table 3 provides the output of the corresponding results from the IBI data. The results for each dyad are provided in Appendix A-D.

Of the four techniques, Cross Recurrence Quantification Analysis was the most successful in this present study (results found in sections to follow). Unlike the other techniques, it does not have any assumptions surrounding data stationarity or linearity. Furthermore, it is the only technique that uses nonlinear methods to draw conclusions on the synchronicity of the data across all periods of time between the two IBI time series, whereas the other methods measure the PBC between individuals at each individual timepoint. The descriptions to follow provide a more thorough description of each technique.

3.2 Cross Correlation Analysis

The Cross Correlation analysis examines the degree of association between two time series by accounting for periods of lag that may occur between the two signals (Behrens et al., 2020). Similar to traditional linear correlation, the correlation coefficient exists in a possible range from -1.0 to +1.0, where values that are closer to 1 suggest more identical time series. However, cross correlation differs from traditional correlation because it takes periods of "lags" as a consideration. The lag describes how far the two-time series are offset, and the sign determines whether the first ingested signal is leading (positive) or trailing (negative). As the lag increases, synchronicity decreases. Lag is reported in the same units as the sampling frequency, which in the case of the Polar IBI data would be one second intervals. Therefore, if there is a lag of 20, the time series "likeness" is offset by 20 seconds. For each windowed segment, the maximum cross correlation ('peak cross correlation') was detected across the different lags and subsequently averaged across all segments. The result of these outputs is found in Table 3 below. Furthermore, the maximum cross correlation value for each dyad and corresponding lag is reported in Appendix A.

3.3 Cross Recurrence Quantification Analysis

Cross Recurrence Quantification Analysis quantifies the degree of similar patterning at arbitrary positions between the signals' trajectories (Meyers et al., 2020). Specifically, unlike other methods used to assess synchronicity, cross recurrence quantification analysis does not take the two signals and attempt to align them; rather, all the common patterns in all the arbitrary locations are assessed for synchronicity. Furthermore, cross recurrence is advantageous because it has no assumptions of linearity, stationarity, and can deal with inherently noisy signals, such as physiological data.

A crucial parameter required to perform cross recurrence quantification analysis is the thresholding value, "epsilon", ε. There are numerous strategies used to determine the optimal value for ε; however, the criterion that holds true for a wide class of processes suggests that ε should be five times greater than the SD of the observational noise from the signal (Marwan et al., 2007). The ε for the Polar H10 IBI data was found to be 0.1.

For the purposes of this analysis, percent recurrence (%REC) was determined. %REC represents the proportion of each time series that is exhibited in the other time series, thus providing a measure of temporal symmetry (Brick et al., 2018). Higher %REC values suggest a greater degree of synchronicity, where one time series is more easily predicted by past or current movements of the other time series. Increased determinism and %REC suggest that more patterned behavior is more predictable than a less deterministic one (Brick et al., 2018). The mean %REC is reported in Table 3 and the %REC value for each dyad is reported in Appendix B.

3.4 Cross Fuzzy Entropy

Cross fuzzy entropy analysis is a measure of divergence between two time series. More specifically, cross fuzzy entropy is the negative natural logarithm of the conditional probability of two time series bounded by an exponential function of the shape of two signals' similarity (Xie, et al., 2009). The output is a non-negative number that provides an interpretation of the synchronicity of patterns between the two signals. Smaller values are indicative of greater signal similarity, whereas larger values indicate larger differences in the pattern of the signal's architecture (Xie, et al., 2010). For simplification purposes, the inverse of the Cross Fuzzy Entropy value was taken so that larger numbers reflected a greater degree of similarity and henceforth could be interpreted within the same context of the other PBC techniques. The inverse Cross Fuzzy Entropy value averaged across all dyads is reported in Table 3 below. The inverse Cross Fuzzy Entropy value for each dyad is reported in Appendix C.

3.5 Magnitude Squared Coherence Analysis

The magnitude squared coherence analysis is a normalized measure of linear correlation as a function of frequency (Singh, et al., 2018). Moreover, it provides a means of understanding the degree to which one signal can be predicted from another signal, using a linear model. Values exist between 0 and 1, with greater values indicative of greater linear association across all frequencies. One of the downfalls of this method is that the signals must have exactly the same length. Therefore, unlike the cross correlation analysis it does not take lags into account, but rather, provides a single value for each point in the two time series. Fortunately, IBI signals from both participants were collected using the same computer, so that they both exist in the same system time. However, there may be some inherent time differences between the two signals due to the way that packets of data were transferred from the device (via Bluetooth Low Energy) to the computer. This may be a limitation for this technique. For the purposes of this analysis, the median magnitude squared coherence value was taken for each windowed IBI segment, and then the value from all windowed segments was averaged; this value is shown in Table 3. The magnitude squared coherence value for each dyad is reported in Appendix D.

Comprehensive Summary of PBC Results

Table 3 below provides the outputs for each of the distinct PBC analysis techniques. It is important to note that the metrics provided by each of these analyses are not of the same units. **Therefore, it is crucial that values from each technique are not compared directly against one another.** Because a gold standard technique for PBC analysis has not yet been identified in the literature, it was important for us to systematically implement and evaluate each of these techniques within the context of our experiment's specific condition of interpersonal coordination dynamics.

To assess whether the results from the PBC analysis were generating similar patterns with regards to the relatedness of dyads IBI signals, the corresponding outputs for each technique were ranked. Although the ranked outputs did not align perfectly, generally the dyads within each condition (fatigue X difficulty) fell into the same tercile across all four techniques. Correspondingly, it is reassuring that the PBC techniques are adhering to the same general pattern of similarity with each technique resulting in subtle, nuanced differences when it comes to order.

Table 3. Output of PBC analysis

Method	M ± SE of IBI Dataset
Cross Correlation	0.2874 ± 0.0109
Cross – Recurrence Quantification Analysis	24.2082 ± 0.6731
Cross Fuzzy Entropy	3.889 ± 0.1424
Magnitude Squared Coherence Analysis	0.1538 ± 0.0136

Standard Error (SE)

To provide context and understanding surrounding whether PBC was significant, Objective 2 and Objective 3 characterize the effects of inherent synchronicity and the effects of the nature of the experimental task, respectively. If the results of these two objectives provide a significant difference in the means of the observed PBC and the "synthetic dyads" then we may presume that at some level PBC was attributed to interpersonal coordination dynamics.

3.6 Results for Objective 2: Determine whether PBC between team members is greater than what is expected by chance.

The purpose of this objective was to determine whether PBC was inherent to the task at hand or due to the fundamental nature of relatedness in biological signals. Detrended Fluctuation Analysis (DFA) provides a fractal measure of long-term correlations. One output of the DFA is alpha (α) , which can be indirectly used to identify noise properties of time series. Larger α values indicate more correlation, while smaller values indicate a more chaotic and random dataset. DFA α coefficients can be further categorized as white ($\alpha = 0.5$), pink ($\alpha = 1$), or brown noise ($\alpha = 1.5$) (Almeida, et al., 2013).

Each time series underwent DFA (N=15), and the corresponding α value was averaged across participants ($\alpha = 0.7198$). The result was a time series that most closely resembles pink noise. It has been suggested that as heart rate increases due to stress, α decreases. Namely, α drops below 0.75 at the aerobic threshold. This is interesting because it suggests that the averaged α value reflects a state of increased arousal similar to that of an individual during exercise.

A synthetic dataset of N = 45,000 pink noise (closest α value) datapoints were created and subsequently randomly partitioned into arrays that corresponded to the length of the original IBI time series (approximately N = 3,000 datapoints), to be termed, "the synthetic dataset". These synthetic arrays then underwent the same PBC techniques as the original IBI time series. The results for each of the methods can be found in Table 4 below. Furthermore, a two-sample t-test of unequal variances was performed to compare the means of the IBI dataset and the synthetic pink noise dataset using an α of 0.05. The results from the t-test can also be found in Table 4 below.

Table 4. Results for PBC Analysis on Original IBI Time Series and Synthetic Dataset.

Method	M ± SE of IBI Dataset	M ± SE of Synthetic Dataset	t(df) = t value	Significance Level (p=0.05)
Cross Correlation	0.2874 ± 0.0109	0.1277 ± 0.0077	t(15.197) = 3.1014	p = 0.007**
Cross – Recurrence Quantification Analysis	24.2082 ± 0.6731	95.1378 ± 0.5286	t(21.792) = -103.24	p < 0.0001***
Cross Fuzzy Entropy	3.889 ± 0.1424	959.1475 ± 9.8331	t(14.386) = -235.82	p < 0.0001***
Magnitude Squared Coherence Analysis	0.1538 ± 0.0136	0.1042 ± 0.0057	t(14.031) = 0.9456	p = 0.3603

Degrees of freedom (df)

As shown above in Table 4, there was a significant difference in mean IBI and mean synthetic data for all the PBC techniques, excluding the magnitude squared coherence analysis. As mentioned previously, it is somewhat unsurprising that magnitude squared coherence analysis did not yield significant results when the other methodologies did. This is largely attributed to the fact that magnitude squared coherence analysis only considers each present IBI value in one team member against the corresponding IBI value during that exact same time period in the other team member. Unlike the other techniques, it does not consider the possibility of lag or past / future time periods.

Despite the non-significant results for magnitude squared coherence analysis, the significant results from the other three PBC methods suggest there is substantial evidence that the PBC observed between teammates wasn't a chance occurrence, but most likely influenced by the task environment. The next objective evaluates whether the influence of the environment was related to completion of the task itself, or rather, interpersonal coordination dynamics between teammates.

3.7 Results for Objective 3: Determine whether PBC was influenced by interpersonal coordination dynamics.

The previous objective established that the observed PBC was greater than what was expected by chance. However, it is still possible that PBC reflects physiological and behavioral responses as a byproduct of the experimental task itself. If PBC is a consequence of completing the task, then it would be expected that the PBC between teammates and random individuals completing the same task would be equal. The purpose of this objective was to examine whether two individuals independently completing the same task exhibited comparable PBC to two team members concurrently / collaboratively completing the task. If PBC was primarily driven by the effects of interpersonal coordination dynamics, then it would be expected that teammates completing the task collaboratively would have greater PBC than their individual counterparts.

To evaluate this objective, data from the Individual level of Team (please refer to Section – *Study Design Background* for clarification) were matched to the same level of Fatigue and Difficulty as the data from the Pair level of Team. Appendix E provides a breakdown of this matching and the corresponding PBC outputs. The IBI data from the pseudo teams were pre-processed using the same procedures described in *Section – Assessing and Correcting for IBI Nonstationary Data and Section - Processing and Windowing.* Please note that due to limited N, some individuals were repeated in the analysis. As shown below, Table 5 presents the outputs of the various PBC techniques for the original teams and pseudo teams.

Table 5. Results for PBC Analysis on Original IBI Time Series and Pseudo IBI Time Series.

Method	M ± SE of Original Dataset	M ± SE of Pseudo Dataset	t(df) = t value	Significance Level (p=0.05)
Cross Correlation	0.2874 ± 0.0109	0.2120 ± 0.0071	t(15.476) = 1.4557	0.1655
Cross – Recurrence Quantification Analysis	24.2082 ± 0.6731	19.1292 ± 0.6317	t(16.842) 2.5751=	0.01977*
Cross Fuzzy Entropy	3.889 ± 0.1424	3.2134 ± 0.2359	t(15.624) = 1.3902	0.184
Magnitude Squared Coherence Analysis	0.1538 ± 0.0136	0.1054 ± 0.0058	t(14.026) = 0.9269	0.3696

As shown in Table 5, the only significant result was from the Cross Recurrence Quantification Analysis, where the mean PBC of the original dyads was greater than the PBC in the pseudo dyads. There were no other significant results for the other techniques; however, the PBC was consistently greater in the original dyads than the pseudo dyads. The results from these analyses suggest that

PBC was heavily influenced by the task itself and may not have been attributed to interpersonal coordination dynamics. Furthermore, collaboration may have impacted PBC in some capacity (as noted by the slightly higher PBC in the original dataset), but the extent of its effect was negligible (as noted by mostly nonsignificant results) compared to completion of the task itself. Specifically, the task itself may have elicited physiological responses that were common across all individuals (regardless of completing the scenario independently or collaboratively) while completing scenarios of varying workloads while in a state of high or low fatigue.

3.8 Results for Objective 4: Understand the relationship of PBC as a function of fatigue, task difficulty, and team performance.

Objective's 2 and 3 helped establish whether PBC was 1.) inherent to due to the relatedness of biological signals and 2.) attributed to the constraints and setup of the task itself. The results from these objectives suggest that there was some level of PBC, but it may have been more influenced by the task itself rather than the cost of collaboration. To this end, we examined the effects of Fatigue (High vs. Low) and Difficulty (Hard vs. Easy) on team's PBC by performing 2 x 2 ANOVA's. The results are found in Table 6 below. There were no significant differences across PBC techniques as a function of Fatigue, Difficulty, or the interaction between Fatigue and Difficulty.

Table 6. 2x2 ANOVA results for PBC as a function of Task Difficulty and Fatigue State

		ANOVA Results	
Method		**F(df) = F value**	**Significance Level (p=0.05)**
Cross Correlation	Fatigue:	F(1) = 0.947	0.351
	Difficulty:	F(1) = 1.621	0.229
	Fatigue X Difficulty:	F(1) = 1.948	0.190
Cross – Recurrence Quantification Analysis	Fatigue:	F(1) = 0.706	0.419
	Difficulty:	F(1) =0.546	0.475
	Fatigue X Difficulty:	F(1) =2.193	0.167
Cross Fuzzy Entropy	Fatigue:	F(1) = 0.111	0.746
	Difficulty:	F(1) = 0.123	0.732
	Fatigue X Difficulty:	F(1) = 0.506	0.491
Magnitude Squared Coherence Analysis	Fatigue:	F(1) = 1.189	0.299
	Difficulty:	F(1) = 1.573	0.236
	Fatigue X Difficulty:	F(1) = 1.723	0.216

Fisher's statistic value (F)

Previous literature has suggested that differences in performance can yield detectable differences in PBC (Ahonen et al., 2016; Elkins et al., 2009); however, this was not found in our results. As shown in Table 7, there were no significant differences in PBC as a function of performance across all four techniques. Furthermore, there was no clear pattern or trend in PBC across different performance levels. Given our limited N, this is somewhat unsurprising, as there were only three top performing, 11 middle performing, and 1 bottom performing team datasets that were usable for this analysis. Furthermore, the nature of the task was largely cognitive in nature and did not inherently elicit great deviations in physiology.

Table 7. One Way ANOVA results for PBC as a function of Performance

Method		**M ± SE PBC**	**F(df) = F value**	**Significance Level (p=0.05)**
Cross Correlation	Top:	0.23 ± 0.01	F(2) = 0.21	0.813
	Middle:	0.31 ± 0.07		
	Bottom:	0.24		
Cross – Recurrence Quantification Analysis	Top:	26.33 ± 0.92	F(2) = 1.859	0.198
	Middle:	23.77 ± 0.69		
	Bottom:	22.68		
Cross Fuzzy Entropy	Top:	3.35 ± 0.11	F(2) = 0.65	0.54
	Middle:	3.86 ± 0.62		
	Bottom:	5.81		
Magnitude Squared Coherence Analysis	Top:	0.10 ± 0	F(2) = 0.147	0.856
	Middle:	0.17 ± 0.07		
	Bottom:	0.11		

4.0 DISCUSSION

The motivation for these analyses was to explore the relationship between PBC and performance. To this end, four objectives were evaluated to appropriately characterize this relationship. The first objective was to implement various PBC analysis techniques. Four techniques were applied on the IBI data: Cross Correlation, Cross Recurrence Quantification Analysis, Cross Fuzzy Entropy, and Magnitude Squared Coherence Analysis. PBC results from these techniques generally yielded the same trends across the remaining objectives, which increased confidence and credibility in the practices and methods used to generate each analysis. However, of the four techniques, Cross Recurrence Quantification Analysis was the most successful. Cross Recurrence Quantification Analysis is the only technique that assessed synchronicity at arbitrary timepoints, opposed to measuring the synchronicity of each aligned IBI value, moment to moment in time. Furthermore, this technique had the least number of assumptions and criteria that needed to be met to implement the technique. Due to the nonstationary nature and noise related to physiological processes, we recommend that Cross Recurrence Quantification Analysis be considered when conducting PBC analysis.

Following successful implementation of the various PBC techniques, the second objective aimed to determine whether PBC during the experimental task significantly differed from synthetic, “inherent” PBC that occurred due to the relatedness of biological signals. Synthetic data was generated by determining the noise level of the original IBI dataset via DFA. Results from the DFA suggested that the IBI dataset most closely resembled pink noise, which is common in biological signals. The synthetic, pink noise dataset underwent the four PBC analysis techniques. PBC in the original dataset was significantly different from PBC in the synthetic dataset in all the techniques, excluding Magnitude Squared Coherence Analysis. Findings from this objective suggest that the PBC found in the original IBI dataset was not attributed to the inherent relatedness of biological data but was rather related to the task environment itself.

The previous objective did not establish whether PBC was due to interpersonal coordination dynamics, or was rather, attributed to the individual level constraints and demands of the task itself. Therefore, the third objective aimed to characterize the relative influence of individual task demands and whether these demands more heavily influenced the outcomes of PBC rather than the demands of interpersonal coordination dynamics. Namely, if two individuals simultaneously, yet disjointly, worked the same task, we would expect that the cognitive demands and their subsequent physiological reactivity would be similar. However, if two individuals were asked to collaboratively complete the task, then the added demands of communicating and working together may evoke a different response in some teams, versus others. To this end, pseudo teams were created by randomly selecting individuals that were completing the same task with the same level of difficulty and fatigue level. PBC analysis was conducted on the pseudo teams; Cross Recurrence Quantification Analysis was the only PBC technique that produced significantly different results between the original dyads and pseudo dyads. The results from Cross Recurrence Quantification Analysis suggest that at some level, interpersonal coordination dynamics were driving IBI PBC. However, this pattern was not observed in the other three PBC analysis techniques. Therefore, we speculate that the observed PBC was predominantly driven by the task constraints rather than as a byproduct of collaboration. Often, the dyads each addressed the Request for Information independently and then worked collaboratively to generate the joint report. During these independent work periods, the degree of interpersonal coordination dynamics would be negligible and would consequently be of a similar premise by which the pseudo teams were established.

Although it was established that the nature of the task itself was most likely the main contributor to PBC amongst dyads, the effects of performance, fatigue, and workload were still evaluated. There were no significant differences in PBC as a function of fatigue and workload or performance. This is somewhat unsurprising; PBC generally provides a moment-to-moment measure of synchronicity between two individuals, and the manipulations of fatigue, workload, and effects of performance were not designed to elicit moment-to-moment changes. Results from the initial Study 2 Technical Report found that there were significant differences in high frequency and low frequency heart rate variability (HRV) as a function of performance; however, this was assessed for each individual within the team and averaged across the entire scenario duration. Moreover, the study was designed to evaluate overall fatigue and workload throughout the entire scenario duration; therefore, it makes sense that there would be significant differences in averaged measures but not high-resolution measures. Furthermore, the nature of the task itself was sedentary in nature and did not introduce stressful stimuli that would evoke large deviations in individual's physiology. Of similar note, the dyads were unconstrained in how they approached the Request for Information (to mimic a naturalistic environment); therefore, there were no explicit points in time where participants were forced to communicate or collaborate in a specific way.

Advanced time series analysis enables the estimation of near-real-time PBC which can have significant implications for understanding team functionality as function of workload, fatigue, etc. In some settings, post-hoc analysis of data is not always beneficial in driving operational success and therefore solutions such as near-real-time monitoring of team dynamics can provide insight into team functioning and on the floor solutions in non-optimal situations. However, the results from this exploratory analysis provides insight into the importance of context dependent applications of PBC. Previous studies have demonstrated great success in measuring PBC while participants completed tasks that required more direct communication and collaboration. The biggest limitation of this study was that it was not originally intended to evaluate PBC; future studies should take more deliberate steps to ensure that interpersonal coordination is occurring throughout the entire scenario duration. Furthermore, other HRV parameters, particularly in the frequency domain, should be evaluated across time.

5.0 CONCLUSION

The primary intent of this supplementary analysis was to characterize whether PBC existed between dyads while completing a scenario in a synthetic task environment resembling analysts' operational work. Four different PBC techniques were evaluated, and Cross Recurrence Quantification Analysis did yield significantly different mean PBC when compared to synthetic, "inherent" PBC data and pseudo dyad IBI data. Ultimately, the results from this study suggest that at some level PBC exists, but it may be more heavily influenced by the nature of the task itself rather than as a byproduct of interpersonal coordination dynamics. To our best knowledge this is the first study to evaluate PBC within the context of intelligence analysis as a function of workload, fatigue, and performance. Although PBC was not significantly impacted by workload, fatigue, or performance, this may have been attributed to our limited N and naturalistic design of the study. Future studies should incorporate greater sample sizes and team sizes to further explore the effects of PBC on performance while also using various HRV or other physiological parameters.

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APPENDIX A: OUTPUTS OF CROSS CORRELATION FOR EACH PARTICIPANT

Team ID	Fatigue State	Scenario Difficulty	Mean of Dyad	Lag
A	High	Califon Hard	0.2599 ± 0.0120	23
	Low	MvO Easy	0.2691 ± 0.0114	23
B	High	Califon Hard	0.2368 ± 0.0141	19
	Low	MvO Easy	0.9910 ± 5.8534 X 10^{-4}	27
C	High	Califon Hard	0.2355 ± 0.0098	15
D	High	MvO Easy	0.2249 ± 0.0089	22
	Low	Califon Hard	0.2427 ± 0.0110	24
E	High	Califon Hard	0.2479 ± 0.0097	24
I	Low	Califon Hard	0.2113 ± 0.0098	19
J	High	MvO Easy	0.2606 ± 0.0269	25
	Low	Califon Hard	0.2115 ± 0.0106	20
K	High	Califon Hard	0.2310 ± 0.0108	23
	Low	MvO Easy	0.2249 ± 0.0090	19
L	High	MvO Easy	0.2354 ± 0.0097	20
	Low	Califon Hard	0.2290 ± .0096	16
		Total (Mean ± SE):	0.2874 ± 0.0109	21

APPENDIX B: OUTPUTS OF CROSS RECURRENCE QUANTIFICATION ANALYSIS FOR EACH PARTICIPANT

Team ID	Fatigue State	Scenario Difficulty	Mean ± SE of IBI Dataset
A	High	Califon Hard	24.3924 ± 0.5003
	Low	MvO Easy	23.2279 ± 0.5335
B	High	Califon Hard	22.6822 ± 1.1673
	Low	MvO Easy	25.6599 ± 1.8722
C	High	Califon Hard	26.0678 ± 0.3095
D	High	MvO Easy	22.8300 ± 0.3487
	Low	Califon Hard	26.2407 ± 0.5088
E	High	Califon Hard	25.7466 ± 0.6512
I	Low	Califon Hard	21.0239 ± 0.3704
J	High	MvO Easy	26.8148 ± 0.7721
	Low	Califon Hard	28.0330 ± 0.5845
K	High	Califon Hard	24.8919 ± 0.5757
	Low	MvO Easy	24.1790 ± 0.5949
L	High	MvO Easy	19.7700 ± 0.7974
	Low	Califon Hard	21.5632 ± 0.5103
		Total (Mean ± SE):	24.2082 ± 0.6731

APPENDIX C: OUTPUTS OF CROSS FUZZY ENTROPY FOR EACH PARTICIPANT

Team ID	**Fatigue State**	**Scenario Difficulty**	**Mean ± SE of IBI Dataset**
A	High	Califon Hard	3.9530 ± 0.1534
	Low	MvO Easy	3.2667 ± 0.0916
B	High	Califon Hard	5.8101 ± 0.1689
	Low	MvO Easy	9.9246 ± 0.8678
C	High	Califon Hard	3.4122 ± 0.0694
D	High	MvO Easy	2.6724 ± 0.0420
	Low	Califon Hard	3.6811 ± 0.0779
E	High	Califon Hard	3.2025 ± 0.0884
I	Low	Califon Hard	2.9821 ± 0.0450
J	High	MvO Easy	3.7772 ± 0.1628
	Low	Califon Hard	3.5032 ± 0.1028
K	High	Califon Hard	3.1305 ± 0.0777
	Low	MvO Easy	2.767 ± 0.0570
L	High	MvO Easy	2.9141 ± 0.0710
	Low	Califon Hard	3.3315 ± 0.0596
		Total (Mean ± SE):	3.8886 ± 0.1424

APPENDIX D: OUTPUTS OF MAGNITUDE SQUARED COHERENCE ANALYSIS FOR EACH PARTICIPANT

Team ID	**Fatigue State**	**Scenario Difficulty**	**Mean ± SE of IBI Dataset**
A	High	Califon Hard	0.1017 ± 0.0065
	Low	MvO Easy	0.1092 ± 0.0072
B	High	Califon Hard	0.1065 ± 0.0085
	Low	MvO Easy	0.8844 ± 0.0969
C	High	Califon Hard	0.1035 ± 0.0081
D	High	MvO Easy	0.1022 ± 0.0066
	Low	Califon Hard	0.1004 ± 0.0068
E	High	Califon Hard	0.0929 ± 0.0050
I	Low	Califon Hard	0.0892 ± 0.0060
J	High	MvO Easy	0.0986 ± 0.0088
	Low	Califon Hard	0.1012 ± 0.0088
K	High	Califon Hard	0.1038 ± 0.0088
	Low	MvO Easy	0.1058 ± 0.0061
L	High	MvO Easy	0.1085 ± 0.0156
	Low	Califon Hard	0.0987 ± 0.0050
		Total (Mean ± SE):	0.1538 ± 0.0136

APPENDIX E: MATCHING INDIVIDUALS TO PAIRS

(NOTE: CC = Cross Correlation; CRQ = Cross Recurrence Quantification; CFEn = Cross Fuzzy Entropy; MSQ = Magnitude Squared Coherence Quantification)

Team ID	Fatigue State	Scenario Difficulty	Individual IDs	CC	CC Std. Error	CRQ	CRQ Std. Error	CFEn	CFEn Std. Error	MSCQ	MSCQ Std. Error
A	High	Califon Hard	1027 & 1029	0.2229	0.0096	13.9093	0.6681	2.7037	0.0648	0.0988	0.0069
	Low	MvO Easy	1027 & 1029	0.2099	0.0061	18.0099	0.8536	2.9111	0.1045	0.1064	0.0056
B	High	Califon Hard	1020 & 1023	0.2162	0.0046	18.1878	0.3774	2.5897	0.0633	0.1022	0.0044
	Low	MvO Easy	1020 & 1023	0.2241	0.0079	21.6664	0.7247	3.2722	0.0970	0.1009	0.0057
C	High	Califon Hard	1026 & 1010	0.1148	0.0074	0	0	4.1337	1.4598	0.1031	0.0062
D	High	MvO Easy	1002 & 1003	0.2546	0.0072	22.7094	0.4563	3.4077	0.1267	0.1016	0.0049
	Low	Califon Hard	1002 & 1003	0.2151	0.0071	19.4345	0.7661	3.5518	0.1238	0.1037	0.0060
E	High	Califon Hard	1006 & 1010	0.2325	0.0060	25.1296	0.5045	2.9482	0.0793	0.1105	0.0063
I	Low	Califon Hard	1002 & 1007	0.2310	0.0070	24.9281	0.4998	3.6720	0.0996	0.0978	0.0050
J	High	MvO Easy	1007 & 1032	0.2214	0.0100	21.8648	0.7474	3.2794	0.1115	0.1082	0.0075
	Low	Califon Hard	1019 & 1007	0.2338	0.0066	25.2026	0.3588	3.4453	0.0735	0.1039	0.0046
K	High	Califon Hard	1020 & 1026	0.1006	0.0044	6.5244	2.1197	2.6445	0.8921	0.1112	0.0067
	Low	MvO Easy	1020 & 1026	0.2623	0.0108	22.8710	0.5243	3.0278	0.0737	0.1120	0.0081
L	High	MvO Easy	1002 & 1007	0.2105	0.0047	21.6003	0.4317	2.9416	0.0697	0.1206	0.0037
	Low	Califon Hard	1002 & 1007	0.2310	0.0070	24.9001	0.4436	3.6720	0.0996	0.0995	0.0057
			Total (Mean ± SE):	**0.2120**	**0.0071**	**19.1292**	**0.6317**	**3.2134**	**0.2359**	**0.1054**	**0.0058**

LIST OF ABBREVIATIONS, ACRONYMS, AND SYMBOLS

1N0	All source Intelligence analyst
1N1	Geospatial Intelligence analyst
1N2	Signals Intelligence analyst
α	Alpha value
AET	Analysis & Exploitation Team
CPP	Cognitive & Physiological Performance
DCGS	Distributed Common Ground System
df	Degrees of Freedom
DFA	Detrended Fluctuation Analysis
ε	Epsilon value
F	Fisher's statistic value
HRV	Heart Rate Variability
Hz	Hertz
IBI	Inter-beat Interval
M	Mean
MvO	Michigan vs. Ohio scenario
N	Sample Size
p	Probability
PBC	Physio-behavioral Coupling
SD	Standard Deviation
SE	Standard Error
t	Student's *t*-statistic
%REC	Percent recurrence