SPECIAL ISSUE: Exploring Cognitive Readiness in Complex Operational Environments: Advances in Theory and Practice, Part I

Predicting Team Performance in a Dynamic Environment: A Team Psychophysiological Approach to Measuring Cognitive Readiness

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ABSTRACT: Teams that operate in complex and dynamic environments must maintain a certain level of cognitive readiness among team members to ensure high levels of performance in response to potentially uncertain and time sensitive situations. In the current study, the authors sought to identify a physiological measure that could help predict team performance during a complex and dynamic task. Specifically, they examined whether measuring team members' autonomic nervous system activity could predict subsequent performance on a dynamic process control task. Thirty-four teams of two (35 males, 33 females) completed a processing plant simulation during four varying levels of individual and team difficulty. Sympathetic and parasympathetic nervous system activity was measured throughout the task with an electrocardiogram and an impedance cardiogram and was combined to create a measure of team autonomic activity. Regression analyses showed that team autonomic activity accounted for 10% of the variance in team performance scores. In conclusion, the current study showed that team performance can be predicted from team autonomic activity, which supports the argument that a team's physiological state could serve as an indicator of cognitive readiness.

KEYWORDS: team psychophysiology, team performance, cognitive readiness, process control

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Introduction

Teams that operate in complex and dynamic environments must maintain a certain level of cognitive readiness among team members to ensure high levels of performance in response to potentially uncertain and time-sensitive situations. There are several varying definitions of cognitive readiness (Bolstad, Cuevas, Costello, & Babbitt, 2008; Consenzo, Fatkin, & Patton, 2007; Morrison & Fletcher, 2002). However, it is generally defined as the knowledge, skills, and abilities (KSAs) required to establish and sustain competent performance levels during a unique performance episode. More specifically, some authors suggest that there are a number of states (e.g., stress and fatigue) and/or external factors that can have an effect on the level of cognitive readiness that a person is able to achieve (Bolstad, Cuevas, Babbitt, Semple, & Vestewig, 2006; Consenzo et al., 2007; Wesensten, Belenky, & Balkin, 2005). Although KSAs can be relatively stable on the magnitude of hours or days, states and other external factors can change constantly, suggesting that near-term changes in cognitive readiness might be more closely associated with shifts in these transient factors. Therefore, measures of an individual's or team's state, such as physiological state, could help assess cognitive readiness in real or near-real time.

In the current study, we sought to identify a measure of team physiological state that could help predict team performance during a complex and dynamic task. We hypothesized that since the definition of cognitive readiness involves the maintenance of performance, one way to determine the effectiveness of a cognitive readiness index would be to measure its ability to predict performance. Drawing on team performance literature, we proposed a psychophysiological approach to the measurement of cognitive readiness of two-person teams (e.g., Henning & Korbelak, 2005). More specifically, this study examined whether the measurement of team members' autonomic nervous system activity could predict subsequent performance on a dynamic process control task.

Objective physiological measures of individual performance have been extensively studied (e.g., Ash & Backs, 2000; Backs, 1998; Lenneman & Backs, 2000), primarily in the context of assessing operator state (e.g., workload), but the formulation of team-based physiological measures has only recently gained prominence in the literature. Studies examining team work and team training have occasionally used psychophysiological measures to investigate individual characteristics of team members (Cacioppo & Petty, 1983), but few studies examine the psychophysiology of the team as a whole. The team-based psychophysiological measure used in those studies was physiological compliance, which has been defined as physiological changes, in two or more people, of a joint nature (Smith & Smith, 1987). Physiological compliance can also be defined as the correlation of physiological measures between team members. Team members whose physiological signals show a greater degree of corresponding change are said to be more compliant. Currently, physiological compliance is the only measure of a team's psychophysiological activity that has been examined in the literature.

Physiological compliance has been used in the past to investigate social and emotional interactions between pairs of people, more specifically, between clinical therapists and clients and between married couples. Several studies have found that the physiology of therapists and clients covary throughout the course of a counseling session (Dimascio, Boyd, Greenblatt, & Solomon, 1955; Malmo, Boag, & Smith, 1957). Studies using married couples have found that physiological compliance can help differentiate whether couples "liked" or "disliked" one another (Kaplan, Burch, & Bloom, 1964) as well as account for some of the variance in marital satisfaction (Levenson & Gottman, 1983). Hatfield, Cacioppo, and Rapson (1994) suggested that these results provide evidence that increased physiological compliance can accompany periods of intense shared emotions.

Henning, Boucsein, and Gil (2001) applied the idea of social-emotional physiological compliance to the context of team performance. The authors measured electrodermal activity, heart rate, and respiration rate of two-person teams while they completed a complex, cooperative tracking task. The task simulated the telemanipulation of an inertial mass through a 2-D path that was controlled by combined joystick inputs from the two team members. This was a projective tracking task, and therefore the team members could communicate and plan for upcoming actions. The results showed that increased physiological compliance of heart rate between the team members was correlated with decreased task completion time and tracking error.

A follow-up study by Henning and Korbelak (2005) investigated the possibility of using physiological compliance as a predictor of task performance. Again, teams of two completed the same tracking task mentioned previously, but in this study, the teams also experienced unexpected shifts in the task control dynamics. These unexpected shifts in task control dynamics were used as an anchor around which to measure the relation between physiological compliance and future task performance. The authors found that physiological compliance before shifts in control dynamics predicted team performance following the change in control dynamics. Teams with greater physiological compliance more effectively adjusted to the changing demands of the control task. This finding suggests that physiological compliance can potentially be used to determine the best pairing of team members (i.e., selection) or as an evaluation of a team's level of training or preparedness (i.e., cognitive readiness).

Recently, Elkins et al. (2009) examined the relation between physiological compliance and performance in teams completing a complex, dynamic task. In this study, participants were trained to perform a military tactic known as building clearing. Building clearing involves a team of soldiers moving through a building searching for combatants and noncombatants. Physiological compliance was recorded during training and compared with each team's performance during subsequent testing. Physiological compliance for measures of parasympathetic nervous system (PNS) cardiac activity, specifically, respiratory sinus arrhythmia (RSA), during training were positively correlated with team performance during testing (Elkins et al., 2009). Interestingly, the correlation between RSA measures was not attributed to physical coactivation, since the task being performed was dynamic and involved different team members fulfilling different roles on the team.

Previous studies have used a variety of physiological measures to assess team autonomic activity. Those measures include electrodermal activity (Henning et al., 2001), respiration (Henning et al., 2001), electromyography (Malmo et al., 1957), and heart rate variability (HRV; e.g., Elkins et al., 2009; Henning, Armstead, & Ferris, 2009; Henning & Korbelak, 2005). Of these studies, HRV, or more specifically, RSA, has been the most promising measure of physiological compliance. RSA is a well-validated measure of PNS influence on the heart (Berntson, Cacioppo, & Quigley, 1994; Grossman, Stemmler, & Meinhardt, 1990). However, previous literature suggests that to obtain a more complete understanding of full autonomic nervous system (ANS) influence on the heart, researchers need to measure both PNS and sympathetic nervous system (SNS) influences (Berntson, Cacioppo, & Quigley, 1991).

Current Study

The purpose of the current study was to investigate the relations between team autonomic activity and team performance to determine whether team physiological state might be an acceptable index of cognitive readiness. Autonomic activity provided a potentially useful conceptual framework from which to devise an objective cardiovascular measure to predict performance and thereby index cognitive readiness. The current study used a two-person process control simulation to investigate the relations between these constructs. Using this simulation, we manipulated the amount of individual and team difficulty while cardiovascular autonomic activity and performance were measured and compared. On the basis of previous research that shows that correlation of physiological indices between team members can predict team performance on a variety of tasks (Elkins et al., 2009; Henning & Korbelak, 2005), we was hypothesized that team autonomic activity could be used to predict team performance.

Method

Participants

Initially, 86 college students (43 teams) participated in the current study. Out of those 43 teams, 34 (12 male teams, 11 female teams, and 11 mixed-gender teams) provided complete autonomic activity data and were included in the study's analyses. Participants were screened to ensure that they were in good health, and those with abnormal heart problems were excluded from participation. After enrolling in the study, participants were told to abstain from alcohol, tobacco, drugs, and vigorous exercise for at least 8 hr before they arrived for a laboratory session.

Apparatus

Electrocardiogram. Electrocardiography (ECG) data were collected to derive RSA, a well-validated index of PNS activity on the heart (Berntson, Cacioppo, & Quigley, 1994; Grossman et al., 1990). ECG data were collected with the use of a Biopac ECG unit (Biopac Systems, Goleta, CA) and an ambulatory monitoring system (VU-AMS; Vrije Universiteit, Amsterdam, Netherlands). A three-lead configuration was used to record the ECG: One active electrode was placed on the collar bone 2 in. to the right of the sternum, another active electrode was placed on the second-to-last rib on the participant's left side, and a reference electrode was placed 3 in. to the right of the participant's naval.

Impedance cardiogram. Impedance cardiography (ICG) data were collected to derive preejection period (PEP) and left ventricular ejection time (LVET), both of which are inverse indices of SNS activity (Berntson, Cacioppo, Binkley, et al., 1994; Thayer & Uijtdehaage, 2001). The ECG data coupled with the ICG data allowed for a comprehensive assessment of ANS activity of the cardiovascular system. ICG data were collected with the use of a NICO100C unit (Biopac Systems, Goleta, CA) and a VU-AMS (Vrije Universiteit, Amsterdam, Netherlands). Participants were randomly assigned to each system, with the constraint that there was a relative equal number of males and females at each unit. The NICO100C recorded data for 18 males and 16 females. The VU-AMS recorded data for 17 males and 17 females. The electrodes were placed at anatomical levels in accordance with the standard tetra-polar configuration suggested by Sherwood et al. (1990). Specifically, one current electrode was placed at the C4 vertebra and one between the T8 and T9 vertebrae. One voltage (or recording) electrode was placed on the anterior surface of the neck at the level of suprasternal notch and one at the bottom of the sternum at the xiphoid process. This pair of electrodes was used to measure the resulting voltage conducted between the two current electrodes.

Process control simulation. The task used in this study was a process control simulation whereby participants had to monitor the functioning of a simulated chemical plant and ensure that they maintained safe levels of operation while maximizing the amount of throughput (Switzer & Idaszak, 1989). The process control simulation contained five tanks that were monitored so that the aforementioned goals were attained. Each operator was personally responsible for two of the tanks; another tank was located between the operators and was a shared responsibility. Each tank had three gauges or parameters that were monitored and adjusted: temperature, level, and pressure. The only exception was the center tank, for which only level and pressure were adjusted; temperature was controlled automatically.

Operators had to monitor both of their tanks simultaneously (Figure 1) and zoom in on one tank when one or more of its gauges deviated from safe levels to correct the problem. Both operators had to be aware of the shared tank in the middle (Figure 1) and communicated with each other so that its parameters stayed within a safe range of operation. If the parameters of the middle tank moved outside of safe levels, then the operators had to decide who was going to take action to correct the problem.

The process control simulation was set up so that the "chemical" or "product" entered from the left side of the system, passing into Tank A1 (Operator A's first

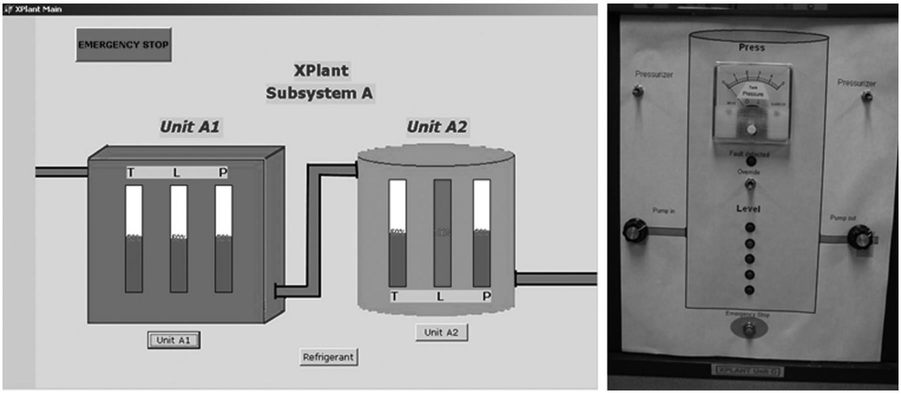

Figure 1. Example of the two tanks each operator was responsible for (left) and the center console that both operators controlled (right).

tank). The product then flowed from Tank A1 into Tank A2 and from Tank A2 into the center tank with its shared responsibility. From the center tank, the product flowed into Tank B1, where it became Operator B's responsibility. From Tank B1, the product flowed into Tank B2, and from B2, it was processed out of the system. The input for Tank A1 controlled the amount of product entering the entire process control simulation at any one time, and the output of Tank B2 controlled the amount of product leaving the entire system at any one time. Since the process control simulation consisted of this linear layout, Operator A and Operator B had to coordinate in an effort to keep total system input and output as similar as possible.

In the process control simulation task, difficulty could be manipulated on both the individual and the team level. The three parameters for each tank could be displayed as a curve (a sine wave in the current study) over time, which represented the state of each parameter if no action was taken by the operator. Task difficulty could be increased by an increase in the amplitude and/or frequency of the sine wave that controlled the computer-mediated variability for each parameter. Deviations in the parameters of the individual tanks would not directly affect the other operator. Team difficulty was manipulated through the level and pressure of the center console. The center console was a shared responsibility, and therefore the operators coordinated between themselves to control its parameters. There were two levels of individual task difficulty (low and high) and two levels of team task difficulty (low and high). Task-difficulty-level parameters were set on the basis of a pilot test with novice and expert users of the process control simulation task.

The process control simulation provided performance scores on both the individual and the team level. Individual performance was measured by how much each temperature, level, and pressure parameter deviated from preset, optimum values. The more successful the operator was at controlling his or her tanks, the smaller the deviation. Team performance was measured as the deviation of the center console pressure and level from optimum values, the deviation between the input and output controls for the center console, and the deviation between the system input in Tank A1 and the system output for Tank B2. Ideally, the team communicated so both the input and output of the center console, and input and output of the total system, were adjusted the same amount at the same time. Also, team members communicated to control the level and pressure parameters for the center console as well as the total input and output for the entire system.

Procedure

The current study involved a within-subjects design. Each experimental session involved one team of two completing four trials of varying task workload. After arrival, the participants provided informed consent and completed a brief demographic questionnaire to ensure that they were eligible to participate.

Before the experimental trials began, participants were randomly assigned to Operator Station A or Operator Station B. Because of constraints of the physiological recording equipment, participants remained at the same station for the entire experiment. Participants were then given a brief tutorial that acquainted them with the process control simulation. The tutorial consisted of a 5-min verbal script explaining how to control the simulation and reinforcing the goal of the simulation. The participants were instructed that they were responsible for their own tanks and needed to coordinate with each other to control the center tank. The goal of the task stated that the participants were to work as a team to maximize the amount of product created by the process control simulation while keeping all of the gauges within their safe levels.

Following the tutorial, the participants were allowed 10 min to practice, as a team, using the process control simulation. The experimental session consisted of four separate 10-min trials of varying individual and team difficulty (see Table 1). We chose these particular combinations of task difficulty to provide variability in both workload and performance, including situations in which team members had to handle both balanced and unbalanced difficulty levels. An example of a balanced difficulty level was when both team members had low task difficulty and the team difficulty was low. An example of an unbalanced difficulty level was when one team member had low task difficulty, yet the other team member had high difficulty, and the team task difficulty was high.

The order of the trials was determined by the use of a Latin square technique. At the completion of the experimental session, the participants were disconnected from the physiological equipment and debriefed to explain the experiment.

Data Reduction

Signal processing. The ECG and ICG signals were sampled at a rate of 1000 Hz. Ensemble averaging was used to reduce respiratory influences and movement artifacts in the dZ/dt signal (Kelsey & Guethlein, 1990; Sherwood et al., 1990). Ensemble averaging involved the signal averaging of the digitized dZ/dt and ECG waveforms across consecutive 1-min periods. The process was similar to the

TABLE 1. Permutations of Difficulty Levels

Difficulty Level	Operator A	Team	Operator B
1	Low	Low	Low
2	High	Low	Low
3	Low	High	High
4	High	High	High

signal averaging of event-related potentials except that the signals were time locked to the R-point in the ECG instead of an external marker (Kelsey & Guethlein, 1990). The time-synchronized, digitized signals for each 1-min period were added together and then divided by the number of synced beats. The resulting "averaged" waveform was then used to calculate the systolic time intervals for that time period. Ensemble averaging not only reduces the influences of respiration and movement, but it also makes it easier to identify the necessary points in the ECG and dZ/dt waveforms required to calculate systolic time intervals (Kelsey & Guethlein, 1990). The ensemble averaging was completed with the software provided by each system, and the fiduciary points used to calculate systolic time intervals were identified by hand.

RSA. Prior to the analysis of interbeat interval (IBI) data, the individual IBIs for each participant were examined for errors. If an IBI file contained uncorrectable errors, the file was discarded; those files with correctable errors were corrected by hand. Correctable errors occurred when an R-spike was missed or when a false R-spike was counted. The first type of error produced an abnormally long IBI, which we corrected by splitting it in half, and the second type of error produced two abnormally short IBIs, which were combined to produce one IBI. We used IBI data to derive RSA scores by using a locally designed program that employed the following process. RSA has been consistently validated as a measure of PNS activity at the heart (e.g., Grossman et al., 1990; Grossman, Karemaker, & Wielding, 1991). We resampled the IBI data at 1 Hz by taking the IBI value present at every 1-s interval. Those resampled data were mean centered, windowed in 64-s periods, and submitted to a Hamming window that tapered the ends of each window to zero to reduce leakage. A fast Fourier transform was performed on each 64-s interval of IBI data with 75% overlap. The bin width for the spectral density estimates was set at 0.016 Hz, and the high-frequency range from 0.15 to 0.5 Hz was used as the measure of RSA. Because RSA data do not form a normal distribution, the data were log transformed (logRSA).

When measuring RSA in an experiment, one should consider the effects of respiration. If respiration significantly varies over time, then a correction must be made to the RSA scores (Grossman & Taylor, 2007). In the current study, we examined respiration rate, measured as cycles per minute, across all four trials to determine whether RSA needed to be adjusted.

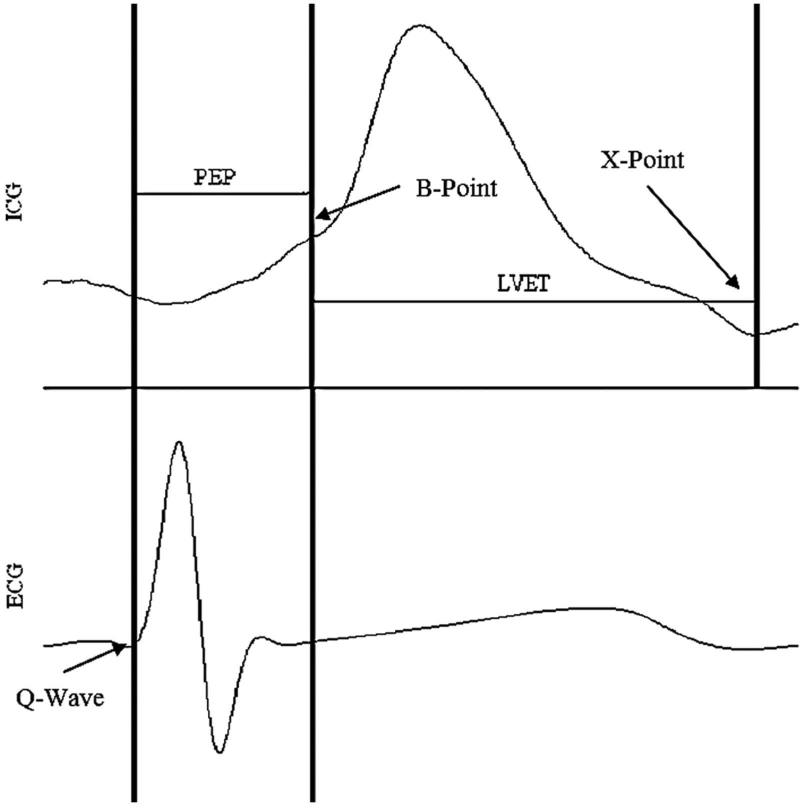

Figure 2. Systolic time intervals.

The location of the high-frequency component of HRV was used to derive participants' respiration rates during this study. Previous research by Thayer, Peasley, and Muth (1996) has shown that the central-frequency location of the high-frequency peak of HRV can be an appropriate index of respiration rate. In their study, they converted the high-frequency peak location into breaths per minute and compared those with respiration frequency as recorded with the use of a mercury strain gauge. The subsequent correlation between the two measures was 0.88 with a resolution of approximately one breath per minute. Therefore, the high-frequency component of HRV is a useful proxy for respiration rate when respiration is not directly measured.

Systolic time intervals. The ICG can be used to derive a variety of different cardiac measures, including cardiac output and systolic time intervals. The current study was concerned with two particular systolic time intervals: PEP and LVET (see Figure 2).

These systolic time intervals have been proposed as indices of SNS activity on the heart (Cacioppo et al., 1994; Thayer & Uijtdehaage, 2001). PEP is the time between the electrical stimulation of the left ventricle (Q-wave) and the physical ejection of the blood from the left ventricle (B-point on the dZ/dt wave). The beginning of the Q-wave on the ECG is often difficult to discern or absent in recordings. Therefore, Berntson, Lozano, Chen, and Cacioppo's (2004) abbreviated PEP, measured from the start of the R-spike to the B-point, was used. Each trial resulted in 10 PEP scores. Therefore, across the four trials, there were 40 PEP scores.

The other systolic time interval that was derived from the ICG was LVET. LVET is the time from the opening of the aorta (B-point) to the closing of the aorta (X-point), or the amount of time it takes for blood to be expelled from the left ventricle. The LVET is measured as the time, in milliseconds, between the B-point and the X-point on the ICG (Sherwood et al., 1990). Each trial resulted in 10 LVET scores. Therefore, across the four trials, there were 40 LVET scores.

Team autonomic activity. Previous research has shown that one of the more effective ways to measure physiological compliance is to correlate the RSA scores between team members over time (Elkins et al., 2009). In the current study, we measured both RSA and an index of SNS activity, either PEP or LVET, and therefore required a somewhat different approach. We used three methods to combine the PNS and SNS indices from each team member into one team autonomic activity score.

The first method included the individual indices of PNS and SNS for each team member in the second step of the regression analysis predicting team error (see Analysis 1 and Analysis 2 in the next section). With this method, we used the regression analyses to combine the individual indices into a team autonomic activity index.

We used the second method to correlate the PNS and SNS scores between the team members. We correlated the 10 logRSA scores for Operator A and the 10 logRSA scores for Operator B to produce a team parasympathetic score for each trial (rlogRSA). Then, we did the same for the 10 PEP (rPEP) and 10 LVET (rLVET) scores of the team members to produce two team sympathetic scores for each trial. See Analysis 3 and Analysis 4.

With the third method, we combined the PNS and SNS scores and then correlated them, which is also known as a canonical correlation (Tabachnick & Fidell, 2001). The canonical correlation worked by creating linear composites of the 10 logRSA, 10 PEP and 10 LVET scores for each trial, for each participant. It then finds the optimal weights for the values to produce the best correlation. The result is one correlation, or team autonomic activity score, for each trial. See Analysis 5.

PC simulator performance (system error). Task performance scores were obtained on an individual and a team level, although in the current study, we were interested only in the team-level error. For the center (team) console, the root mean squared deviation (RMSD) of pressure and level were calculated with the following optimum values: pressure, 6; level, 500. The RMSD was also obtained between the values for the input control knob and the output control knob. Similarly, the RMSD between the values for the total system input and output were also obtained. We added the deviations for these four parameters to produce a total team error score for each trial.

Data Analysis

We conducted five multiple regression analyses to predict performance (i.e., team error) from autonomic activity. Each analysis is referred to as Analysis 1, Analysis 2, and so on. Parameters were estimated with the use of ordinary least squares. Because the current study contained a within-subject repeated-measures variable, task difficulty level was dummy coded, producing a total of three dummy variables (i.e., d_1LLL, d_2HLL, d_3LHH; Neter, Kutner, Nachtsheim, & Wasserman, 1996). Specifically, when the difficulty level for Operator A, the team, and Operator B were all low, d_1LLL = 1, and 0 otherwise. When the difficulty level for Operator A, the team, and Operator B were, respectively, high, low, and low, d_2HLL = 1, and 0 otherwise. When the difficulty level for Operator A, the team, and Operator B were, respectively, low, high, and high, d_3LHH = 1, and 0 otherwise. Thus, the fourth difficulty level served as the reference group. Note that for each regression analysis, task difficulty was entered into the first step.

In Analysis 1 and Analysis 2, the individual measures of PNS and SNS activity for both team members, respectively, were added in the second step, predicting team error. In Analysis 3 and Analysis 4, the correlation between PNS measures and the correlation between SNS measures, respectively, were entered in the second step, predicting team error. In Analysis 5, the canonical correlation between the PNS and SNS measures for both team members was entered in the second step, predicting team error. Additional correlations were also conducted examining the relation between team performance and team autonomic activity at each level of task difficulty.

Results

Table 2 presents the results of the five regression analyses predicting team performance (viz., team error) from team autonomic activity. As can be seen in Step 1 of all the analyses, the proportion of variance accounted for in team error was .10 and was statistically significant. This variance was attributable to the manipulation of task difficulty levels. In Step 2 of Analysis 1, the proportion of variance explained in team error, because of changes in the independent indices of PNS and SNS activity, was .10 and was statistically significant. Specifically, the standard partial regression coefficient for Operator A's LVET was –0.26 ($p < .05$), and the coefficient for Operator B's LVET was –0.15 ($p < .10$). Increases in LVET scores for both operators were associated with decreases in team error, and because LVET is inversely related to SNS activity, these results suggest that as SNS activity for both operators increased team error increased.

In Step 2 of Analysis 2, the proportion of variance explained in team error, because of changes in the independent indices of PNS and SNS activity, was .10 and was statistically significant. More specifically, the standard partial regression coefficient for Operator A's PEP was 0.19 ($p < .05$), and the coefficient for Operator B's PEP was –0.26 ($p < .10$). Unlike in Analysis 1, increases in PEP scores for Operator A were associated with increases in team error, whereas increases in PEP scores for Operator B were associated with decreases in team error. In other

Table 2. Multiple Regression Analyses Predicting Team Error

Variable	R^2	ΔR^2	β	ΔF	*p*
Analysis 1[a]					
Step 1	.10	.10		4.60	<.01
d_1LLL			−.33**		
d_2HLL			−.34**		
d_3LHH			−.20**		
Step 2	.20	.10		3.62	<.01
alogRSA			.05		
blogRSA			−.05		
aLVET			−.26**		
bLVET			−.15*		
Analysis 2[a]					
Step 1	.10	.10		4.60	<.01
d_1LLL			−.33**		
d_2HLL			−.34**		
d_3LHH			−.20**		
Step 2	.20	.10		3.78	<.01
alogRSA			.08		
blogRSA			−.02		
aPEP			.19**		
bPEP			−.26**		
Analysis 3[b]					
Step 1	.10	.10		4.60	<.01
d_1LLL			−.33**		
d_2HLL			−.34**		
d_3LHH			−.19*		
Step 2	.11	.01		.72	>.05
rlogRSA			−.10		
rLVET			−.03		
Analysis 4[a]					
Step 1	.10	.10		4.60	<.01
d_1LLL			−.33**		
d_2HLL			−.34**		
d_3LHH			−.19*		
Step 2	.12	.02		1.14	>.05
rlogRSA			−.11		
rPEP			−.08		
Analysis 5[b]					
Step 1	.10	.10		4.60	<.01
d_1LLL			−.33**		
d_2HLL			−.34**		
d_3LHH			−.19**		
Step 2	.13	.03		4.00	<.05
Canonical correlation			−.17**		

Note. d_1LLL = Difficulty Level 1; d_2HLL = Difficulty Level 2; d_3LHH = Difficulty Level 3 (see Table 1); logRSA = log transformed respiratory sinus arrhythmia; LVET = left ventricular ejection time; PEP = preejection period. The letter *a* preceding variable refers to Operator A; the letter *b* preceding variable refers to Operator B; the letter *r* preceding variable refers to the correlation between team members.

a. $n = 128$.

b. $n = 127$.

*$p < .10$. **$p < .05$.

words, increased SNS activation in Operator A were accompanied by decreases in team error, whereas increased SNS activation in Operator B were accompanied by increases in team error.

Although Step 2 of Analyses 3 and 4 were not statistically significant, Step 2 of Analysis 5 was statistically significant. However, it accounted for a small proportion of variance in team error.

Discussion

The current study was one of the first to examine the relation of both PNS and SNS measures to team performance. The purpose of this study was to determine whether a team's autonomic activity could be used to predict team performance and, by predicting team performance, to index cognitive readiness. Previous research on the topic of physiological compliance (Elkins et al., 2009; Henning & Korbelak, 2005) suggested that positive correlations between team members' physiological indices would be associated with higher levels of performance. Because these previous studies examined only one branch of the ANS, it is understandable that correlations provided the best relation between physiological indices and performance. The novelty of the current study was that we measured both branches of the ANS; therefore it was initially unclear which combination of the team's autonomic activity should be used when examining the relation with team performance. As a result, analyses contained both models whereby individual physiological indices were combined into a single measure before analysis, similar to the physiological compliance literature, and models whereby the individual indices were entered as a set via the regression analyses to combine them into one measure. The key distinction was that in the pre-analyses combination, a linear relation between the physiological variables was assumed, whereas with the regression analysis, the optimum linear or nonlinear combination was found. Of the three team autonomic activity models used to predict performance, the models containing the individual autonomic indices of Operators A and B were the best predictors (see Table 2). Those models showed that team autonomic activity could account for up to 10% of the variance in team performance scores above and beyond task difficulty.

Interestingly, the results of the current analyses showed that the individual indices of autonomic activity were better predictors of team performance than were the various combined measures of team autonomic activity (rlogRSA, rLVET, rPEP, and canonical correlation). Previous studies have primarily focused on creating some measure of combined team physiological activity to relate to performance (Elkins et al., 2009; Henning et al., 2001; Henning & Korbelak, 2005), but perhaps a simpler approach of using the individual indices of team members together in one model would provide the same, if not more, information about team activity.

When we examined the results, it became clear that the significant predictors within the models, other than task difficulty, were the measures of SNS activity (Analyses 1 and 2). The model predicting team performance using LVET showed the expected relation between SNS activity and performance, where increases in SNS activity were associated with increases in team error (see Table 2, Analysis 1). That is, higher levels of team "physiological arousal" were accompanied by lower levels of team performance. Surprisingly, even though PEP is also a measure of SNS activity, it did not share the same relation with team performance as LVET. When examining the regression using PEP (Table 2 Analysis 2), we discovered that whereas Operator B's PEP scores shared the expected relation with team performance, Operator A's PEP scores showed the opposite relation. Increases in Operator A's SNS activity were associated with decreases in team error, which suggests that higher levels of Operator A's physiological arousal were associated with better team performance. These differences in the relation between PEP scores of the two operators and performance were unexpected, although there are several possible explanations.

One explanation is that the difference could be a response to the different combinations of task difficulty levels that the two operators experienced. Operator B always experienced a balanced level of difficulty between his or her individual workload and the team workload. For example, whenever team workload was low, Operator B's workload was low, and whenever team workload was high, Operator B's workload was high. On the other hand, Operator A experienced two trials of unbalanced individual and team difficulty: one trial in which Operator A's workload was low and team workload was high and one trial in which Operator A's workload was high and team workload was low. These differences in the combinations of task difficulty between the two operators could explain the discrepancy in PEP scores.

Another explanation could be the small differences in task responsibility between Operator A and Operator B. Although the two operators had the same individual responsibilities (i.e., they both control two tanks and monitor the middle tank), their location in the production line creates differences related to the overall system performance. Operator A is responsible for the total system input; therefore Operator B must coordinate with Operator A to efficiently increase the chemical flow into the second half of the system. Similarly, Operator B controls the output for the entire system; therefore Operator A must coordinate with Operator B to efficiently increase the amount of chemical flowing out of the first half of the system. Because of this interdependence, either operator can act as a bottleneck to efficient system production at any given time during the process control task. A bottleneck may occur if one operator is subjected to an increase in task difficulty, which could cause that operator to focus more on his or her individual task and less on the needs of the other operator. These potential bottlenecks could also be responsible for the different results between Operator A and Operator B PEP data. Additionally, the potential for bottlenecks within the system may suggest that the use of cross-correlations could yield important insights into the explanation of team autonomic data. Although previous studies did not produce significant results from cross-correlations (Elkins et al. 2009), it is possible that the unique task structure in the current study would be more amenable to those types of analyses. In future studies involving sequential process control tasks, researchers should consider the inclusion of cross-correlations in their analyses.

Last, although both LVET and PEP have been used as indices of SNS activity, it has been suggested that they do not measure the exact same effects of the SNS on the heart (Thayer & Uijtdehaage, 2001; Uijtdehaage & Thayer, 2000). Whereas PEP may be an index of the inotropic (force-related) effects of the SNS on the heart, Thayer and Uijtdehaage (2001) suggest that LVET is an index of chronotropic (rate-related) effects of the SNS on the heart. It was not expected that those two measures would have different relations with performance, but it is possible that these fundamental differences could explain the differences in the current results. Unfortunately, it is unclear why the current task would produce differences in chronotropic and inotropic SNS activity on the heart. Therefore, further research is required to determine whether these differences are replicable.

Limitations

To our knowledge, this was the first study to measure team autonomic activity and attempt to relate it to team performance. Given that we were the first to design such an experiment, there are inherently some limitations that result. The first of these limitations is that the equipment used to measure SNS activity was not the same between the two operator stations. Operator A's SNS activity was recorded with a VU-AMS system, whereas a Biopac system was used to record Operator B's SNS activity. Although manufacturers of the system were different, the same type of physiological signal was used for both systems, as was the data reduction process. Therefore, any possible differences in the operators' SNS activity measures attributable to differences in the two systems were minimal. Despite this, in the future, researchers should attempt to use the same physiological recording hardware to assess all team members.

Another limitation of the current study was that although the main hypothesis was to predict team performance from team autonomic activity, the task seemed to be more influenced by differences in individual difficulty rather than team difficulty. If this was indeed the case, it would mean that any relation between team performance and the other variables would be more difficult to uncover. This possible discrepancy in the influence of difficulty levels also suggests that what relations were found in the current study may be even stronger during a more strongly manipulated team difficulty task.

Finally, although the teams of operators were explicitly instructed to coordinate control of the entire system, (e.g., coordination of inputs and outputs and the center console), they were not given a specific strategy to follow, nor were their communication and coordination methods captured. It is possible that differing communication and coordination strategies between teams could have affected the results of the current study and increased the variability within team-level data. If we had captured each team's strategy, it may have been possible to control for those differences and identify stronger relations between team autonomic activity and performance. It is also possible that an additional relation could exist between communication and coordination strategies and team autonomic activity. In future studies of team autonomic activity, researchers should consider potential communication and coordination methods and strategies within a team and take those variables into account during the study design and the analysis of the resulting data.

Conclusions

In the current study, we investigated whether team autonomic activity was predictive of team performance to show its potential as a measure of team cognitive readiness. Given past research (e.g., Backs, 2001; Berntson et al., 1991), measures of autonomic activity were chosen for the current study because we believed that they would provide more information than either PNS measures or SNS measures in isolation. By measuring both sides of the ANS, we were able to discern that SNS activity helped to predict approximately 10% of the variance in team performance scores. Therefore, findings provide evidence that the measurement of a team's full autonomic space can be a useful tool in the investigation of team performance.

Findings may also reflect the moderating role of physiological state in the measurement of cognitive readiness. On the basis of the work of Bolstad et al. (2006), Consenzo et al. (2007), and Wesensten et al. (2005), cognitive readiness could be defined as a dynamic measure of cognitive preparedness, as compared to the KSAs, and emergent states (cognitive, affective, and physiological) required to establish and sustain competent performance levels during a unique performance episode. According to this definition, cognitive readiness is determined by a person's KSAs but could be moderated by changes in cognitive, affective, or physiological states. It is possible that the same moderating role may be present at the team level. However, at the team level, it may be necessary to also examine the moderating effects of team level processes, such as communication and coordination, when examining the cognitive readiness of a team as a whole.

If that relation is supported, then it could be expected that for given levels of KSAs, team members' cognitive readiness may largely be determined by changes in their collective cognitive, affective, or physiological states. If supported, that hypothesis suggests that team members' cognitive readiness could be assessed on a near-real-time basis to help inform decision making within dynamic and complex environments (e.g., emergency response, military operations). Future research is needed, first, to determine whether the results of this study are replicable and, second, to specifically test the moderating effect that a team's physiological state may have on its ability to apply a given set of KSAs to sustain competent performance.

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