8-2010

PREDICTING TEAM WORKLOAD AND PERFORMANCE USING TEAM AUTONOMIC ACTIVITY

Alexander Walker
Clemson University, alexanderdwalker@gmail.com

PREDICTING TEAM WORKLOAD AND PERFORMANCE USING TEAM AUTONOMIC ACTIVITY

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Human Factors Psychology

---

by
Alexander D Walker
August 2010

Committee:

Dr. Eric Muth, Committee Chair
Dr. Adam Hoover
Dr. Fred Switzer
Dr. Patrick Rosopa

ABSTRACT

The development of a team measure of autonomic activity has a wide variety of applications. During team training, an index of team autonomic activity could potentially have added value for real-time feedback, team selection and performance evaluation. The primary purpose of this study was to investigate the relation between autonomic activity measures, workload, and performance, on both an individual and team level. Specifically, this study sought to determine whether changes in workload could be detected in measures of autonomic activity and whether changes in the autonomic measures related to changes in performance. 34 teams of two (35 males, 33 females) completed a processing plant simulation during 4 varying levels of individual and team difficulty. Sympathetic and parasympathetic nervous system activity was measured throughout the task using an electrocardiogram (ECG) and an impedance cardiogram (ICG), in addition to the NASA-TLX. SNS and PNS measures were combined to produce a team autonomic activity measure that was used to predict team workload and performance. Results showed that workload and performance varied across the task difficulty levels with higher difficulty producing higher workload and worse performance. Regressions conducted predicting team performance from team autonomic activity showed that team autonomic activity accounted for 10% of the variance in team performance scores. Further exploratory analyses showed interesting relations between autonomic activity and performance when examining the task difficulty levels separately. These analyses discovered that during the mixed individual difficulty levels, one team member's physiology was consistently correlated with the other team member's

performance. In conclusion, the current study showed that team performance can be predicted from team autonomic activity, and that individual team member physiology has the potential to provide an index of team related behaviors (e.g. mutual performance monitoring and back-up behaviors).

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Eric Muth, for introducing me to research and for all of his help and support during this long process. Dr. Muth has been instrumental in the development of the type of scientist and professional I have become. I would also like to thank my other committee members, Dr. Adam Hoover, Dr. Fred Switzer and Dr. Patrick Rosopa for their support and unique guidance during this research.

I would also like to thank my future wife Olga who has stood by me through all of my years of graduate school. I am not sure that I would have sanely completed this laborious process if it were not for her support. Finally, I would like to thank my parents for their ever present support and encouragement that has been the guiding force behind all of my achievements.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Teams are an ever increasing resource within both industry and the military. With the increasing use of teams comes an increasing need to understand and evaluate how individuals work in a team, as well as what determines an effective team. Due to the paucity of team-based measures available, the development and evaluation of new measures could be seen as a high priority in the current culture of team-based work and operations.

The primary purpose of this study was to investigate the relation between autonomic activity measures, workload, and performance, on both an individual and team level. Specifically, this study investigated whether changes in workload could be detected in measures of autonomic activity and whether changes in the autonomic measures related to changes in performance.

Development of a team measure of autonomic activity has a wide variety of applications. During team training, an index of team autonomic activity could potentially have added value for real-time feedback. For tasks that are highly complex and require a high level of workload, anything that enables the team to train quickly to a high level of proficiency is beneficial (Kirlik et al., 1998). The addition of a team autonomic activity index may show instructors how the trainees are physiologically responding to the various tasks being performed. Team autonomic activity recorded in real-time could help instructors single out specific sections of a task, where there is a high level of team workload that may require additional attention. Team autonomic activity could also be utilized before training begins or in its early stages to help identify teams that have a greater level of physiological compatibility among its members. This would allow the instructors to restructure the teams to produce an optimal measure of team autonomic activity.

Autonomic Nervous System

The body's nervous system is responsible for the receipt and delivery of all information within the human body. Conceptually, the human nervous system can be broken down into a hierarchy of functional components. The first level of division is between the central nervous system (CNS), which is primarily comprised of the neurons within the brain and spinal column, and the peripheral nervous system, which is comprised of the neurons that lie outside of the brain and spinal column. For a more in depth discussion of the CNS, see Cacioppo, Tassinary, and Berntson (2007). The peripheral nervous system can be further divided into the somatic nervous system, which is responsible for voluntary movement (striated muscle), and the autonomic nervous system (ANS), which is primarily responsible for the involuntary control of the body's internal organs (e.g., the heart). It is important to note that these divisions are mainly a conceptual breakdown of the various functions of the nervous system as a whole. Though there are functional, anatomical, and neurotransmitter differences between some of these systems, the divisions are gross generalizations used to understand an intricately complicated network.

The ANS is the nervous system of interest in the current study. The ANS is further divided into three separate systems, the enteric nervous system, the parasympathetic nervous system (PNS), and the sympathetic nervous system (SNS). The enteric nervous system controls the gastrointestinal tract relatively independent of the CNS (Stern, Koch, Levine, & Muth, 2007). Because the current study measured cardiovascular activity, further discussion of the ANS will focus on the PNS and the SNS. For further discussion of the gastrointestinal system and its associated innervations see Stern, Koch, and Muth (2007).

The parasympathetic and sympathetic branches of the ANS are anatomically different from the somatic nervous system. While the neurons of the somatic nervous system exit the CNS and innervate striated muscle without synapse, the ANS synapses once outside of the CNS. The anatomical structures formed by these synapses outside the CNS but before the target organ are called ganglion (Stern, Ray, & Quigley, 2001). Differences in the length of the pre- and post-ganglionic fibers, as well as functional and neurotransmitter differences, help differentiate between the two branches of the ANS.

Parasympathetic nervous system. In general, the PNS acts as a calming influence on the human body, it exerts control of the organs to maximize their efficiency when the body is at a relative state of rest. The PNS is also known as the craniosacral division of the ANS, since the pre-ganglionic fibers for the PNS exit the CNS nervous system either from the cranium or from the sacral region of the spinal column. Most ganglia in the PNS lay close to the innervated organs causing the pre-ganglionic fibers to be longer that the post-ganglionic fibers. The length of the fibers is not the only thing that distinguishes the PNS from the SNS, it also uses different neurotransmitters at its synapses. Acetylcholine of the nicotinic subtype is the neurotransmitter at the pre-ganglionic synapse and acetylcholine of the muscarinic subtype is the used at the post-ganglionic synapses (Stern, Ray, & Quigley, 2001). All of these differences help to show that the PNS, though part of the ANS, serves a different function from the SNS.

Sympathetic nervous system. In general, the SNS prepares the human body for the variety of reactions that can be thought of as “fight or flight.” For the majority of the organs in the body, an increase in SNS activity causes them to increase activity (i.e., increased heart rate or skin conductance). The SNS is also known as the thoracolumbar system because of the anatomical arrangement of its neurons into a chain of ganglia known as the sympathetic trunk. Pre-ganglionic neurons from the SNS exit the spinal column and enter this sympathetic trunk where they synapse with post-ganglionic neurons. As opposed to the PNS, the pre-ganglionic neurons of the SNS are relatively short and the post-ganglionic neurons are relatively long. Also, the SNS uses norepinephrine to exert control on the target organs that it innervates (Stern, Ray, & Quigley, 2001). Because norepinephrine is used as the post-ganglionic neurotransmitter, any norepinephrine that is released as a hormone into the blood stream can generally activate most organs that are innervated by the SNS.

The PNS and SNS have many functional and structural differences that set them apart, but in the end they are two parts of one system. Trying to understand the functioning of the ANS while only measuring one of these two branches presents only half of the information required. The only way to understand the full effects of the ANS on any specific organ is to measure both the PNS and the SNS and how they relate to each other. This relation between the two systems can be thought of as autonomic space.

Autonomic Space

The doctrine of autonomic space was first presented by Berntson, Cacioppo, and Quigley (1991). Prior to this work, the effects of the ANS on the various organs of the body, particularly the heart, were thought to follow a reciprocal pattern otherwise known as the doctrine of autonomic reciprocity. In general, autonomic reciprocity proposed that when one of the branches of the ANS increased activation, the other branch decreased activation. Using the heart as an example, according to autonomic reciprocity when the SNS increased activation, the PNS would withdraw, leading to an increase in heart rate. Therefore, the end state of the organ could give you a fairly clear understanding of the underlying inputs from the ANS. Berntson, Cacioppo, and Quigley (1991) showed that this was too simplistic of an explanation and that autonomic reciprocity was just one of the patterns of activity subsumed by the doctrine of autonomic space.

The doctrine of autonomic space described by Berntson, Cacioppo, and Quigley (1991) is a two dimensional space with PNS and SNS on each axis (Figure 1.1). According to this newer conceptualization, the ANS can display three different types of activity: uncoupled, reciprocal, and co-activity. Uncoupled activity occurs when there is activity in one branch of the ANS while activity in the other remains unchanged. Reciprocal activity, as described above, occurs when there is increased activity of one branch and decreased activity of the other branch. Coactivity occurs when there is increased or decreased activation in both branches, in the same direction. In a follow-up study, the authors provided a validation of the doctrine of autonomic space by examining the effects of pharmacological blockades on autonomic control of the heart (Berntson, Cacioppo, & Quigley, 1994).

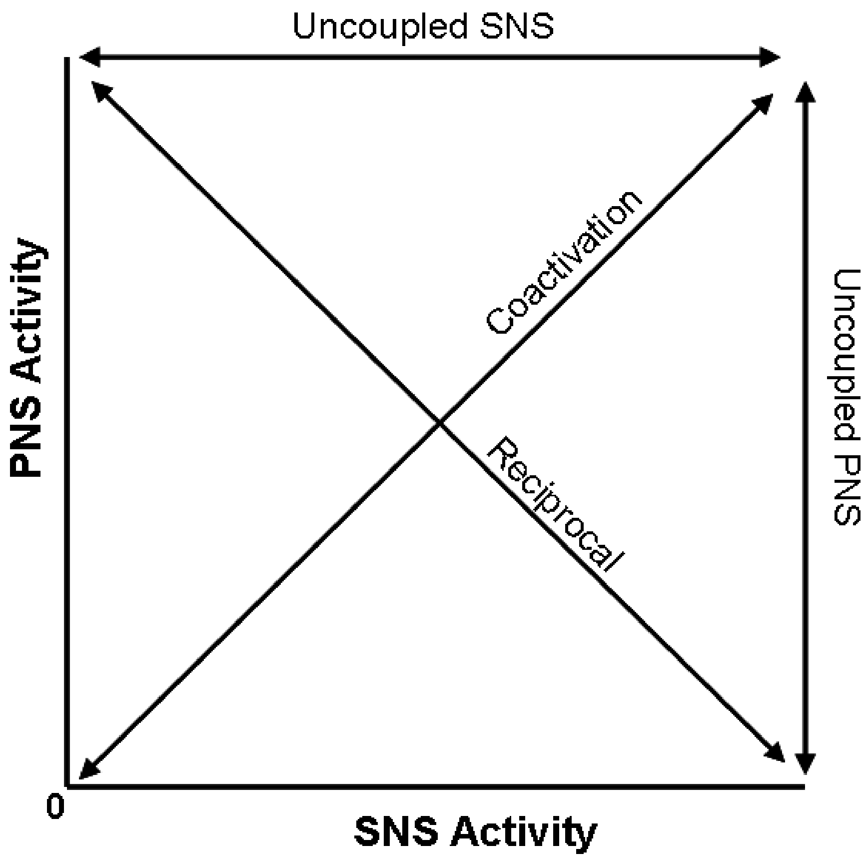

Figure 1.1. Autonomic space with the different types of activation

With the 2-D representation of autonomic activity found in Figure 1.1, it is no longer informative to examine the end state of the organ in order to understand the underlying activity of the PNS and SNS. For example, an increase in heart rate can occur due to uncoupled SNS activation, uncoupled PNS withdrawal, reciprocal SNS activation and PNS withdrawal, or SNS and PNS co-activation where the SNS increases to a greater degree. Because varying inputs can lead to the same result in the target organ, it is more meaningful to measure the individual branches of the ANS to gain a more complete understanding of the pattern of ANS activity. Also, Berntson, Cacioppo and Quigley (1991) suggest that when choosing autonomic space measures one should use measures derived from the same organ (i.e., the heart). Once autonomic space has been measured it can then be compared and correlated with a wide range of other factors that commonly interest researchers, specifically for this proposal, workload and performance.

Workload, Performance, and Autonomic Activity

One of the many rationales for using psychophysiological recordings, such as measures of autonomic space, when studying human performance is that they have the potential to inform the researcher of a person's level of workload. Workload has been widely studied over the years, primarily because of its apparent link to performance (Eggemeier, 1988; Gopher & Donchin, 1986). According to Hart and Staveland (1988) workload is a human-centered construct that represents the "…cost incurred by a human operator to achieve a particular level of performance" (p. 240). This means that workload is not only a function of how difficult a task is, but it also depends on what level of performance the operator wishes to achieve as well as any external (environmental) or internal (perceptual, behavioral, etc.) factors the operator has to deal with.

Numerous studies have found that high levels of workload can lead to decreases in individual (Beith, 1987; Hart & Hausers, 1987) and team (Urban et al., 1995) performance. However, Urban et al. (1995) found that the link between workload and team performance is not necessarily straight forward. The authors found that during higher levels of workload, ineffective teams had worse performance, but effective teams were able to compensate for the increases in workload in order to maintain their performance. Therefore, while individual performance may be a function of an operator's level of workload, team performance is dependent on both workload and team efficiency. These differences between individual and team workload make the assessment of workload a difficult task.

The most popular and widely accepted method for assessing workload is the NASA task load index (TLX), developed by Hart and Staveland (1988). The NASA-TLX is a subjective questionnaire that allows the operator to self-assess his or her level of workload. Over the years, the NASA-TLX has been used in hundreds of studies assessing workload and is commonly used as the benchmark for assessing a person's perceived level of workload (Hart, 2006). While the TLX is useful for assessing subjective workload, it still has its limitations. For example, the TLX requires conscious effort to complete and therefore the task must be interrupted or finished before it is administered. It is also based on the subjective perceptions of the operator and is therefore open to response bias. Also, the questionnaire is an individual measure with no clear framework from which to derive a measure of team workload. It is possible that objective psychophysiological measures of workload may be able to make up for some of these limitations.

Objective psychophysiological recordings have the benefit of being measured continuously, relatively unobtrusively, and without the risk of potential response biases. Also, a tentative framework has been developed to combine individual physiological measures into a composite team physiological measure (i.e., physiological compliance).

In order for a psychophysiological measure to become commonly used to measure workload, it needs to be better than the established subjective measures (Backs, 1995). Though many different physiological measures of workload have been studied, the most widely investigated measure has been heart rate.

Heart rate has shown some limited applicability in the assessment of workload. Changes in heart rate have been associated with numerous instances in both real and simulated flight that are known to elicit a high level of workload (e.g., Comens, Reed, & Mette, 1987; Hart & Hauser, 1987; Lindholm & Cheatham, 1983; Nicholson et al. 1970; Wilson, 1993, 2002). Unfortunately, while heart rate has been shown to have a high degree of sensitivity, it has a very limited range of diagnosticity. Sensitivity refers to an index's ability to detect changes in the level of workload present (O'Donnell & Eggemeier, 1986), while diagnosticity refers to an index's ability to "…discriminate the amount of workload imposed on different operator capacities or resources" (O'Donnell & Eggemeier, 1986, pp. 42-43). Backs (2001) proposed that one way to increase the level of diagnosticity of cardiovascular measures of workload is to measure cardiac autonomic space. By using autonomic space to assess workload, it may be possible to discover specific autonomic patterns that correspond to different types or levels of workload.

Recently, several studies have used the doctrine of autonomic space to investigate the various autonomic patterns that accompany workload during different tasks. Several studies have investigated autonomic patterning in response to a visual-manual compensatory tracking task (Ash & Backs, 2000; Backs, 1998; Lenneman & Backs, 2000). The results of those studies provided evidence that, during a tracking task, changes in perceptual information processing demands were accompanied by changes in uncoupled PNS activity, indexed using respiratory sinus arrhythmia (RSA), while changes in central processing demands were accompanied by uncoupled SNS activity, indexed using pre-ejection period (PEP; Backs et al., 2003). This helps show that even during a simple task different types of workload are accompanied by different patterns of autonomic activity.

Further research has been conducted in the more complex environment of aviation. Back, Lenneman, and Sicard (1999) investigated autonomic patterning during simulated flight in a large Boeing 727 simulator. Based on the results of that experiment, the authors were able to develop a tentative hierarchy of autonomic cardiovascular control for different levels of mental workload. Backs, Lenneman, and Sicard (1999) laid out the following hierarchy: reciprocal control was demonstrated during conditions involving low workload, uncoupled SNS activation was demonstrated during conditions of high but manageable workload, and coactivation was demonstrated during conditions involving critical tasks that required immediate attention. The authors agree that this is only a tentative linkage between autonomic activity and workload, but the potential for increased diagnosticity is evident. Measures of autonomic space hold promise for the evaluation of individual workload, but they could also be combined to study the workload and performance of a whole team.

Team Psychophysiology

Studies examining team work and team training have occasionally used psychophysiological measures to investigate individual characteristics of individual team members (Cacioppo & Petty, 1983), but few studies examine the psychophysiology of the team as a whole. Team psychophysiology, also known as physiological compliance, 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.

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 co-vary throughout the course of a counseling session (Dimascio et al., 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 et al. (2001) took the idea of social-emotional physiological compliance and applied it in the context of team performance. The authors measured electrodermal activity (EDA), heart rate (HR) and respiration rate of two person teams while they completed a complex, cooperative tracking task. The task simulated the tele-manipulation 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 above, but in this study the teams also experience unexpected shifts in the task control dynamics. The authors found that physiological compliance was a predictor of team performance on the tracking task. This 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.

Recently, Elkins et al. (2009) examined the relation between physiological compliance and performance in teams completing a complex dynamic task. In this study, subjects 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 non-combatants. Physiological compliance was recorded during training and compared to each team's performance during subsequent testing. The authors found that physiological compliance for measures of PNS cardiac activity, specifically RSA, during training was positively correlated with team performance during testing. Another interesting finding was that it was unlikely that the correlation between RSA measures was due to physical co-activation since the task being performed was dynamic and involved different team members fulfilling different roles on the team (Henning, et al. 2001).

Previous studies have used a variety of different physiological measures to assess physiological compliance in teams. Those measures include electrodermal activity (Henning et al. 2001), respiration (Henning et al. 2001), electromyography (Malmo, Boag, & Smith, 1957), and heart rate variability (HRV; e.g., Elkins et al. 2009, Henning et al. 2005; 2009). Of these studies, HRV has been the most promising measure of physiological compliance. HRV, or more specifically RSA, provides an indirect measure of PNS influences on the heart. However, as stated above, in order to obtain a more complete understanding of ANS influence on the heart, researchers need to measure both PNS and SNS influences. Measuring both PNS and SNS branches of the ANS would allow for the development of task and context specific autonomic patterns.

Measures of Autonomic Activity

Measuring autonomic space can be complicated because it requires the measurement of both parasympathetic and sympathetic activity independently of each other, within the same organ (Berntson, Cacciopo, & Quigley, 1991). Through the years, various attempts have been made to measure PNS activity independently of SNS activity. So far the most progress has been made by measuring the key component of the cardiovascular system, the heart. The PNS innervates the heart primarily through the vagus nerve at several different locations; each of these innervation pathways is responsible for different effects on the heart. There are three different ways that the PNS can affect the heart: chronotropic control regulates heart rate, dromotropic control regulates conductivity, and inotropic control regulates cardiac contractility. The PNS exerts most of its influence on the heart through its chronotropic control and has the least amount of influence in inotropic control (Cacioppo, Tassinary, & Berntson, 2007). It is through this dominant chronotropic control that scientists have been able to parse out vagal influence of the PNS on the heart.

Respiratory sinus arrhythmia. RSA is used to describe the oscillation of HR around the respiratory frequency. During inhalation the heart speeds up, causing HR to increase and the time in between beats, also known as heart period (HP), to get shorter. During exhalation the heart slows down causing a slowing of HR and a lengthening of HP (Grossman & Taylor, 2007). This rhythmic fluctuation occurs due to both a central respiratory generator and respiratory gating of central nervous system outflows to the sino-atrial (S-A) node of the heart (Berntson et al., 1997). The S-A node of the heart lies in the upper wall of the right ventricle and primarily controls the chronotropic (time-based) influences on the heart. Though the S-A node of the heart is innervated by both branches of the ANS, the cardio-effector synapses of the sympathetic branch inherently impose a low-pass filter on sympathetic outflows to the heart. This means that at the higher respiratory frequencies sympathetic activity is virtually absent at the S-A node. The vagal outflows to the heart have no such filter and therefore exert influence on the heart at all frequencies (Cacioppo et al. 1994).

The dominant influence of the PNS on the control of RSA has been confirmed over the years through blockade studies (e.g., Grossman, Stemmler, & Meinahrdt, 1990; Grossman, Karemaker, & Wieling, 1991). Blockade studies employ neurotransmitter antagonists to limit the activity of one or both of the ANS branches. Though pharmacological blockade is the best non-invasive way of examining ANS influence on the heart, it does introduce some biases in the estimation of cardiac control. Systematic biases can arise due to potential interactions between the SNS and the PNS at the heart, reflexive changes in the unblocked branch, the nonselective nature of the antagonists, or partial blockades (Berntson, Cacioppo & Quigley, 1994). In response to these potential biases, Berntson, Cacioppo, and Quigley (1994) developed a method that would reduce the effect of the biases in the estimation of cardiac control during pharmacological blockade. In subsequent work (Cacioppo et al., 1994), the authors used this new method to determine the best non-invasive indices of both branches of the ANS on cardiac control. The results of this investigation found that the high frequency oscillations of HP (i.e., RSA) were strongly determined by vagal control.

The numerous methods proposed to measure the oscillations of HP in the respiratory frequency fall into 2 categories: time-based measures and frequency-based or spectral measures. There are a wide variety of time-based measures including: the mean of the absolute value of the successive differences between heart periods (MSD; Allen, Chambers, & Towers, 2007), the mean of the squared successive differences between heart periods (MSSD; Allen, Chambers, & Towers, 2007), the square root of MSSD (RMSSD; Von Neumann et al., 1941), the Porges method involving a moving polynomial filter (MPF; Porges, 1985), and the peak-to-valley method (Grossman & Svebak, 1987; Grossman, Van Beek, & Wientjes, 1990; Katona & Jih, 1975).

All three measures of successive differences are simple to calculate and do not require complex algorithms or patented processes. Therefore, for large-scale studies or for researchers just starting to work with HRV one of these measures is a good starting point considering their fairly high correlation with other more complicated analyses (Allen et al. 2007; Goedhart et al. 2007). The peak-to-valley method is similarly easy to use but it requires the additional measurement of respiration. The most complicated of the time-based measures is the Porges moving polynomial filter method. This method uses its polynomial filter to remove any non-respiratory variations in the inter-beat-interval (IBI) series, which makes it superior to the other time-based measures of RSA (Porges, 1985).

Frequency-based measures use a variety of spectral analyses to decompose the IBI time-series into specific frequency bands. These types of measures are analogous to passing white light through a prism in order to break it up into underlying colors. Three of the more popular frequency-based measures are: wavelet analysis, auto-regression, and fast Fourier transform (FFT). All three of these methods are highly related and produce a value that represents how much of the original time-series is made up of activity in the high-frequency band (Hayano et al., 1991; Houtveen & Molenaar, 2001).

Allen et al. (2007) compared the most widely used time-based and frequency-based measures in order to determine which would provide the best index of heart rate variability at the respiratory frequency. The authors found that while almost all of the measures provided some index of high frequency variability, the ones that produced the most accurately summarized cardiac variability at the respiratory frequency were the band filtered IBI series (i.e., the Porges method) and the spectral analyses. Due to the results of Allen et al. (2001) and the measure's prolific use in the literature, the current study used an FFT which isolates the spectral power of the HF band as an index of cardiac vagal tone.

When measuring cardiac vagal tone using the HF band of HRV it is important to consider the possible influences of respiration on any resulting measure. Because RSA is essentially a measure of HP oscillations associated with inspiration and expiration, it is possible that changes in respiration frequency and volume could alter RSA independently of vagal effects on the heart (Grossman & Taylor, 2007). The confounding effect of respiration on RSA has been a long standing debate among several psychophysiologists (e.g. Berntson et al., 1997; Denver, Reed, & Porges, 2007; Grossman & Taylor, 2007).

Grossman and Taylor (2007) present one side of the argument stating that respiration is closely linked to RSA and that link is substantial enough to warrant some form of control for respiration when using RSA as an index of cardiac vagal tone. It was suggested that respiration should be addressed when either: respiration rate or volume differs between conditions or groups, or when respiratory and cardiac parameters do not co-vary with each other.

Two general solutions have been suggested to help remove the effects of respiration on RSA. One solution is to pace the subjects' breathing throughout the experiment, which would ensure that respiration rate would not vary between subjects or across conditions (Grossman, Stemmler, & Meinhardt, 1990). Paced breathing may introduce a certain level of discomfort for the subjects and may also increase cognitive workload above levels intended for the experimental manipulation (Grossman & Taylor, 2007). Another solution is to statistically control for the effects of respiration by conducting a within-subjects regression between RSA and respiration then using the residuals (Grossman, Karemaker, & Wieling, 1991). The residuals would represent the amount of variance in RSA that is not associated with changes in respiration.

Although respiration volume is not considered as important to control for as respiration rate (Berntson, et al. 1997; Porges & Byrne, 1992), it can still be an important consideration during studies recording RSA. Since tidal volume has been shown to have significant effects on RSA magnitude (Hirsch & Bishop, 1981; Grossman, Karemaker, & Wieling, 1991, Grossman, Wilhem, & Spoerle, 2004) some researchers have suggested that it should be controlled for if it varies significantly within or between experimental conditions (Grossman & Taylor, 2007). Although a transfer function between RSA and tidal volume can be calculated and used to control for the effects of tidal volume on metabolically associated changes in RSA, the transfer function does not seem sufficient to control for the effects of tidal volume during less active experimental conditions (Grossman & Taylor, 2004). Primarily, researchers should be aware of the potential confound and take it into consideration when designing their experiments and analyzing RSA data.

Denver, Reed, and Porges (2007) present the other side of the respiration argument suggesting that it is unnecessary to control for respiration when analyzing RSA. The authors found no evidence of a causal relationship between respiration frequency and the amplitude of RSA during a resting baseline. Also, during varying doses of a PNS blockade, respiration frequency accounted for less than 10% of the variance in the amplitude of RSA. Other studies also provide evidence that there is no statistical difference between RSA corrected for respiration rate and uncorrected RSA (Burleson et al., 2003; Gianaros et al., 2001; Houtveen et al., 2002; Thayer, Friedman, & Borkovec, 1996). Instead of controlling for respiration frequency when it differs across conditions, Denver et al. (2007) suggest that the researcher should try to understand why it differs from a conceptual standpoint. It is possible that respiration frequency is sensitive to an aspect of the experimental effect that may be overlooked solely by examining RSA.

Both sides present valid arguments that are not necessarily mutually exclusive. It would seem that the best course of action when measuring RSA in response to some stimulus is to measure RSA and respiration and then compare the corrected and uncorrected measures (Houtveen, Rietveld, & De Geus, 2002). Measuring both indices and comparing them provides the experimenter with the maximum amount of data and allows him or her to better understand the influences of respiration on RSA.

Alternative PNS measures. Although the analyses of HRV are the most widely used and validated indices of PNS activity there are a few alternative measures that do not use HRV which are sometimes used. One example of those alternatives is tear volume. The theory behind using tear volume is that reflex tear secretion is primarily controlled by the PNS (Beuerman, Mircheff, Pflugfelder, & Stern, 2004). Tamura et al. (1990) used an electronic resistance measuring device to measure tear volume before and after parasympathetic blockade with atropine. They found that tear volume was significantly reduced by parasympathetic blockade and therefore concluded that an electronic resistance measuring device could be used as a quantitative index of PNS activity. Unfortunately, placing devices on a person's face may be uncomfortable and interfere with the completion of tasks.

SNS measures. As with the PNS, researchers have sought independent indices of SNS activity on the heart over the years. Unlike indices of PNS, it has taken longer to discover such indices and there is far less consensus on which one is the best index of SNS activity. Though the sympathetic nerve also innervates the S-A node of the heart, it is not able to exert much chronotropic influence. Instead the sympathetic nerve primarily innervates the ventricular myocardium and therefore dominates the inotropic control of the heart, also known as cardiac contractility (Cacioppo et al., 1994). Cardiac contractility refers to how hard the heart is beating and is typically indexed by measuring various systolic time intervals. There are several systolic time intervals that have been proposed as indices of SNS activity on the heart, two of the more prominent intervals are pre-ejection period (PEP) and left ventricular ejection time (LVET).

Pre-ejection period. The most widely used systolic time interval in the literature is PEP. PEP is a measure of the time (ms) between the electrical signature of the beginning of left ventricular contraction and the actual physically contraction of the heart muscle (Figure 1.2). The shorter the time between these two events, the harder the heart is contracting, which is theoretically a sign of increased SNS activity of the heart (Sherwood et al. 1990). Cacioppo et al. (1994) lent support to this claim using pharmacological blockades of SNS influences on the heart. A wide array of systolic time intervals were examined and it was determined that PEP was the most sensitive index of sympathetic influences on the heart. A follow-up study conducted by Berntson, Cacciopo, & Quigley (1994) also showed that PEP was a reliable index of increased SNS activity in response to several stressful tasks, including a reaction time task, a speech task, and a mental arithmetic task. Previous research has also shown that PEP is inversely related to myocardial contractility, therefore, it is suggested that it can be used as an index of sympathetic (beta-adrenergic) influences on the heart (Ahmed et al., 1972; Cousineau et al., 1978; Harris et al., 1967; Martin et al., 1971; McCubbin et al., 1983; Newlin et al., 1979; Obrist et al., 1987). Of all of the systolic time intervals available, PEP seems to be the most promising index of sympathetic, inotropic control of the heart.

When using PEP as an index of SNS control of the heart, it is important to understand what other factors, besides direct sympathetic stimulation of the ventricles, might influence the measurement of PEP. Because PEP is a measure of overall ventricular performance it can be influenced by factors other than ventricular contractility (Lewis et al., 1974). Pre- and after-load influences on the heart must also be taken into consideration when evaluating any measure of PEP (Obrist et al., 1987; Sherwood et al., 1990). Pre-load refers to myocardial muscle stretch in the ventricles; an increase in pre-load will shorten PEP independently of contractility. After-load refers to end-diastolic aortic pressure or how much pressure there is on the aortic valve keeping it closed. An increase in after-load will lengthen PEP independently of contractility (Riese et al., 2003). If changes in pre-load and after-load can be measured or controlled then PEP should provide an index of sympathetic inotropic influences on the heart.

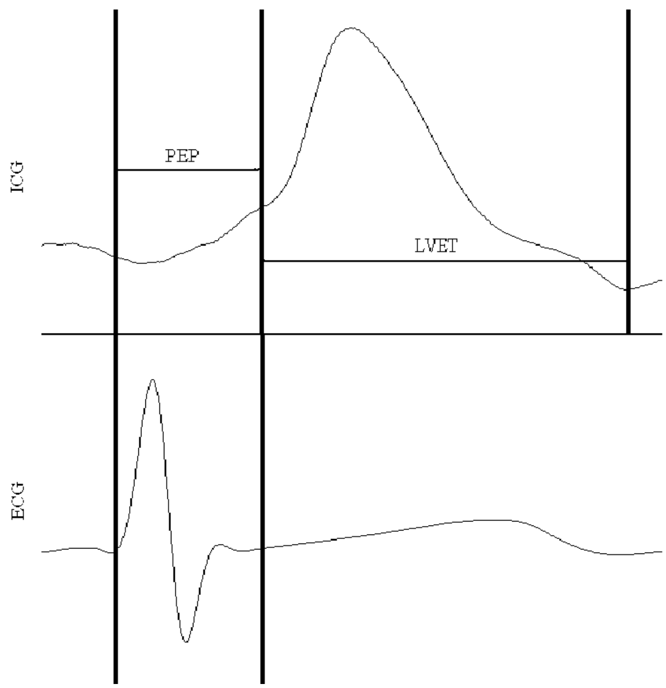

Figure 1.2 Systolic time intervals

Left ventricular ejection time. Measuring PEP provides one of the most promising indices of the inotropic effects of the SNS on the heart, whereas measuring LVET may be a better index of the chronotropic influences (Uijtdehaage & Thayer, 2000). LVET is measured as the time between the opening and closing of the aortic valve, in ms (Figure 1.2).As previously mentioned, there are 3 types of general heart activity (chronotropic, inotropic and dromotropic) each with its own unique relationship with the two branches of the ANS. Most studies which examine ANS influences on the heart use RSA, an index of the chronotropic effects of the PNS on the heart, and one or more systolic time intervals. Uijtdehaage and Thayer (2000) suggested that it would be logical to find the best index of chronotropic effects of the SNS on the heart to pair up with RSA. In their article the authors suggest that a good chronotropic systolic time interval should: 1) reflect chronotropic activity and therefore correlate with heart rate, and 2) correlate highly with heart rate corrected for RSA, or residual heart rate. These residuals would primarily reflect sympathetic and non-neural influences on heart rate. The results of the study showed that LVET met both of those criteria. In addition, Thayer and Uijtdehaage (2001) used a principle components analysis to show that LVET loaded on the factor representing chronotropic indices. Based upon this evidence, measuring RSA and LVET might provide a fairly comprehensive understanding of the ANS influences on the chronotropic activity of the heart.

Alternative SNS measures. Though PEP and LVET might prove to be the best measures of SNS activity on the heart there are other alternative measures that do not rely on cardiac contractility. Those measures include, but are not limited to: blood pressure, pulse transit time (PTT), skin conductance, skin sympathetic nerve activity (SSNA), and muscle sympathetic nerve activity (MSNA). Each one of these measures has been examined as a potential index of SNS activity.

Blood pressure can be used as an index of SNS activity because all of the body's blood vessels are innervated primarily by the SNS (Andreassi, 2000). An increase in sympathetic tone causes blood vessels to constrict which increases blood pressure. Blood pressure can be measured invasively, by inserting a catheter into an artery, or non-invasively using a variety of different methods the most common of which is the sphygmomanometer. A sphygmomanometer consists of an inflatable cuff attached to a tube containing mercury. During non-invasive measurement the cuff is placed around a person's bicep and inflated until no sound can be heard at the brachial artery below the cuff. Then the cuff is slowly deflated until faint tapping sounds can be heard and the pressure of the cuff is recorded in mm of mercury (mmHg), and is considered the systolic pressure. The cuff continues to be deflated until no tapping sounds can be heard and this pressure is recorded as the diastolic pressure. Though parts or all of this process can be automated the basic idea is the same for most non-invasive blood pressure procedures.

There are several drawbacks to using blood pressure measurements in the experimental setting. The first of these drawbacks is that blood pressure cannot be measured continuously and it is recommended that recordings not be made more frequently than once per minute (Shapiro, et al. 1996). Also, blood pressure is not a static number. Research has found that blood pressure readings can vary as much as 30 mmHg in a one minute recording session, using the more accurate direct invasive technique (Tursky, 1974).

Pulse transit time (PTT) has also been proposed as a potential measure of SNS activity. PTT is the time between the R-spike in an ECG and the peak of the pulse wave in a peripheral location, typically the finger. The problem with PTT is that it is influenced by both cardiac contractility and the stiffness of the peripheral arteries (Steptoe, Godaert, Ross, & Schreurs, 1983). While an increase in PTT might be the result of increased ventricular contractility, it might also be the result of increased vascular tone.

Measuring skin conductance is one way to attain an index of SNS activity that does not involve measuring the cardiovascular system. Skin conductance measures the activity of eccrine sweat glands by measuring the conductance of an electrical signal across the skin, between two electrodes. Because the eccrine sweat glands are primarily innervated by the SNS, increased SNS activity causes sweat to be produced in these glands and rise towards the skin. The more SNS activation the more eccrine glands activated. Interestingly, increased activity is caused by acetylcholine, which is the neurotransmitter for the PNS, instead or norepinephrine. Skin conductance, measured in microsiemens, is linearly related to SNS activation (Stern, Ray, & Quigley, 2001).

Skin conductance is measured using two electrodes placed on the palm of a hand or the bottom of a foot where the eccrine glands are highly concentrated. An electrical signal with a constant voltage is passed between the two electrodes to derive a measure of conductance. Typically researchers are either interested in a phasic skin conductance response (SCR) or a tonic skin conductance level (SCL). Regardless of whether SCR or SCL is measured, skin conductance can be affected by a number of variables: age, sex, race, environmental temperature, humidity, and time of day to name a few (Stern, Ray, & Quigley, 2001). Also, while recording skin conductance it is important to keep the limb connected to the electrodes as still as possible. This becomes problematic for studies that require a lot of movement on the part of the subjects.

Skin sympathetic nerve activity (SSNA) and muscle sympathetic nerve activity (MSNA) are two additional non-cardiovascular indices of SNS activity. Both SSNA and MSNA are measured using microneurography. Microneurography involves inserting a small needle electrode into a spindle of nerves and recording bursts of activity from the sympathetic nervous system (Vallbo, Hagbarth, & Wallin, 2004). These needle electrodes can either be inserted into nerves in the skin (SSNA) or nerves in skeletal muscle (MSNA). Though microneurography has been shown to reflect changes in sympathetic activity (Hagbarth, et al. 1972) the procedure is somewhat invasive and requires a high level of training. If the experimenter is not careful he or she could potentially cause the subject nerve damage (Vallbo, Hagbarth, & Wallin, 2004).

Current Study

The overall purpose of the current study was to investigate the relations between autonomic activity, workload, and performance at both an individual and team level. Autonomic activity provided a potentially useful conceptual framework from which to devise an objective cardiovascular measure of both workload and performance. The current study used a two-person process control simulation to investigate the relations between these constructs. Using this simulation, the amount of individual and team workload was manipulated while cardiovascular autonomic activity and perceived workload were measured and compared.

There were three hypotheses in the current study. First, as workload and measures of ANS activity have been correlated in the past (Comens, Reed, & Mette, 1987; Hart & Hauser, 1987; Lindholm & Cheatham, 1983; Nicholson, et al. 1970; Wilson, 1993, 2002), it was hypothesized that a measure of autonomic activity could be used to detect changes in task workload, on both the individual and team level. Past research has shown a relation between workload and performance (Beith, 1987; Hart & Howers, 1987; Urban et al., 1995), therefore it was also hypothesized that changes in workload, as indexed by autonomic activity, would be related to performance in that increases in workload would be accompanied by decreases in performance. Lastly, based on previous research which shows that physiological compliance between team members can predict team performance on a variety of tasks (Elkins et al. 2009, Henning et al. 2005) it was hypothesized that team autonomic activity could be used to predict team performance.

CHAPTER 2

METHOD

Subjects

Initially 86 college age subjects (43 teams) participated in the current study. Out of those 43 teams, 34 teams (12 teams of all males, 11 teams of all females, and 11 teams of 1 female and 1 male) provided complete sets autonomic activity data and were included in the study's analyses. Subjects were screened to ensure that they were in good health, specifically, subjects with abnormal heart problems were excluded from participation. Also, subjects were told to abstain from alcohol, tobacco, drugs, and vigorous exercise for at least 8 hours before they arrived.

A power analysis was conducted to ensure that the above sample size provided sufficient power to obtain the expected effect size for this type of study. There are few studies in the literature with a similar paradigm and the closest example that could be found was a study conducted by Backs et al. (2003) on cardiac measures during driving performance. In their study the authors measured RSA and PEP while drivers navigated a road with curves of varying radii representing different levels of difficulty. The results showed significant changes in RSA and PEP across the different curves with $\acute{\eta}^2$'s of .238 and .224 respectively. The lowest of these two effect sizes was used to calculate the total sample size needed to obtain a power of .80. The results of the power analysis showed that a sample size of 9 teams per group (i.e. male/male, female/female, or male/female group) was necessary to obtain effect sizes similar to those in the Backs et al. (2003) study. Because the current study used data quantification and analysis techniques that have not been reported in the literature before, the author felt it was necessary to use a sample size of at least 10 teams per group to account for any unexpected variance.

Apparatus

Electrocardiogram. Electrocardiography (ECG) data were collected using a Biopac ECG unit (Biopac Systems, Inc., Goleta, CA) and an ambulatory monitoring system (VU-AMS; Vrije Universiteit, The Netherlands). A three lead configuration was used to record the ECG: one active electrode was placed on the collar bone 2 inches to the right of the sternum, another active electrode was placed on the second to last rib on the participants left side and a reference electrode was placed 3 inches to the right of the participants naval (Figure 2.1).

Impedance Cardiogram. Impedance cardiography (ICG) data were collected using a NICO100C unit (Biopac Systems, Inc., Goleta, CA) and a VU-AMS (Vrije Universiteit, The Netherlands). Subjects were randomly assigned to each system, with the caveat that there were 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 NICO100C supplied a 400µA 50kHZ constant current. The VU-AMS supplied a 350µA 50kHz constant current. Both units used a standard four lead system with spot electrodes. Past research has found that spot electrodes are highly correlated with band electrodes when recording systolic time intervals (McGrath et al., 2005). Spot electrodes also have the added benefit of being easy to apply, more comfortable for the subject than band electrodes and can potentially reduce movement artifacts (Sherwood et al., 1990). The electrodes were placed at anatomical levels in accordance with the standard tetra-polar configuration (Figure 2.1) suggested by Sherwood et al. (1990). Specifically, one current electrode was placed at the C4 vertebrae and one between the T8 and T9 vertebrae. The voltage (or recording) electrodes were placed one 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 that is being conducted between the 2 current electrodes.

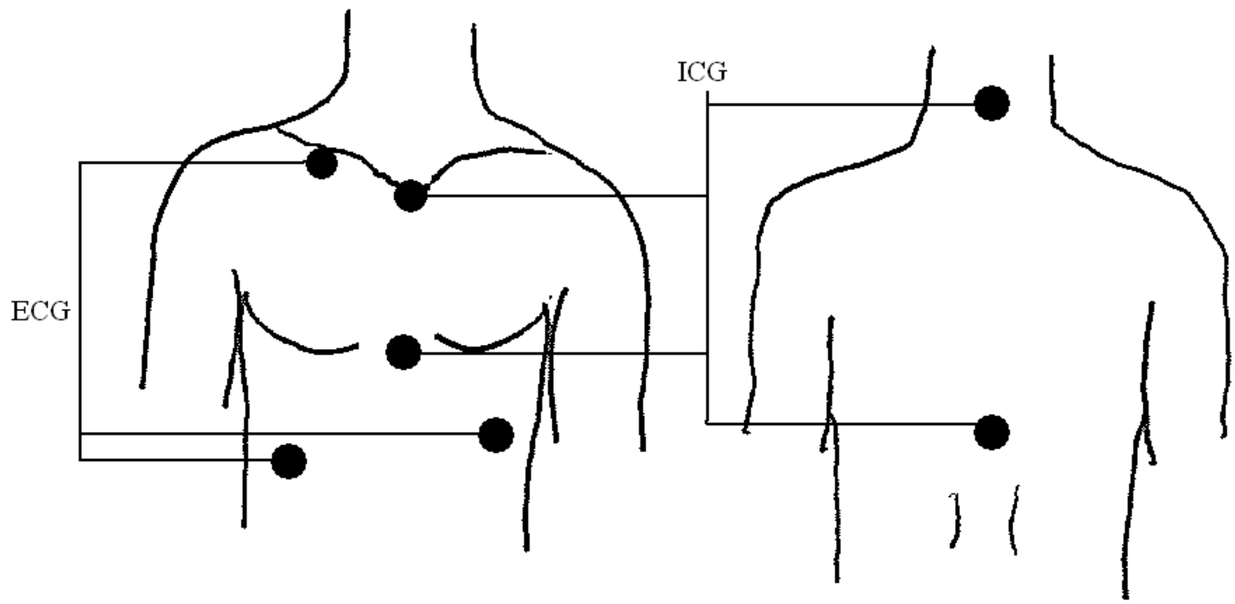

Figure 2.1. Electrode configuration for the ECG and ICG.

Process Control Simulation. The task used in this study was a process control (PC) simulation where subjects 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 PC simulation contained 5 tanks that were monitored so that the above mentioned goals were attained. Each operator was personally responsible for 2 of the tanks (Figure 2.2) while another tank was located between the operators and came with a shared responsibility (Figure 2.2). Each tank had 3 gauges or parameters that were monitored and adjusted: temperature, level, and pressure. The only exception was the center tank, only level and pressure were adjusted, temperature was controlled automatically. The temperature parameter represented the temperature of a tank that could be manipulated by turning on and off a heater and refrigerator. The level parameter represented the amount of “product” that was passing through a particular tank, which could be adjusted by increasing or decreasing the input and output for that tank. The pressure parameter represented the amount of pressure that had been built up within a tank, which could be adjusted by turning the tank’s pressurizer or opening a vent.

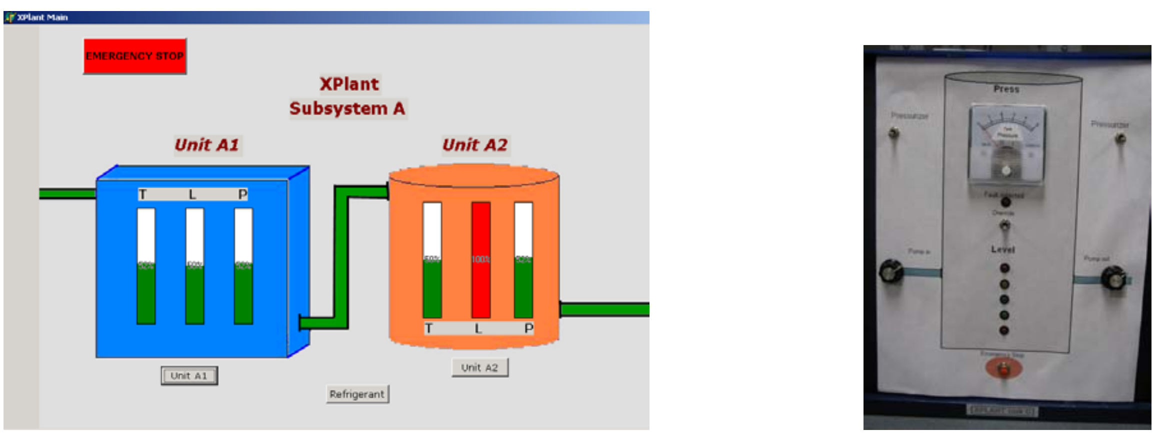

Figure 2.2. Example of the two tanks each operator was responsible for (left) and the center console that both operators controlled (right).

Operators had to monitor both of their tanks simultaneously and zoom in on one tank when one or more of its gauges deviated from safe levels in order to correct the problem (Figure 2.3). Both operators had to be aware of the shared tank in the middle 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.

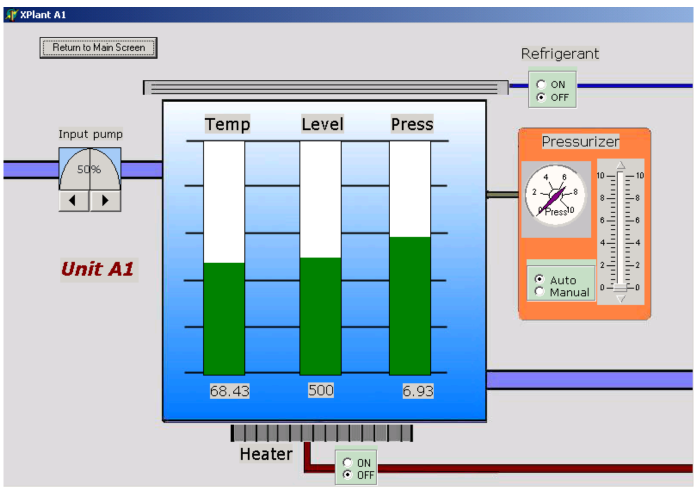

Figure 2.3. Example of a zoomed view of one operator tank.

The PC 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 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 PC simulation at any one time, and the output of tank B2 controlled the about of product leaving the entire system at any one time. Since the PC 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. See the task tutorial in Appendix C for a more detailed description of the operators' responsibilities.

In the PC simulation task, workload could be manipulated on both the individual and team level. The three parameters for each tank could be represented as a curve over time, which represented the state of each parameter if no action was taken by the operator. Task workload could be manipulated by changing the amplitude and frequency of the curve for each parameter (see Appendix D for details on each difficulty curve). Deviations in the parameters of the individual tanks would not directly affect the other operator. Team workload 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. During this study, there were two levels of individual task workload (low and high) and two levels of team task workload (low and high).

The PC simulation provided performance scores on both the individual and 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.

NASA Task Load Index. The NASA task load index (NASA-TLX) is a multi-dimensional questionnaire used to asses a person's subjective level of workload either during or after a task (Hart & Staveland, 1988). The NASA-TLX has 6 dimensions (mental demand, physical demand, temporal demand, frustration, performance, and effort) that are weighted based on each individual's personal definition of workload. These weighted sub-scores are combined to obtain an overall workload score for each administration of the questionnaire. The NASA-TLX has been used in hundreds of studies assessing workload and is commonly used as the benchmark for assessing a person's level of workload (Hart, 2006).

Procedure

The current study used a within-subjects design. Each experimental session involved one team of two completing 4 trials of varying task workload. Upon arrival the subjects completed a brief demographic questionnaire to ensure that they were eligible to participate. Subjects also completed informed consent forms, approved by the university's institutional review board, before receiving a brief explanation regarding what they would be doing during the experiment. Following this explanation the experimenters helped connect the subjects to the physiological recording devices, as described above.

Before the experimental trials began, subjects were given a brief tutorial to acquaint them with the PC simulation. The tutorial consisted of 5-minute verbal script explaining how to control the simulation and reinforcing the goals of the simulation. Following the tutorial the subjects were allowed 10-minutes of practice to get acquainted with the PC simulation. The experimental session consisted of 4 separate 10-minute trials of varying individual and team difficulty (Table 1). These particular combinations of task difficulty were chosen in order to provide variability in both workload and performance, including situations where team members had to deal with 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, but the other team member had high difficulty and the team task difficulty was high. Pilot tests prior to the experiment were conducted in order to ensure that the task was able to produce the expected variability in perceived workload and performance.

The order of the trials was determined using a Latin square technique. After each condition the subjects completed the electronic version of the NASA-TLX, resulting in a total of 8 administrations. At the completion of the experimental session the subjects were disconnected from the physiological equipment and given a debriefing to explain the experiment and answer any questions the subjects might have.

Table 1. *Permutations of workload levels*

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

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 a consecutive 1 minute time periods. The process was similar to the signal averaging of ERPs 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 minute 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 using the software provided by each system and the fiduciary points used to calculate systolic time intervals were identified by hand.

Respiratory sinus arrhythmia. Prior to the analysis of IBI data, the individual IBIs for each subject 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 was corrected by splitting it in half, and the second type of error produced two abnormally short IBIs, which were combined to produce one IBI.

IBI data were used to derive RSA scores by using a locally designed program that employed the following process. The IBI data were re-sampled at 1 Hz by taking the IBI value present at every 1 second interval. Those re-sampled data were mean-centered, windowed in 64s periods and submitted to a Hamming window that tapered the ends of each window to zero to reduce leakage. A fast Fourier transform (FFT) was performed on each 64s interval with an overlap of 75%. 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 had to be log transformed before further analyses, creating a new variable labeled logRSA.

When measuring RSA in an experiment, the effects of respiration should be considered. If respiration significantly varies over time, then a correction must be made to the RSA scores. In the current study respiration rate, measured as cycles per minute (CPM), was examined across all 4 trials in order to determine if RSA needed to be adjusted.

The location of the high frequency component of HRV was also 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 to respiration frequency as recorded using a mercury strain gauge. The subsequent correlation between the two measures was 0.88 with a resolution of approximately 1 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 (Figure 1.2) , one of which is referred to as the pre-ejection period (PEP). 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 et al. (2004) have suggested the use of an abbreviated PEP measured from the start of the R-spike to the B-point. In their study, Berntson and colleagues found that the abbreviated PEP corresponds closely with the regular PEP and therefore since the R-spike is much easier to detect it has been suggested that future research use the abbreviated PEP (Berntson et al., 2004; Sherwood et al., 1990). Each trial resulted in 10 PEP scores, therefore over the 4 trials there were 40 PEP scores.

The other systolic time interval that will be derived from the ICG was left ventricular ejection time (LVET). LVET is the time from the opening of the aorta to the closing of the aorta, or the amount of time it takes for blood to be expelled from the left ventricle. The LVET is measured as the time, in ms, between the B-point and the X-point on the ICG (Sherwood et al. 1990). Each trial resulted in 10 LVET scores, therefore over the 4 trials there were 40 LVET scores.

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

The first method correlated the PNS and SNS scores between the team members. The 10 logRSA scores for team member 1 and the 10 logRSA scores for team member 2 were correlated to produce a team parasympathetic score for each trial (rlogRSA). Then the same was done for the 10 PEP (rPEP) and 10 LVET (rLVET) scores of the team members to produce 2 team sympathetic scores for each trial.

The second method combined the PNS and SNS scores and then correlated them, 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 subject. 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.

PC simulator performance (system error). Task performance scores were obtained on an individual and team level. Each of the operator stations provided the values of each parameter, for each tank at a sampling rate of 1 Hz. The RMSD was calculated for each parameter, for each trial, using these optimum values: pressure - 6, level – 500, temperature - 70. The deviations for all 6 parameters were added together for each person to produce a total individual error score for each trial.

For the center console, the RMSD of pressure and level were calculated using 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. The deviations for these 4 parameters were added to produce a total team error score for each trial.

Data Analysis

Hypothesis 1: Autonomic activity could be used to detect changes in task workload. First, a series of 2 x 4 repeated measures analysis of variances (ANOVAs) were used to determine if perceived workload and performance differed across task difficulty levels. This analysis was conducted to confirm that task workload varied with task difficulty levels. A series of 2 x 4 multivariate repeated measures (ANOVA) were then conducted to determine if individual and team autonomic activity varied by task workload level. If Mauchly's test of sphericity was significant, then a multivariate repeated measures ANOVA was used to avoid any bias due to unequal covariances. Multivariate repeated measures ANOVAs were always used to analyze the autonomic activity data because repeated measures physiological data often violate the assumption of sphericity (Vasey & Thayer, 1987).

Hypothesis 2: Changes in autonomic activity were related to changes in task performance and perceived workload. A series of within-person and within-team correlations were conducted to determine the relations between autonomic activity, performance and workload across all four trials. In order to correlate individual autonomic scores with performance and workload scores, the 10 logRSA, 10 PEP, and 10 LVET scores were averaged to produce 1 logRSA, 1 PEP, and 1 LVET score for each trial, per person. The following within-person correlations were conducted to investigate relations at the individual level: individual error and autonomic activity measures (logRSA, PEP, and LVET), NASA-TLX scores and autonomic activity measures, NASA-TLX scores and individual error. The scores for each of the four trials were correlated together to produce one within-person correlation for each subject, then the correlations for each subject were averaged together to produce one correlation for each of the above relations.

To investigate relations at the team level the following within-team correlations were conducted: team error and team autonomic activity.

Hypothesis 3: Team autonomic activity could be used to predict performance. A series of regressions was conducted attempting to predict performance from autonomic activity. Because the current study contained a within subject repeated measures variable, each task difficulty level was dummy coded which produced a total of 3 dummy coded variables. To determine whether a team's autonomic activity predicted team performance 3 separate regressions were conducted. In the first regression, task difficulty was entered into the first step of the model and the individual measures of PNS and SNS activity for both team members were added into the second step, predicting team error. In the second regression, task difficulty was entered into the first step of the model, and then the correlation between PNS measures and the correlation between SNS measures was entered into the second step, predicting team error. In the third regression, task difficulty was entered into the first step of the model, and then the canonical correlation between the PNS and SNS measures for both team members was entered into the second step, predicting team error. The preceding regressions were also conducted using operator A's error as the DV and operator B's error as the DV.

Exploratory analyses. Additional correlations were also conducted examining the relation between performance, autonomic activity, and workload at each level of task difficulty. These correlations were conducted at both the team and individual level.

CHAPTER 3

RESULTS

Outliers

Upon examining the performance data it was determined that two teams represented outliers and were removed from the analyses. When the data were sorted based on teams' overall performance (individual performance plus team performance) it was clear that the majority of teams had the best performance during the LLL trial and the worst performance during the HHH trial. This was not the case for teams 40 and 21. All of the trials for these two teams were among the worst scores for the entire sample. This suggests that these teams did not respond the same way to the experimental manipulation as the rest of the sample and therefore were removed from the analyses.

Hypothesis 1: Autonomic activity could be used to detect changes in task workload

The test for sphericity was significant for individual workload; therefore a multivariate approach was used. There were significant differences in workload across task difficulty, $F(3,60) = 48.53$, $p < 0.05$, $\acute{\eta}_p^2 = .71$, with a significant interaction between operator and difficulty level, $F(3,60) = 41.07$, $p < 0.05$, $\acute{\eta}_p^2 = .67$ (Figure 3.1). Post-hoc analyses showed that there were significant differences in workload between all 4 levels of task difficulty. The interaction between difficulty and operator occurred during the HLL and LHH trials. During the HLL trial, operator A's workload was higher than operator B's, and the opposite occurred during the LHH trial. There were no significant differences between operators.

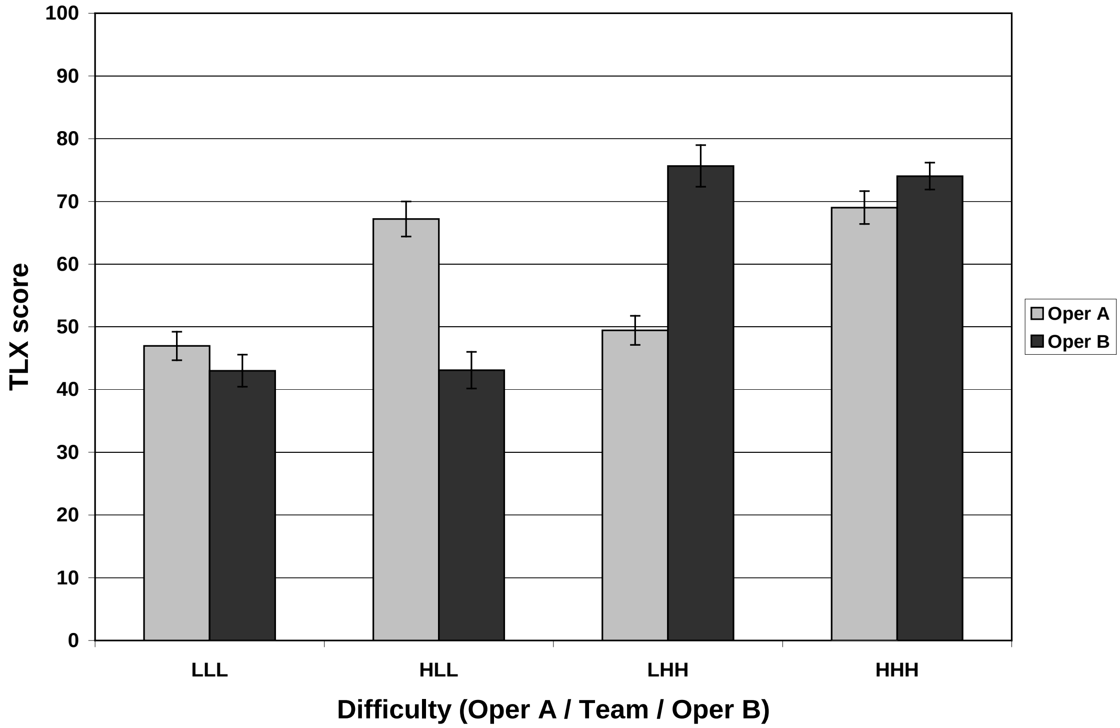

Figure 3.1. Individual workload scores across task difficulty levels for Operator A and Operator B

There were also significant differences in individual error across task difficulty levels, $F(3,186) = 31.544$, $p < 0.05$, $ή_p^2 = .34$, with a significant interaction between operator and difficulty level, $F(3,186) = 20.80$, $p < 0.05$, $ή_p^2 = .25$ (Figure 3.2). Post-hoc analyses showed that there were significant differences in error between all 4 levels of task difficulty. The interaction between difficulty and operator occurred during the HLL and LHH trials. During the HLL trial, operator A's error was higher than operator B's, and the opposite occurred during the LHH trial. There were no significant differences between operators.

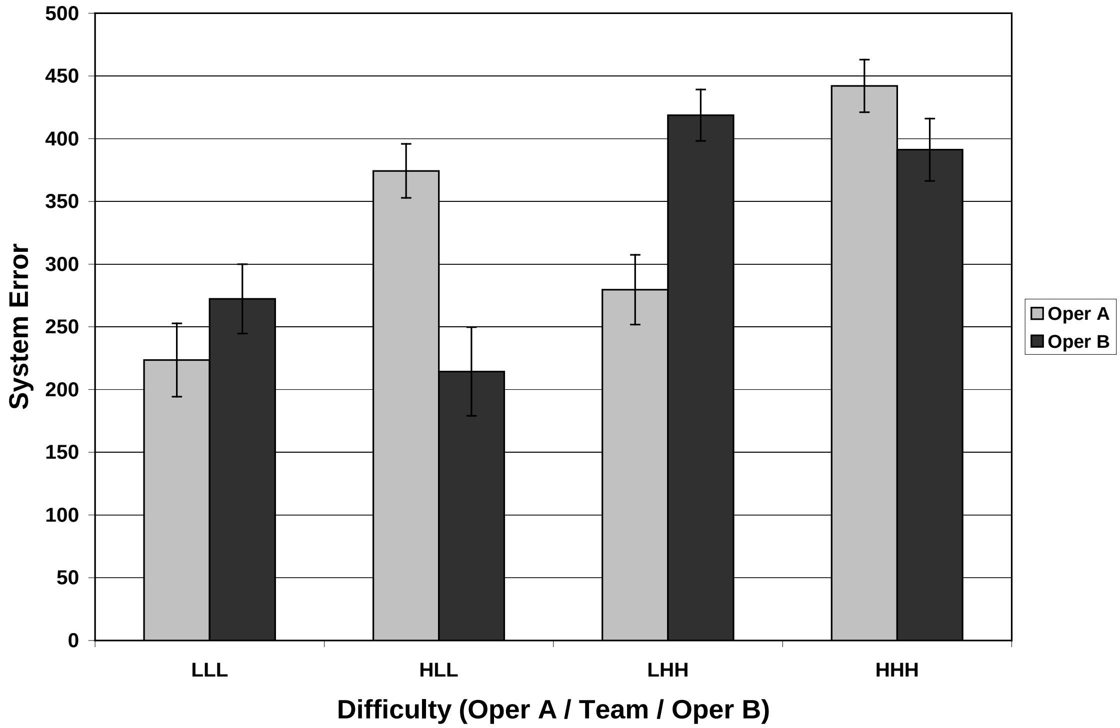

Figure 3.2. Individual error scores across task difficulty levels for Operator A and Operator B

At the team level of analysis there were significant differences in team error across task difficulty, $F(3,93) = 10.41$, $p < 0.05$, $ή_p^2 = .25$. Post hoc analyses showed significant differences in team error between all difficulty levels except the following: LLL and HLL; and LLL and LHH (Figure 3.3).

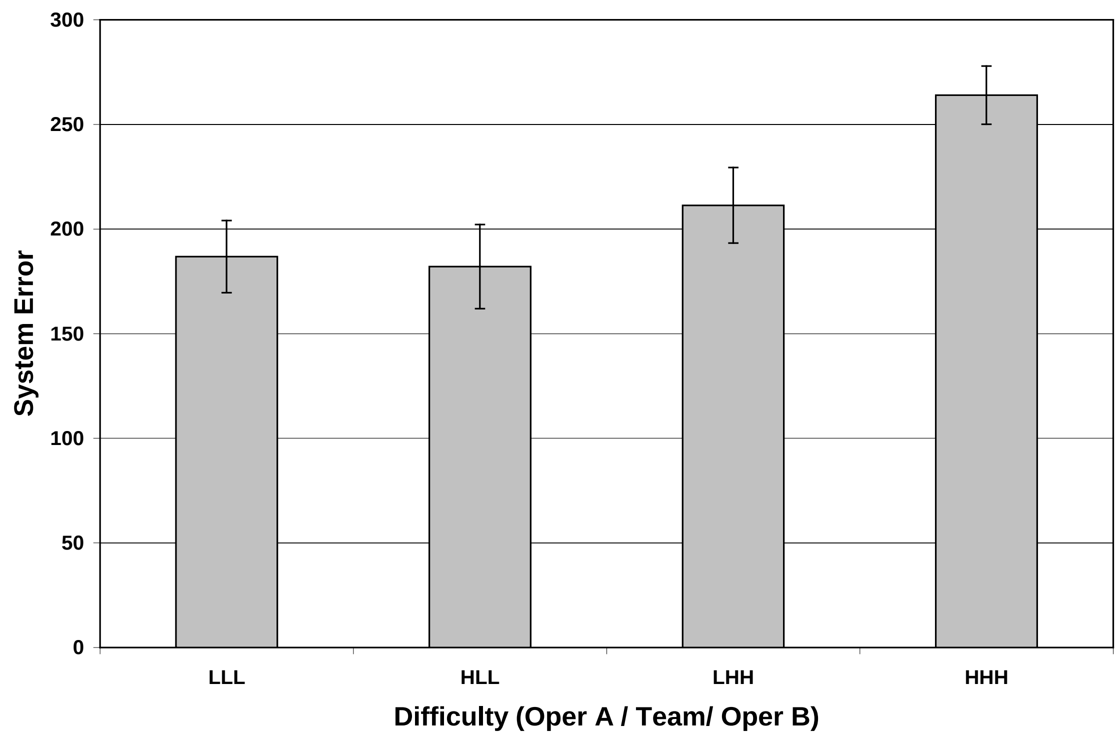

Figure 3.3. Team error across task difficulty levels.

Analysis of respiration rate (Table 2) showed that it did not significantly differ across the 4 difficulty levels, $F(3, 189)= 1.12$, $p > 0.05$, therefore RSA was not adjusted for respiration rate. LogRSA was used in all of the analyses for the current study. Analyses of the individual physiological data resulted in only one significant main effect. There were significant differences in logRSA scores across task difficulty, $F(3,60) = 2.52$, $p < 0.10$, $\acute{\eta}_p^2 = .12$ (Figure 3.4). Post hoc analyses showed that logRSA scores were significantly higher in the LLL trial than in the HHH trial. There was no significant interaction or difference between operators. There were no significant main effects of the team autonomic activity measures across task difficulty.

Table 2. *Respiration rate across the 4 difficulty levels*

	LLL	HLL	LHH	HHH
Mean	13.95	14.23	13.84	14.05
Standard Deviation	1.71	1.85	2.43	2.19

Note: *n* = 64

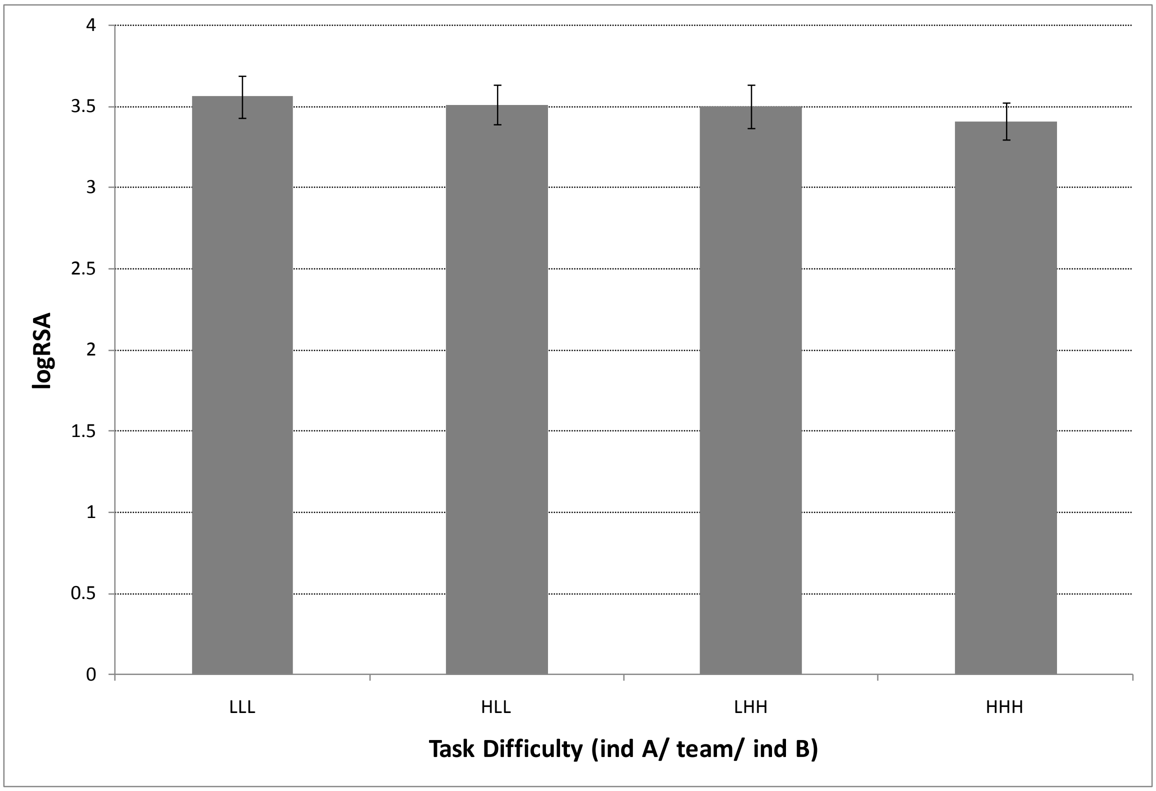

Figure 3.4. LogRSA scores across task difficulty levels.

Hypothesis 2: Changes in autonomic activity were related to changes in task performance and perceived workload

Table 3 contains the within-person correlations for the individual level of task performance, perceived workload and physiological data. 3 correlations were conducted, 1 including all subjects, 1 including only data from operator A, and 1 including only data from operator B. The only significant correlations were those between perceived workload and error.

Table 3. *Individual level data correlations*

		logRSA	PEP	LVET	Individual Error
All Subjects n = 64	Workload (TLX)	-0.16	0.12	-0.15	0.62
	Individual Error	-0.19	0.04	-0.14	-
Operator A n = 32	Workload (TLX)	-0.15	0.12	-0.09	0.54
	Individual Error	-0.22	-0.07	-0.09	-
Operator B n = 32	Workload (TLX)	-0.18	0.13	-0.21	0.71
	Individual Error	-0.17	0.15	-0.19	-

Table 4 contains the within-team correlations for the team level data comparing team autonomic activity and team task performance. There were no significant correlations present at this level of analysis.

Table 4. *Team level data correlations*

	rlogRSA	rLVET	rPEP	Canonical Correlations
Team Error	-0.10	0.10	-0.09	-0.03

Note: n = 32

Hypothesis 3: Team autonomic activity could be used to predict performance

Table 5 contains the regressions predicting team performance from team autonomic activity. Table 6 contains the regressions predicting operator A's performance from team autonomic activity. Table 7 contains the regressions predicting operator B's performance from team autonomic activity.

Table 5 : *Regressions predicting team performance*

Variable		R^2	ΔR^2	β	ΔF	*p*
Team error predicted by task difficulty (d_1,d_2,d_3) & alogRSA, blogRSA, aLVET, bLVET(*n*=128)						
Step 1		.10	.10		4.60	.00
	d_1LLL			**-.33**		
	d_2HLL			**-.34**		
	d_3LHH			**-.20**		
Step 2		.20	.10		3.62	.00
	alogRSA			.05		
	blogRSA			-.05		
	aLVET			**-.26**		
	bLVET			-.15*		
Team error predicted by task difficulty (d_1,d_2,d_3) & alogRSA, blogRSA, aPEP, bPEP(*n*=128)						
Step 1		.10	.10		4.60	.00
	d_1LLL			**-.33**		
	d_2HLL			**-.34**		
	d_3LHH			**-.20**		
		.20	.10		3.78	.00
	alogRSA			.08		
	blogRSA			-.02		
	aPEP			**.19**		
	bPEP			**-.26**		
Team error predicted by task difficulty (d_1,d_2,d_3) & rlogRSA, rLVET (*n*=127)						
Step 1		.10	.10		4.60	.00
	d_1LLL			**-.33**		
	d_2HLL			**-.34**		
	d_3LHH			-.19*		
Step 2		.11	.01		.72	.01
	rlogRSA			-.10		
	rLVET			-.03		
Team error predicted by task difficulty (d_1,d_2,d_3) & rlogRSA, rPEP (*n*=128)						
Step 1		.10	.10		4.60	.00
	d_1LLL			**-.33**		
	d_2HLL			**-.34**		
	d_3LHH			-.19*		
Step 2		.12	.02		1.14	.01
	rlogRSA			-.11		
	rPEP			-.08		
Team error predicted by task difficulty (d_1,d_2,d_3) & canonical correlation (*n*=127)						
Step 1		.10	.10		4.60	.00
	d_1LLL			**-.33**		
	d_2HLL			**-.34**		
	d_3LHH			**-.19**		
Step 2		.13	.03		4.00	.00
	Canonical Correlation			**-.17**		

Note: Standardized regression coefficients (β) in **bold** are significant ($p < 0.05$), * are significant ($p < 0.10$)

Table 6 : *Regressions predicting operator A's performance*

Variable		R^2	ΔR^2	β	ΔF	*p*
A error predicted by task difficulty (d_1,d_2,d_3) & alogRSA, blogRSA, aLVET, bLVET (*n*=128)						
Step 1		.28	.28		16.07	.00
	d_1LLL			**-.61**		
	d_2HLL			**-.20**		
	d_3LHH			**-.42**		
Step 2		.34	.06		2.62	.00
	alogRSA			**-.16**		
	blogRSA			-.07		
	aLVET			-.08		
	bLVET			-.10		
A error predicted by task difficulty (d_1,d_2,d_3) & alogRSA, blogRSA, aPEP, bPEP (*n*=128)						
Step 1		.28	.28		16.07	.00
	d_1LLL			**-.61**		
	d_2HLL			**-.20**		
	d_3LHH			**-.42**		
Step 2		.37	.09		4.35	.00
	alogRSA			-.07		
	blogRSA			-.04		
	aPEP			-.02		
	bPEP			**-.25**		
A error predicted by task difficulty (d_1,d_2,d_3) & rlogRSA, rLVET (*n*=127)						
Step 1		.28	.28		16.02	.00
	d_1LLL			**-.61**		
	d_2HLL			**-.20**		
	d_3LHH			**-.42**		
Step 2		.28	.00		.11	.00
	rlogRSA			.03		
	rLVET			-.03		
A error predicted by task difficulty (d_1,d_2,d_3) & rlogRSA, rPEP (*n*=128)						
Step 1		.28	.28		16.07	.00
	d_1LLL			**-.61**		
	d_2HLL			**-.20**		
	d_3LHH			**-.42**		
Step 2		.29	.01		.77	.00
	rlogRSA			.01		
	rPEP			-.09		
A error predicted by task difficulty (d_1,d_2,d_3) & canonical correlation (*n*=127)						
Step 1		.28	.28		16.02	.00
	d_1LLL			**-.61**		
	d_2HLL			**-.20**		
	d_3LHH			**-.42**		
Step 2		.29	.01		.89	.00
	Canonical Correlation			-.07		

Note: Standardized regression coefficients (β) in **bold** are significant ($p < 0.05$), * are significant ($p < 0.10$)

Table 7 : *Regressions Predicting Operator B's Performance*

Variable		R^2	ΔR^2	β	ΔF	*p*
B error predicted by task difficulty (d_1,d_2,d_3) & alogRSA, blogRSA, aLVET, bLVET (*n*=128)						
Step 1		.24	.24		13.36	.00
	d_1LLL			**-.30**		
	d_2HLL			**-.43**		
	d_3LHH			.09		
Step 2		.27	.02		.84	.00
	alogRSA			-.09		
	blogRSA			.07		
	aLVET			-.05		
	bLVET			-.08		
B error predicted by task difficulty (d_1,d_2,d_3) & alogRSA, blogRSA, aPEP, bPEP (*n*=128)						
Step 1		.24	.24		13.36	.00
	d_1LLL			**-.30**		
	d_2HLL			**-.43**		
	d_3LHH			.09		
Step 2		.26	.02		.48	.00
	alogRSA			-.10		
	blogRSA			.05		
	aPEP			.00		
	bPEP			-.01		
B error predicted by task difficulty (d_1,d_2,d_3) & rlogRSA, rLVET (*n*=127)						
Step 1		.24	.24		12.81	.00
	d_1LLL			**-.31**		
	d_2HLL			**-.44**		
	d_3LHH			.08		
Step 2		.24	.00		.39	.00
	rlogRSA			.04		
	rLVET			-.06		
B error predicted by task difficulty (d_1,d_2,d_3) & rlogRSA, rPEP (*n*=128)						
Step 1		.24	.24		13.36	.00
	d_1LLL			**-.30**		
	d_2HLL			**-.43**		
	d_3LHH			.09		
Step 2		.25	.01		.26	.00
	rlogRSA			.03		
	rPEP			-.04		
B error predicted by task difficulty (d_1,d_2,d_3) & canonical correlation (*n*=127)						
Step 1		.24	.24		12.81	.00
	d_1LLL			**-.31**		
	d_2HLL			**-.44**		
	d_3LHH			.08		
Step 2		.25	.01		1.74	.00
	Canonical Correlation			-.11		

Note: Standardized regression coefficients (β) in **bold** are significant ($p < 0.05$), * are significant ($p < 0.10$)

Exploratory Analyses

Table 8 contains the correlations between team performance and combined team autonomic activity indices. Table 9 contains another variation of within-team correlations. This method involved correlating all 40 physiological data points for each team member, over the entire experiment. This created a team physiological compliance correlation across the entire experiment, instead of by difficulty level. This experiment level physiological compliance scores for each team were then correlated with the total experimental performance scores for each team. Table 10 contains the correlations between performance and individual team autonomic activity indices.

Table 8. *Correlations between performance and team autonomic measures*

	rlogRSA	rPEP	rLVET	CanCor
LLL	**-0.43***	-0.26	-0.20	**-0.40***
HLL	0.00	-0.04	-0.09	**-0.52****
LHH	**0.35***	0.33	0.08	0.27
HHH	-0.02	-0.19	0.10	0.08

Note: $n = 32$
* Correlation significant at $p < 0.05$ (2-tailed).
** Correlation significant at $p < 0.01$ (2-tailed).

Table 9. *Team level data correlations over the entire experiment*

	rlogRSA	rLVET	rPEP	CanCor
Team Error	-0.22	0.21	0.08	-0.17

Note: $n = 32$

Table 10. *Correlations between performance and individual indices*

		alogRSA	blogRSA	aPEP	bPEP	aLVET	bLVET	aTLX	bTLX	aError	bError
LLL	aError	0.20	-0.07	-0.08	-0.16	-0.14	**-0.35***	0.07	0.31	**-**	**0.67****
	bError	0.03	-0.03	-0.10	0.02	-0.05	-0.22	0.20	**0.45****	**0.67****	**-**
	Team Error	-0.06	-0.24	0.20	-0.25	-0.29	-0.28	-0.04	0.25	**0.47****	**0.48****
HLL	aError	**-0.37***	-0.28	-0.09	**-0.52****	-0.17	0.01	0.15	0.21	-	0.23
	bError	0.13	-0.12	-0.08	-0.08	0.15	0.09	-0.09	**0.42***	0.23	**-**
	Team Error	-0.05	-0.17	0.30	-0.34	-0.22	-0.03	**0.38***	0.01	0.32	0.17
LHH	aError	-0.26	-0.25	-0.04	**-0.54****	-0.23	-0.07	0.09	0.24	-	0.15
	bError	**-0.55****	0.19	-0.03	-0.02	-0.13	0.07	0.04	**0.35***	0.15	**-**
	Team Error	0.01	-0.14	0.15	-0.23	-0.31	-0.28	0.1	0.23	**0.44***	0.14
HHH	aError	-0.34	0.06	0.16	-0.19	-0.16	-0.13	-0.20	0.24	-	0.15
	bError	-0.07	0.15	0.17	-0.14	-0.29	-0.18	0.09	**0.38***	0.15	**-**
	Team Error	0.00	0.10	0.23	-0.18	-0.28	-0.14	0.10	0.03	0.20	**0.46****

Note: $n = 32$
* Correlation significant at $p < 0.05$ (2-tailed).
** Correlation significant at $p < 0.01$ (2-tailed).

CHAPTER 4

DISCUSSION

Hypothesis 1: Autonomic activity could be used to detect changes in task workload

Analyses of perceived workload (Figure 3.1) and performance (Figures 3.2 & 3.3), across the different task difficulty levels, showed that the current task paradigm was effective at manipulating task workload. Though task workload showed a significant amount of variability during this study, the first hypothesis was somewhat unsupported. The only evidence that autonomic activity was related to workload was that individual PNS activity (logRSA) was significantly higher during the easiest difficulty level (LLL) than during the hardest (HHH; Figure 3.4). Looking back at previous literature, it is not surprising that RSA was only able to differentiate between the two extreme levels of task workload.

As discussed previously, HR and HRV measures are sensitive to gross changes in workload (e.g., Comens, Reed, & Mette, 1987; Hart & Hauser, 1987; Lindholm & Cheatham, 1983; Nicholson et al. 1970; Wilson, 1993, 2002), but lack the diagnosticity to show differences between more complex manipulations of workload. For example, a study conducted by Moss et al. (2009) examined 7 different tasks of varying difficulty that measured the basic skills necessary to become a pilot. Although those different tasks tested different skill sets, and different levels of complexity within those skill sets, when RSA and NASA-TLX scores were examined across all tasks, those measures only differentiated between tasks that were generally low in workload and tasks that were generally high in workload. More specific diagnosticity was beyond the scope of those fairly traditional indices of workload.

A study by Fishel et al. 2007, examining the relation between workload and physiological arousal on a complex training system, offers possible explanations for the results of the RSA data in the current study. Fishel et al. (2007) used a computer based, military forward observer simulation to examine the link between workload and HRV. The authors found that while there were differences in workload between the low and high conditions of the task, both conditions still had relatively high subjective reports of workload when compared to studies involving very simplistic tasks (e.g., card sorting; Temple et al. 2000). What this suggests is that, even though a task may be designed to have high or low levels of difficulty, those difficulty levels are still bound by the inherent characteristics of that single task. Therefore, while workload may vary within a task, those variations are still relatively small when considered against the full spectrum of possible physiological activation that a person can experience, from a state of sleep to intense exercise. With that in mind, it may not be difficult to understand why a singular measure of cardiovascular autonomic activity cannot differentiate between the various combinations of difficulty in the current task.

Another finding from that study considers what aspects of behavior HRV indexes. Even though HRV is a reliable index of PNS activity on the heart (Grossman & Taylor, 2007), there are numerous phenomena other than workload that can affect PNS activity, such as task type (Walker et al., 2009), fatigue (Jouanin et al., 2004), and executive function (Hansen, Johnsen, & Thayer, 2003). Not only are there other variables that can affect PNS activity, but often those variables are present during a task manipulating workload. For example, Fishel et al. (2007) found that, in addition to changes in workload, HRV may also measure additional behavioral states (e.g. fatigue, boredom, effects of training). This suggests that while subjective measures (e.g., NASA-TLX) may more specifically measure the amount of perceived workload involved in a task, HRV measures a combination of variables, including workload, which can affect task performance. This is why a singular physiological measure may lack the diagnosticity to differentiate between more complex manipulations of workload, within a task. Conversely, this ability of physiological measures to detect other behaviors involved in task performance opens up the possibility of measuring factors other than workload, especially when a combination of physiological factors are measured, as suggested by Backs (2001). This idea is further discussed below in the context of using physiological measures to index other behaviors related to team performance.

Unlike some of the previous studies discussed above comparing physiology to workload, this study did measure more than just PNS activity. What is interesting is that, even though there were changes in task workload, there were no changes in the SNS indices between the different difficulty levels. One potential explanation for the lack of variance in the SNS indices could be the nature of the task. Though the current study was able to achieve variability in workload between the difficulty levels, and within the PNS index, it is possible that the task was not stressful enough to evoke a change in SNS activity. As stated above, according to the theory of autonomic space, there can be three different types of autonomic patterning between PNS and SNS activity in response to a stimulus (Berntson, Cacioppo, & Quigley, 1991). There can be reciprocal activity when, for example, there is an increase in SNS activity and a decrease in PNS activity. There can be coactivity when, for example, there is an increase in both SNS and PNS activity. Finally, there can be uncoupled activity when, for example, there is a decrease in PNS activity, but no change in SNS activity. Because the PC simulation is essentially a vigilance task, it is possible that the workload produced during its operation was accompanied by a pattern of uncoupled PNS activity. This pattern of uncoupled activation could explain the lack of variability in the SNS indices between the difficulty levels.

Another possible explanation for the lack of differences in the physiological data could be that cardiovascular measures were not the best indices of ANS activity during the current task. HRV and systolic time intervals were chosen because they are measures of PNS and SNS activity from the same organ, which is recommended when examining autonomic space (Berntson, Cacioppo, & Quigley, 1991). While RSA, PEP and LVET are common measures of ANS activity, they are not the only ones available.

HRV is an established index of PNS activity on the heart (Grossman & Taylor, 2007), and it was capable of detecting gross differences in workload. Despite that, it is possible that an alternative measure of PNS activity, such as tear volume (Tamura, et al. 1990), could have been more sensitive to specific changes in workload. It is unknown whether measuring tear volume would have been a more sensitive measure of PNS activity during this task. What is known is the apparatus for its measurement must be worn on the face which could have been uncomfortable for the length of the task and possibly interfered with team interactions. Therefore, HRV is still the most logical choice for indexing PNS activity in the current study.

The alternative indices for the measurement of SNS activity are more numerous and validated. For instance, blood pressure is a widely used index of SNS effects on the cardiovascular system (Andreassi, 2000). Unfortunately, with the length of the current task, the repeated measurement of blood pressure may also have become too uncomfortable for the subjects. If blood pressure were measured during the current study, over the course of the experiment each subjects' cuff would have to be inflated at least 40 separate times. That many repeated measurements could have temporarily affected the tissue of the subjects' arms, which would have led to biased measurements.

Another established measure of SNS activity that is not associated with the cardiovascular system is skin conductance (Stern, Ray, & Quigley, 2001). Skin conductance measures the changes in activation of eccrine sweat glands on the palms or soles of the feet, which are primarily enervated by the SNS. What makes skin conductance different from other measures of SNS activity is that the post-ganglionic neurotransmitter is acetylcholine, not the traditional norepinephrine. It is possible that this neurochemical difference with skin conductance could have allowed it to detect changes in SNS activity for which systolic time intervals were not sensitive. If skin conductance had been used in the current study, the electrodes would have been placed on the soles of the feet considering that most subjects used both hands to operate the PC simulator. Unfortunately, one of the drawbacks of skin conductance is its sensitivity to movement artifacts which, with the length of the experiment and the fact that the electrodes would be on the feet, could have been a problem with recording this type of data.

Though there are other measures of ANS activity available which may have produced different results during the current experiment, HRV and systolic time intervals were the best choices of measures based on the constraints of the experimental design. Future research examining the relation between autonomic activity and workload should investigate an experimental paradigm that would allow for the recording of these alternative measures.

Hypothesis 2: Changes in autonomic activity were related to changes in task performance and perceived workload

Based on previous literature (e.g. Fishel et al., 2007; Moss et al., 2009) it was expected that autonomic activity would be related to changes in perceived workload and therefore, would be related to changes in task performance. The results of the within-person and within-team correlations suggest that there were no relations between autonomic activity and perceived workload or autonomic activity and performance, at either the individual or team level (Tables 3 & 4). This is surprising considering that there was variability in workload and performance throughout the experiment, which was further confirmed through the high positive correlation between perceived workload and error.

It was expected that there would have been negative correlations between the individual autonomic activity measures, workload, and individual error, as well as between the physiological compliance measures and team error. While not significant, the correlations between logRSA, workload and individual error, and LVET, workload and individual error were in the expected direction. This suggests that increases in PNS activity would be associated with decreases in error and workload, while increases in SNS activity would be associated with increases in error and workload. Conversely, PEP displayed non-significant, positive correlations with workload and error. This suggests that increases in SNS activity would be associated with decreases in error and workload.

There were similar discrepancies between the SNS measures at the team autonomic activity level. At the team level, the physiological compliance measures using rlogRSA, rPEP and the canonical correlations showed the expected negative correlation with team error. This suggests that increases in physiological compliance would be associated with decreases in team error. Similar to what was discussed previously with PEP, the physiological compliance measure using rLVET showed a positive correlation with team error, which suggests that increases in SNS physiological compliance would be associated with increases in team error. This difference in the results produced by the SNS measures was a recurring theme in the current study and is discussed in more detail below.

The lack of any significant relations between autonomic activity and performance or workload could be due to the type of analysis used to examine the data. In the current study, the within-person correlations involved correlating autonomic activity scores with performance and workload scores across the four task difficulty levels, for each person or team. Those resulting correlations were then averaged over all 64 subjects or 32 teams. Therefore, while there may have been 64 subjects, there were essentially only 4 data points in each correlation. Unfortunately, this is one of the problems of within-person correlations and may explain the lack of relation between the autonomic activity, workload and performance variables.

Another explanation for the lack of correlation among the autonomic activity, workload and performance variables could be that the relations may change with the various combinations of difficulty throughout the task. Though the correlations for operator A and operator B were all in the same direction (Table 3), there were still some differences between the operators. This would be expected considering that operators A and B received different combinations of individual and team difficulty. At the same time, as discussed above, the lack of significant correlations could be a result of the physiological measures indexing more than just workload during a team task. Both of these possibilities are discussed below with the results of a series of exploratory correlations (see Table 8 & 9).

Hypothesis 3: Team autonomic activity could be used to predict performance

The results of the regressions for hypothesis 3 showed that team autonomic activity could account for up to 10% of the variance in team performance scores above and beyond task difficulty. Of the three models used to predict performance, the models containing the individual autonomic indices of operator A and B were the best predictors (see Table 5). When examining those regressions further it became clear that the significant predictors within the models, other than task difficulty, were the measures of SNS activity (both LVET and PEP). This is somewhat contradictory to the previous results of the ANOVAs showing that only RSA differed between difficulty levels. An explanation for the difference between the ANOVA and regression results is that there may have been large individual differences between the teams within the various difficulty levels. If this were the case, it would be difficult to find differences with an ANOVA, but a regression could detect changes in physiology after accounting for changes in task difficulty levels that are related to performance.

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 5). In other words, higher levels of team “stress” were accompanied by lower levels of team performance. What is surprising is that, 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 it was discovered that while 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 where associated with decreases in team error, which suggests that higher levels of operator A’s “stress,” were associated with better team performance. This difference in PEP scores could be a response to the different combinations of task difficulty levels that they two operators experienced. Operator B always experienced a balanced level of difficulty between his 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 where operator A’s workload was low and team workload was high, and one trial where 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. Though the two operators have 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 in order 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 in order to efficiently increase the amount of chemical flowing out of the first half of the system. Because of this interdependence, at any given time during the process control task, either operator can act as a bottleneck to efficient system production. 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 physiological data.

While both LVET and PEP have been used as indices of SNS activity, it has been suggested previously that they do not measure the exact same effects of the SNS on the heart (Uijdehaage & Thayer, 2000; Thayer & Uijdehaage, 2001). While PEP may be an index of the inotropic (force-related) effects of the SNS on the heart, Thayer and Uijdehaage (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 if these differences can be replicated.

Interestingly, the results of the current analyses also showed that the individual indices of autonomic activity were better predictors of team performance than 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 (Henning et al., 2007; Henning & Korbelak, 2005; Elkins et al., 2009), 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.

While team autonomic activity was a significant predictor of team performance, the results were not as clear cut when trying to predict individual performance of the different operators. The regressions predicting operator A's performance showed that team autonomic activity accounted for 6% (model including LVET) and 9% (model including PEP) of the variance (see Table 6). Further examination of the results found that the model including LVET showed that the strongest predictor of error was operator A's RSA, but the model including PEP showed that operator B's PEP scores were an even stronger predictor of operator A's error. According to these results, increases in operator B's SNS activity were associated with increases in operator A's error; which can be interpreted as increases in operator B's "stress" were accompanied by decreases in operator A's performance.

This same type of relation was not repeated when attempting to predict operator B's performance from team autonomic activity (see Table 7). The lack of a consistent relation between operator A and operator B's results could be an indicator of a spurious correlation between B's physiology and A's performance. Despite the possibility of spurious results, a series of exploratory analyses were conducted to further investigate the possible relations between team members' autonomic activity and performance.

Exploratory Analyses

The results of these analyses showed some interesting relations between the various combinations of task difficulty at both the team (Table 8) and individual level (Table 10). Even though the various measures of physiological compliance were not significant predictors of team performance throughout all levels of difficulty, there were significant correlations during several of the difficulty levels. During the easiest task difficulty level, when operator difficulty was low and team difficulty was low, two measures of physiological compliance (rlogRSA and canonical correlation) were correlated with team performance. The relation at the LLL difficulty level follows the hypothesis that increases in physiological compliance are accompanied by decreases in team error. A similar relation was found during the HLL condition, but only with the canonical correlation.

Interestingly, this expected relation was not found during the LHH difficulty level or the hardest (HHH) difficulty level. In fact, during the unbalanced workload level of LHH, one measure of team autonomic activity was significantly positively correlated with team error. This suggests that during this level, increases in physiological compliance were associated with increases in team error. This is the opposite of what was found above for the two easier conditions. One possible explanation for this positive relation between physiological compliance and team error is that there may be certain task situations where a team's physiology should not be correlated. If the task difficulty or workload is unbalanced, meaning that one team member is under higher levels of workload than the other, then it seems plausible that a well functioning team would not share positively correlated patterns of physiological activation. For example, if one team member is reacting to a low level of individual difficulty with a high level of SNS activation, that team member is not effectively coping with their workload, regardless of how correlated that person is with his or her team member. In fact, the positive correlation between team autonomic activity and error, might suggest that when team members' autonomic activity is negatively correlated, during certain task situations, team error decreases. When examining the hardest level of task difficulty (HHH), neither a positive nor a negative relation was found between physiological compliance and team performance.

It is unclear why the expected relation between physiological compliance and team performance was found during some of the task levels, but not during all of them. Perhaps the tasks used in the previous literature have provided a relatively low level of balanced workload to the teams (Henning, Boucsein, & Gill, 2001; Henning & Korbelak, 2005; Elkins et al., 2009), and that the previous measures of physiological compliance do not hold up under levels of unbalanced workload or instances of task overload. This is only a suggestions and further research needs to be conducted to determine if the predictive ability of physiological compliance holds up under different tasks and workload conditions.

When examining the individual operator indices by difficulty level there were also some interesting relations (Table 10). One result that stands out across all difficulty levels is, based on previous literature it was expected that NASA-TLX scores would be the best predictor of performance (Beith, 1987; Hart & Hausers, 1987; Urban et al., 1995), but that was not the case. TLX scores for operator B were always positively correlated with operator B's performance scores, but operator A's TLX scores were not. The reason for this discrepancy is unclear, but it is possible that it was the result of an inherent difference in operator B's responsibilities. Perhaps being the second operator in process simulation added an extra characteristic to that team member's task that was not previously expected.

Another interesting finding in these exploratory correlations was that, during the unbalanced task difficulty levels, the factor that shared the highest correlation with an operator's performance was often the other operator's autonomic activity. For example, during both unbalanced difficulty levels, decreases in operator B's SNS activity were associated with decreases in operator A's error. Also, during the LHH level, increases in operator A's PNS activity were associated with decreases in operator B's error. What this suggests is that physiologically relaxed state in one team member is associated with better performance in the other team member. These findings suggest that physiological compliance may not be the best mechanism for measuring team physiology during these unbalanced difficulty levels. Instead, a more complex relation between team members' physiology and performance may be a result of different team behaviors required to deal with these situations.

An explanation of these team behaviors and interactions necessary for effective team work may be found in the team literature. Salas, Sims and Burke (2005) outlined a set of "Big Five" factors which help to define the behaviors that contribute to effective teamwork. Those factors are: team leadership, mutual performance monitoring, backup behavior, adaptability, and team orientation. Of those five factors, mutual performance monitoring and backup behavior may help to explain some of the results discussed above.

Briefly, mutual performance monitoring occurs when team members monitor each other's work and progress to ensure that all aspects of the task are functioning as they should (McIntyre & Salas, 1995; Salas, Sims, & Burke, 2005). Salas, Sims & Burke (2005) also note that there is currently no effective way to objectively measure mutual performance monitoring because there is no overt representation of the behavior. Typically, the only way to determine if it occurs is if a team member engages in some type of backup behavior in order to address a potential problem.

Backup behavior occurs when one team member recognizes the unbalanced distribution of workload within the team and takes actions to support another team member in order to avoid a potential problem (Porter et al., 2003). The results from the analysis of TLX scores shows that there is clearly an unequal distribution of workload within the HLL and LHH difficulty levels, which suggests that the correlations between team members' performance and physiology could be evidence of one or both of the aforementioned behaviors. It is possible that when a team member was more physiologically "relaxed" it provided him or her with more of an opportunity to engage in mutual performance monitoring. Also, this increase in monitoring could lead to an increase in backup behaviors supporting the other team member, which would explain the higher levels of performance. Of course it is also possible that when one team member is performing well, then the other operator does not need to worry about their team member's performance, which in turn could lead to that operator's "relaxed" state. Because physiology has not commonly been used to measure the specific behaviors outlined by Salas, Sims, and Burke (2005), this conclusion is exploratory and there is a possibility that the correlations were spurious.

If these correlations can be replicated, they hold some interesting possibilities for the assessment of team workload. It has been mentioned above that the relation between team workload and team performance is not a simple one. Urban et al. (1995) suggest that the relation may be mediated by the effectiveness of a team, where effective teams can overcome the negative influences of high team workload. Future studies should attempt to discover if this mediating factor could be measured using team autonomic activity, as it is suggested in the preceding section. If team autonomic activity can detect changes in the various behaviors that represent an effective team, then a more comprehensive model could be created to judge the relation between team workload and performance.

Limitations

To the author's knowledge, this is the first study to measure team autonomic activity and attempt to relate it to team performance and task difficulty. By being 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 using a VU-AMS system, while a Biopac system was used to record operator B's SNS activity. While 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 operator's SNS activity measures, due to differences in the two systems, should have been as small as possible.

Another limitation of the current study is that while 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.

After an examination of the results, another limitation is the lack of any measurement of team workload or other team behaviors. To the author's knowledge, there are currently no validated measures of team workload and therefore it may be excusable that none were used in the current study. On the other hand, there are other tools available to measure the various behaviors necessary for effective team performance. If those measures had been added to the current study, the relation between team member physiology and mutual performance monitoring or back up behavior may have had more reliable evidence.

Finally, the current study was designed to examine the relations between autonomic activity, workload and performance across all difficulty levels. Therefore, when the results were analyzed by each specific difficulty level in the exploratory analyses above, the sample size was less than desired. Any future studies that seek to investigate some of the possible differences between balanced and unbalanced workload conditions should ensure large enough samples sizes at each level of difficulty.

Conclusions

The current study investigated the possible relations between team autonomic activity, workload and performance. Based on past research (e.g. Backs, 2001: Berntson, Cacciopo, & Quigley, 1991), measures of autonomic activity were chosen for the current study because it was believed that they would provide more information than either PNS measures or SNS measures in isolation. By measuring both sides of the ANS, the current study was able to discern that PNS activity could detect large changes in task difficulty, and that SNS activity helped to predict approximately 10% of the variance in team performance scores. Also, by measuring both sides, the current study was able to identify some interesting relations between one team member's physiology and the other team member's performance. Therefore, the current study provides evidence that the measurement of a teams' full autonomic space can be a useful tool in the investigation of team performance.

The results of this study also provide a springboard from which to pursue new and interesting lines of research between team physiology and team behaviors. The potential predictive nature of team autonomic activity on team performance could be applicable for team training and adaptive automation. During team training, measures of team autonomic activity may provide an index of team performance when other measures of performance are unavailable. Also, if a regression model can be developed for a given task, then the real-time autonomic activity of a team might be entered into the model to help predict the future performance of that team. This prediction would allow the system to adapt to changes in the team in order to prevent decreases in performance.

In conclusion, though physiological indices may not always be the best method to measure team performance and workload, they do provide researchers with another option when presented with the daunting task of investigating the numerous aspects of how people work together in teams. As future tasks and systems become more complex the need for teams will only increase. The increasing need for teamwork creates an increasing need to understand how effective teams interact. The current study opens the door to the possibility of using team autonomic activity as a supplement to the measures of team performance and team effectiveness that are currently available.

APPENDICES

A: Questionnaires

Demographic Questionnaire

Subject number:_______________ Gender: M / F Age: Date:__________________

Screening Questions

Questions	Answers	Comments
Any heart problems?	Y / N	
Any vision problems (other than corrective lenses)?	Y / N	
Currently taking any medication? If yes, please provide the name of the medication.	Y / N	
Do you smoke?	Y / N	
If yes, when was the last time you had a cigarette?		
If female, are you pregnant?	Y / N	
How many hours of sleep did you get last night?		
What is your major/occupation?		
Are you now or have you ever served in one of the armed forces?	Y / N	
If yes, which one and for how long?		
Have you ever played a team sport? If yes, which one and for how long?	Y / N	
Do you know the person you are completing this experiment with? If yes, how long have you known him/her?	Y / N	
Please list any other experience you have had with teams		
Height:_________ Weight:_____________		

NASA TLX Workload Questionnaire

Workload Survey

Here we are interested in examining the experiences that you think that you will have during the mission. In the most general sense, we are examining the sense of “workload” experienced during the mission(s).

Workload is a difficult concept to define precisely. The factors that influence your experience of workload may come from several factors. This survey is divided into four sections which will serve to assess workload. As two sections deal with assessing perceptions of your workload and two sections deal with assessing your perception of workload, please read the instructions for each section carefully before completing.

Instructions: Place an X on each scale at the point that best represents your experience of workload during the mission. Marks must be placed inside the box, not on the lines.

1. Mental Demand:

How much mental and perceptual activity did the mission require of you (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)?

Low Medium High

2. Physical Demand:

How much physical activity did the mission require of you (e.g., pushing, pulling, turning, controlling, activating, etc.)? This refers to you not your soldier.

Low Medium High

3. Temporal Demand:

How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred?

Low Medium High

4. Performance:

How successful do you think you were in accomplishing the goals of the task? How satisfied were you with your performance in accomplishing these goals?

Bad Average Good

5. Effort:

How hard did you have to work (mentally and physically) to accomplish your level of performance?

Low Medium High

6. Frustration:

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Low Medium High

Instructions: For each of the pairs (for example, mental demand vs. effort) choose which one of the two items was more important to your experience of workload. (Circle).

KEY

Effort:	Mental and physical work required to accomplish your level of performance.
Temporal:	Pressure due to the rate or pace at which the task or parts of the task occurred.
Physical:	Physical activity required (e.g., pushing, pulling, turning, controlling, activating, etc.).
Performance:	Satisfaction with your performance.
Frustration:	Frustration (i.e., insecure, discouraged, irritated, stressed, and annoyed) felt during the task.
Mental:	Mental and perceptual activity required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.).

Effort **or** **Performance**	**Temporal Demand** **or** **Frustration**	**Performance** **or** **Frustration**
Temporal Demand **or** **Effort**	**Physical Demand** **or** **Frustration**	**Physical Demand** **or** **Temporal Demand**
Physical Demand **or** **Performance**	**Temporal Demand** **or** **Mental Demand**	**Frustration** **or** **Effort**
Performance **or** **Mental Demand**	**Performance** **or** **Temporal Demand**	**Mental Demand** **or** **Effort**
Mental Demand **or** **Physical Demand**	**Effort** **or** **Physical Demand**	**Frustration** **or** **Mental Demand**

B: Experimental Protocol

Pre-experiment setup

- Prepare two subject folders: label folder and all forms with (Ss#, team # and date)
  - Demographic Questionnaire
  - Consent form
  - Team Factors Questionnaire
  - Team Workload Questionnaire
- Set out electrodes and prep supplies
  - 10 electrodes per person (20 total)
- Check batteries for the 3991's and AMS
- Turn on laptop and Biopac
  - Start Biopac software, make sure it is syncing with laptop. If not try unplugging and replugging the USB cable
  - Set up "Acquisition" to 3 hours and 1000 Hz
  - Set up Analog Channels according to paper
  - Set up Calculation Channels according to paper
- Turn on PC sim computers
  - Make sure there are no TLX files on the desktop
- Figure out the trial order (from master sheet) and write the coded version on the white board
- Set out tutorial script

Experimental session

- Greet subjects and have them sit at the two stations
- Have Ss fill out the demographic questionnaire
  - Check that they are eligible
- Explain briefly what they will be doing: "Today you will be working as a team to complete a process control simulation on the PCs in front of you. You will complete 4 trials of the simulation while connected to physiological equipment that will monitor your cardiovascular activity"
- Have them read the consent form, initial the bottom right corner of each page and sign the last page
- "Any questions?"
- Explain to the Ss that you will next help them put on the electrodes.
  - "Next we're going to place electrodes on you, they are just like little stickers. They are going to go [show where each will go]"
- Apply electrodes using prep gel and gauze
  - Follow figure on white board
  - Measure distance between electrodes and record
- Connect subjects to devices and **begin recording**
- Read Ss the tutorial
- Have the Ss introduce themselves to one another
- Explain that they will complete 10 minutes of practice to get acquainted with the system
- Re-emphasize their goals –

- “The goals of this task are to work as a TEAM to maximize the amount of product created while keeping everything within their safe levels”
- Setup A → C , B → A
- Time Practice → 10 minutes
- Reset center knobs and switches
- Begin experimental trials
  - Trial labels: subject number, trial number, operator letter
  - Ex → s1t2a (subject 1 trial 2 operator A)
- Following each trail:
  - Have operators click on “Emergency Stop”
  - **<u>MARK EACH DEVICE!!!!!!!!!!!!! All 4</u>**
  - Cross out the previous trial on the white board
  - Have them complete the TLX using same file ID as the trial ID
  - Reset center knobs and switches
  - Setup the next trial on A and B
  - Set timer to 10 mins
  - **<u>MARK EACH DEVICE!!!!!!!!!!!!! All 4</u>**
  - Start B
  - Start A
- At completion of last trial
  - Have them complete TLX
  - Have them also complete the Team Factors and Team Workload questionnaires
  - Give them alcohol wipes and tell them they can remove their electrodes
  - Briefly explain what the experiment is about and answer any questions they may have
  - Have them fill out the payment sheet

Post-Experiment

- Save Biopac file onto laptop
- Download AMS data onto Station A
- Download 3991 data onto laptop
- Move workload files and performance files into a new folder
- Copy all physio files, workload files and performance files onto USB drive
- Erase memory on 3991’s

C: Task Tutorial

Welcome to the XPlant chemical plant simulator. In this study you'll be operating a simulated chemical plant. The exact chemical process isn't important and you don't need to know any chemistry, but what is important is that you learn how to operate the plant efficiently and safely as a **Team**.

Please look at the diagrams in front you. You'll see that fluid enters the plant from the left side, goes through the pipes into unit A1, then into A2, then into the center section, then into B1, then B2, and then out of the plant. Your job is to monitor the processing tanks as a team and make sure that the plant is running correctly.

The left operator will have control over tanks A1 and A2 and the right operator will have control over tanks B1 and B2. You'll both have control over the center tank. All of the controls for your tanks can be controlled with your mouse. But the center panel pumps are manual controls – these are the black knobs on either side of the center panel lights. Any questions so far?

For each tank there are three important parameters to monitor: the level of the fluid in each tank, the tank temperature, and the tank pressure. Note that the one exception is the center panel – you only have to monitor the fluid level and pressure in this tank – temperature is taken care of automatically.

All of the tanks, including the center panel tank, have color coded visual indicators or lights that will tell you the status of the various parameters. If the indicators or lights are green, then everything is okay. Yellow means you're a little too high or low (the visual indicator will tell you which) and red means you're way out of limits and need to take corrective action immediately.

The most complicated part of the system is the fluid level. For each tank, the fluid level depends on the amount of fluid going into the tank and the amount of fluid coming out of the tank. The amount of fluid going in and out of the tank is controlled by adjustable pumps. Each tank has a pump coming into it and going out of it. But because the tanks are linked, the pump that controls the fluid coming out of a tank also controls the amount of fluid going into the NEXT tank. So you have to be careful when you change a pump – it will affect both the tank in front of it ("upstream" from it) and the tank after it ("downstream")

This is especially important to remember for the center panel. The operator on the left controls the pump that is the input for the center tank and the operator on the right controls the pump that is the output for the center tank. Turning the knobs to the right increase flow and turning to the left decreases flow. It is essential that both operators cooperate and communicate to control both the center panel tank and the inputs and outputs of their own tanks.

Any questions so far?

You also have to monitor and control the temperatures and pressures in each individual tank. This is relatively simple. Most (but not all) of the tanks have heaters that you can switch on if the temperatures get too low, or refrigerator units that you can switch on if the temperatures get too high. Note that not all of the processing tanks have both heaters and refrigerators. You'll just have to work with these limitations.

Likewise pressure can be controlled to some extent using either the vents (to reduce pressure) or the "pressurizers" to increase tank pressure. Some of the pressurizers have manual controls but it should be obvious how to use them. The pressure for the center panel is controlled by the pressurizer switches to either side of the gauge. Switching on both of the pressurizers will raise the pressure faster. There is no way to reduce the pressure in the center console. Also, be sure to keep the center pressure at the blue mark on the gauge.

You will also have to monitor the fuel and refrigerant supplies for your tanks. Operator A controls the Refrigerant Supply for the entire system and Operator B controls the Fuel Supply for the entire system. On screen messages will notify you when either is low. When you see those messages you must inform your teammate so that they can increase your supply of either fuel or refrigerant. This is accomplished by clicking the button at the bottom of the screen that says either Fuel Supply or Refrigerant Supply, and increasing the level.

Another goal of this task is to maximize the amount of chemical you produce. This is represented by the production units in the top right of Operator B's screen. These production units are increased or decreased by increasing or decreasing the output of tank B2. Also be aware that in order for the plant to operate efficiently you need to match the output units with the input units in the upper left of Operator A's screen. Input units are controlled by the input pump for tank A1.

Any Questions??

We're about ready to begin. Remember that your goals for the plant are to work as a team to keep all the tanks within their safety parameters, but also to maximize production – to move as much fluid as you can through the plant. But your first priority is keeping the tanks within their safety ranges. So we recommend that you start slow – make only small changes to the fluid levels at first. Remember this is a team task that requires communication and coordination in order to be completed successfully.

Any questions before we begin?

Appendix D: Difficulty curves for each parameter of the process control simulator

Ranges & optima	Pressure	Temp	Level
Starting & optimal:	6 bar	70C	500kl
Total range:	1-11	20-120	0-999
Green range:	5-7	60-80	400-600
Yellow range:	3-5,7-9	30-40,80-90	200-400, 600-800

Note: “sin” = sin wave variability **(Frequency, amplitude, offset)**
A1 = component 1 of Subsystem A (i.e, first tank), B2 is the last tank, etc. CP is Center Panel.

Individual difficulty

	Low	High
A1 level variability	no computer-initiated variability	no computer-initiated
A1 temp {A1 has htr & refrig}	no computer-initiated variability	sin 20,31,60
A1 press {Press only}	sin 70, 0.9, 6	sin 40,2.0, 4.5
A2 level variability	no computer-initiated variability	no computer-initiated
A2 temp {Htr only}	sin 40,4,70	sin 40,33,40
A2 press {A2 has vent & press.}	no computer-initiated variability	sin 60, 2.5, 6
CP level variability	no computer-initiated variability	no computer-initiated
CP press variability	no computer-initiated variability	no computer-initiated
B1 level variability	no computer-initiated variability	no computer-initiated
B1 temp {Htr only}	sin 40, 4,70	sin 40,33,40
B1 press {B1 has vent & press.}	no computer-initiated variability	sin 60, 2.5, 6
B2 level variability	no computer-initiated variability	no computer-initiated
B2 temp {B2 has htr & refrig}	no computer-initiated variability	sin 20,31,60

B2 press {Press. Only}	sin 90, 0.5, 6	sin 40, 2, 4.5

<u>Team difficulty (except for CP these are starting levels; ---- = 500)*</u>

A1 level	no computer-initiated variability	70, 310, 500
A2 level	no computer-initiated variability	no computer-initiated variability
CP level	no computer-initiated variability	sin 70, 310, 500
CP press	no computer-initiated variability	simple leak = -0.20/sec
B1 level	no computer-initiated variability	no computer-initiated variability
B2 level	no computer-initiated variability	76.5, 225, 500

REFERENCES

Allen, J.J.B., Chambers, A.S., & Towers, D.N. (2007). The many metrics of cardiac chronotropy: A pragmatic primer and a brief comparison of metrics. *Biological Psychology*, *74*, 243-262.

Ahmed, S.S., Levinson, G.E., Schwartz, C.J., & Ettinger, P.O. (1972). Systolic time intervals as measures of the contractile state of the left ventricular myocardium in man. *Circulation*, *46*, 559-571.

Andreassi, J.L. (2000). *Psychophysiology: Human behavior & physiological response (4th Ed.)*. Mahwah, NJ: Lawrence Erlbaum Associates.

Ash, I. & Backs, R.W. (2000, August). *Cardiac measures of attentional resource demands during continuous manual tracking*. Paper presented at the 3rd International Conference on Psychophysiology in Ergonomics, San Diego, CA.

Backs, R.W. (1995). Going beyond heart rate: Modes of autonomic control in the cardiovascular assessment of mental workload. *International Journal of Aviation Psychology*, *5*, 25-48.

Backs, R.W. (1998). A comparison of factor analytic methods of obtaining cardiovascular autonomic components for the assessment of mental workload. *Ergonomics*, *41*, 733-745.

Backs, R.W. (2001). An autonomic space approach to the psychophysiological assessment of mental workload, In P.A. Hancock & P.A. Desmond (Eds.), *Stress, Workload, and Fatigue* (pp. 279-289), Mahwah, NJ: Erlbaum.

Backs, R.W., Lenneman, J.K., & Sicard, J.L. (1999). The use of autonomic components to improve cardiovascular assessment of workload in flight simulation. *International Journal of Aviation Psychology, 16,* 57-68.

Backs, R.W., Lenneman, J.K., Wetzel, J. M., & Green, P. (2003). Cardiac measures of driver workload during simulated driving with and without visual occlusion. *Human Factors, 45*, 525-538.

Beith, B.H. (1987). Subjective workload under individual and team performance conditions. *Proceedings of the Human Factors Society 31st Annual Meeting,* pp. 67-71, Santa Monica, CA: Human Factors Society.

Berntson, G.G., Bigger, Jr., J.T., Eckberg, D.L., Grossman, P., Kaufmann, P. G., Malik, M., Nagaraja, H.N., Porges, S.W., Saul, J.P., Stone, P.H., & Van Der Molen, M.W. (1997). Heart rate variability: Origins, methods, and interpretive caveats. *Psychophysiology*, *34*, 623-648.

Berntson, G.G., Cacioppo, J.T., & Quigley, K.S. (1991). Autonomic determinism: The modes of autonomic space, and the laws of autonomic constraint. *Psychological Review, 98*, 459-487.

Berntson, G.G., Cacioppo, J.T., & Quigley, K.S. (1994). Autonomic cardiac control. I. Estimation and validation from pharmacological blockades. *Psychophysiology, 31*, 572-585.

Beuerman, R.W., Mircheff, A., Pflugfelder, S.C., & Stern, M.E. (2004). The lacrimal functional unit. In Pflugfelder, S.C, Beuerman, R.W., & Stern, M.E. (Eds.), Dry eye and ocular surface disorders, Oxford: UK, Taylor & Francis, Inc.

Burleson, M.H., Poehlmann, K.M., Hawkley, L.C., Ernst, J.M., Berntson, G.G., Malarkey, W.B., Kiecolt-Glaser, J.K., Glaser, R., & Cacioppo, J.T. (2003). Neuroendocrine and cardiovascular reactivity to stress in mid-aged and older women: Long-term temporal consistency of individual differences. *Psychophysiology, 40*, 358-369.

Cacioppo, J.T., Berntson, G.G., Binkley, P.F., Quigley, K.S., Uchino, B.N., & Fieldstone, A. (1994). Autonomic cardiac control. II. Noninvasive indices and basal response as revealed by autonomic blockades. *Psychophysiology, 31*, 586-598.

Cacioppo, J.T., Petty, R.E. (1983). Social Psychophysiology: A sourcebook. Guilford Press; New York.

Cacioppo, J.T., Tassinary, L.G., Berntson, G.G. (2007). *Handbook of Psychophysiology*. Cambridge, NY: Cambridge University Press.

Comens, P., Reed, D., & Mette, M. (1987). Physiologic responses of pilots flying high-performance aircraft. *Aviation, Space, and Environmental Medicine, 58,* 205-210.

Cousineau, D., LaPointe, L., & de Champlain, J. (1978). Circulating catecholamines and systolic time intervals in normotensive and hypertensive patients with and without left ventricular hypertrophy. *American Heart Journal, 96*, 227-234.

Denver, J.W., Reed, S.F., & Porges, S.W. (2007). Methodological issues in the quantification of respiratory sinus arrhythmia. *Biological Psychology, 74*, 286-294.

DiMascio, A., Boyd, R.W., Greenblatt, M., & Solomon, H.C. (1955). The psychiatric interview: A sociophysiological study. *Diseases of the Nervous System*, 16, 4-9.

Eggemeier, F.T. (1988). Properties of workload assessment techniques. In Hancock, P.A. & Meshkati, M. (Eds.), *Human Mental Workload*, pp. 41-62, Amsterdam: North-Holland.

Elkins AN, Muth ER, Hoover AW, Walker AD, Carpenter TL & Switzer FS (2009). Physiological Compliance and Team Performance. *Applied Ergonomics, 40,* 997-1003.

Fishel, S.R., Banks, L., Brewer, L.N., Player, J., Hoover, A.W., & Muth, E.R. (2007). Physiological arousal in response to low and high workload conditions in a military forward observer PC simulator task. *Augmented Cognition International, Baltimore, MD*, October 2007.

Gianaros, P.J., Quigley, K.S., Mordkoff, J.T., & Stern, R.M. (2001). Gastric myoelectric and autonomic cardiac reactivity to laboratory stressors. *Psychophysiology, 38*, 642-652.

Grossman, P., Karemaker, J., Wieling, W. (1991). Prediction of tonic parasympathetic cardiac control using respiratory sinus arrhythmia: the need for respiratory control. *Psychophysiology, 28*, 201-216.

Grossman, P., Stemmler, G., Meinhardt, E. (1990). Paced respiratory sinus arrhythmia as an index of cardiac parasympathetic tone during varying behavioral tasks. *Psychophysiology, 27*, 404-416.

Grossman, P., & Svebak, S. (1987). Respiratory sinus arrhythmia as an index of parasympathetic control during active coping. *Psychophysiology, 24*, 228-235.

Grossman, P., & Taylor, E.W. (2007). Toward understanding respiratory sinus arrhythmia: Relations to cardiac vagal tone, evolution and biobehavioral functions. *Biological Psychology, 74*, 263-285.

Grossman, P., Van Beek, J., & Wientjes, C. (1990). A comparison of three quantification methods for estimation of respiratory sinus arrhythmia. *Psychophysiology, 27*, 702-714.

Grossman, P., Wilhem, F.H., Spoerle, M. (2004). Respiratory sinus arrhythmia, cardiac vagal control, and daily activity. *American Journal of Physiology – Heart and Circulatory Physiology*, *287*, 728-734.

Goedhart, A.D., Van der Sluis, S., Houtveen, J.H., Willemsen, G., & De Geus, E.J.C. (2007). Comparison of time and frequency domain measures of RSA in ambulatory recordings. *Psychophysiology*, *44*, 203-215.

Gopher, D. & Donchin, E. (1986). Workload: an examination of the concept. In Boff, K.R., Kaufman, L., & Thomas, J.P. (Eds.), Handbook of Perception and Human Performance, pp. 41-49, NewYork: Wiley.

Hagbarth, K.E., Hallin, R.G., Hongell, A., Torebjork, H.E., & Wallin, B.G. (1972). General characteristics of sympathetic activity in human skin nerves. *Acta Physiologica Scandinavica, 84*, 164-176.

Hansen, A.L., Johnsen, B.H., Thayer, J.F. (2003). Vagal influence on working memory and attention. *International Journal of Psychophysiology*, *48*, 263-274.

Harris, W.S., Schoenfeld, C.D., & Weissler, A.M. (1967). Effects of adrenergic receptor activation and blockade on the systolic pre-ejection period, heart rate and arterial pressure in man. *Journal of Clinical Investigation*, *46*, 1704-1714.

Hart, S.G. (2006). NASA – task load index (NASA-TLX); 20 years later. In the *Proceedings of the Human Factors and Ergonomics Society 50th annual meeting*, pp. 904-908, Santa Monica, CA: Human Factors and Ergonomics Society.

Hart, S.G., & Hauser, J.R. (1987). Inflight application of three pilot workload measurement techniques. *Aviation, Space, and Environmental Medicine*, *58*, 402-410.

Hart, S.G., & Staveland, L.E. (1988). Development of NASA task load index (TLX): Results of empirical and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), *Human Mental Workload*, Amsterdam: North Holland Press (pp. 239-250).

Hatfield, E., Cacioppo, J.T., & Rapson, R.L. (1994). Emotional Contagion. Cambridge, UK: Cambridge University Press.

Hayano, J., Sakakibara,Y., Yamada, A., Yamada, M., Mukai, S., Fujinami, T., et al., (1991). Accuracy of assessment of cardiac vagal tone by heart rate variability in normal subjects. *American Journal of Cardiology, 67*, 199-204.

Henning, R.A., Armstead, A.G., & Ferris, J.K. (2009). Social psychophysiological compliance in a four-person research team. Applied Ergonomics, 40, 1004-1010.

Henning, R.A., Boucsein, W., & Gil, M.C. (2001). Social-physiological compliance as a determinant of team performance. *International Journal of Psychophysiology, 40,* 221-232.

Henning, R.A., & Korbelak, K. (2005). Social-psychophysiological compliance as a predictor of team performance. *Psychologia*, *48*, 84-92.

Hirsch, J.A., & Bishop, B. (1981). Respiratory sinus arrhythmia in humans: how breathing pattern modulates heart rate. *American Journal of Physiology, 241*, 620-629.

Houtveen, J.H., & Molenaar, P.C.M. (2001). Comparison between the Fourier and Wavelet methods of spectral analysis applied to stationary and nonstationary heart period data. *Psychophysiology, 38*, 729-735.

Houtveen, J.H., Rietveld, S., De Geus, E.J. (2002). Contributions of tonic vagal modulations of heart rate, central respiratory drive, respiratory depth and respiratory frequency to respiratory sinus arrhythmia during mental stress and physical exercise. *Psychophysiology, 39*, 427-436.

Jouanin, J., Dussault, C., Peres, M., Satabin, P., Pierard, C., Guezennec, C. Y. (2004). Analysis of heart rate variability after a ranger training course. *Military Medicine, 169*, 583-587.

Kaplan, H.B., Burch, N.R., & Bloom, S.W. (1964). Physiological covariation and sociometric relationships in small peer groups. In P.H. Leiderman & D. Shapiro (Eds.), *Psychobiological approaches to social behavior*, Stanford, CA: Stanford University Press.

Katona, P.G., Jih, F. (1975). Respiratory sinus arrhythmia: noninvasive measure of parasympathetic cardiac control. *Journal of Applied Physiology, 29*, 801-805.

Kelsey, R.M., & Guethlein, W. (1990). An evaluation of the ensemble averaged impedance cardiogram. *Psychophysiology, 27*, 24-33.

Kirlik, A., Fisk, A.D., Walker, N. & Rothrock, L. (1998). Feedback augmentation and part-task practice in training dynamic decision-making skills. In Cannon-Bowers, J. A. & Salas, E. (Eds.). *Making decisions under stress: implications for individual and team training*. Washington, DC: American Psychological Association.

Lenneman, J.K. & Backs, R.W. (2000). The validity of factor analytically derived cardiac autonomic components for mental workload assessment. In R.W. Backs & W. Boucsein (Eds.), *Engineering psychophysiology: Issues and applications* (pp. 161-174). Mahwah, NJ: Erlbaum.

Levenson, R.W. & Gottman, J.M. (1983). Marital interaction: physiological linkage and affective exchange. *Journal of Personality and Social Psychology, 45*, 587-597.

Lewis, R.P., Leighton, R.F., Forester, W.F. & Weissler, A.M. (1974). Systolic time intervals. In A.M. Weissler (Ed.), *Noninvasive cardiology* (pp.301-368). NewYork: Grune & Stratton.

Lindholm, E., & Cheatham, C.M. (1983). Autonomic activity and workload during learning of simulated aircraft carrier landing task. *Aviation, Space, and Environmental Medicine, 54*, 435-439.

Malmo, R.B., Boag, T.J., & Smith, A.A. (1957). Physiological study of personal interaction. *Psychosomatic Medicine*, 19, 105-119.

Martin C.E., Shaver J.A., Thompson M.E., Reddy P.S., & Leonard J.J. (1971). Direct correlation of external systolic time intervals with internal indices of left ventricular function in man. *Circulation, 44*, 419-431.

McCubbin, J.A., Richardson, J.E., Langer, A.W., Kizer, J.S., & Obrist, P.A. (1983). Sympathetic neuronal function and left ventricular performance during behavioral stress in humans: The relationship between plasma catecholamines and systolic time intervals. *Psychophysiology*, *20*, 102-110.

McGrath, J.J., O'Brien, W.H., Hassinger, H.J., & Shah, P. (2005). Comparability of spot versus band electrodes for impedance cardiography. *Journal of Psychophysiology, 19*, 195-203.

McIntyre, R.M. & Salas, E. (1995). Measuring and managing for team performance: emerging principles from complex environments. In R.A. Guzzo & E. Salas (Eds.), *Team effectiveness and decision making in organizations* (pp. 9-45). San Francisco: Jossey-Bass.

Moss, J.D., Walker, A.D., Phillips, J.B., & Muth, E.R. (2008). Assessment of workload during an aviator selection test battery. *Proceedings of the 7th International Conference on Psychophysiology in Ergonomics , 7*.

Newlin, D.B., & Levenson, R.W. (1979). Pre-ejection period: Measuring beta-adrenergic influences upon the heart. *Psychophysiology, 16*, 546-553.

Nicholson, A.N., Hill, L.E., Borland, R.G., & Ferres, H.M. (1970). Activity of the nervous system during the let-down, approach and landing: A study of short duration high workload. *Aerospace Medicine, 41*, 436-446.

O'Donnell, R.D., & Eggemeier, F.T. (1986). Workload assessment methodology. In Boff, K.R., Kaufman, L., & Thomas, J.P. (Eds.), *Handbook of Perception and Human Performance, Vol. II: Cognitive Processes and Performance*, pp. 1-49, New York: Wiley Interscience.

Obrist, P.A., Light, K.C., James, S.A., & Strogatz, D.S. (1987). Cardiovascular response to stress: I. Measures of myocardial response and relationship to high resting systolic pressure and parental hypertension. *Psychophysiology, 24*, 65-78.

Porges, S.W. (1985). Respiratory sinus arrhythmia: an index of vagal tone. In: Orlebeke, J.F., Mulder, G., Van Domen, L.J.P. (Eds.), *Psychophysiology of Cardiovascular Control: Models, Methods, and Data* (pp.-437-450). New York: Plenum.

Porges, S.W., & Byrne, E.A. (1992). Research methods for measurement of heart rate and respiration. *Biological Psychology, 34*, 93-130.

Porter, C.O.L.H., Hollenbeck, J.R., Ilgen, D.R., Ellis, A.P.J., West, B.J. & Moon, H. (2003). Backup behavior in teams: the role of personality and legitimacy of need. *Journal of Applied Psychology, 88*, 391-403.

Riese, H., Groot, P.F., van den Berg, M., Kupper, N.H.M., Magnee, E.H.B., Rohaan, E.J., Vrijkotte, T.G.M., Willemsen, G., de Gues, E.J.C. (2003). Large-scale ensemble averaging of ambulatory impedance cardiograms. *Behavior Research Methods, Instruments, & Computers, 35*, 467-477.

Salas, E., Sims, D., Burke, C.S., (2005). Is there a "big five" in teamwork? *Small Group Research, 36*, 555-599.

Shapiro, D., Jamner, L.D. Lane, J.D., Light, K.C., Myrtek, M., Sawada, Y., & Steptoe, A. (1996). Blood pressure publication guidelines. *Psychophysiology, 33*, 1-12.

Sherwood, A., Allen, M.T., Fahrenberg, J., Kelsey, R.M., Lovallo, W.R., & van Doornen, L.J.P. (1990). Methodological guidelines for impedance cardiography. *Psychophysiology, 27*, 1-23.

Smith, T.J. & Smith, K.U. (1987). Feedback control mechanisms of human behavior. In: Salvendy, G. (Eds.) *Handbook of Human Factors*. Wiley, New York, 251-293.

Stern, R.S., Koch, K.L., Levine, M.E., & Muth, E.R. (2007). Gastrointestinal response. In Cacioppo, J.T., Tassinary, L.G., Berntson, G.G. (Eds.) *Handbook of Psychophysiology*. Cambridge, NY: Cambridge University Press, pp. 211-230.

Stern, R.M., Ray, W.J., & Quigley, K.S. (2001). *Psychophysiological recording*. Oxford: Oxford University Press.

Steptoe, A., Godaert, G., Ross, A., & Schreurs, P. (1983). The cardiac and vascular components of pulse transmission time: a computer analysis of systolic time intervals. Psychophysiology, 26, 251-259.

Switzer, F.S. III, & Idaszak, J. (1989) Effects of crew coordination and level of instruction of process control operator behavior. In *Proceedings of the Human Factors Society 33rd Annual Meeting.* Denver, CO: Human Factors Society. Pp. 788-791.

Tabachnick, B.G. & Fidell, L.S. (2001). *Using multivariate statistics, 4th ed*. Needham Heights, MA: Allyn & Bacon.

Tamura, N., Shimazu, K., Yamamoto, T., Nakazato, Y., & Hamaguchi, K. (1990). A new quantitative test for parasympathetic nervous function by means of tear volume measurement--application of electronic resistance measuring device (Periotron), *Rinsho Shinkeigaku, 30*, 574-576.

Temple. J.G., Warm, J.S., Dember, W.N., Jones, K.S., LaGrange, C.M., & Matthews, G. (2000). The effects of signal salience and caffeine on performance, workload, and stress in an abbreviated vigilance task. *HumanFactors, 42*(2), 183-194.

Thayer, J.F., Friedman, B.H., & Borkovec, T.D. (1996). Autonomic characteristics of generalized anxiety disorders and worry. *Biological Psychiatry, 39*, 255-266.

Thayer, J.F., Peasley, C. & Muth, E.R. (1996). Estimation of respiration frequency from auto-regressive spectral analysis of heart period. *Biomedical Sciences Instrumentation, 32*, 93-99.

Thayer, J.F., & Uijtdehaage, S.H.J. (2001). Derivation of chronotropic indices of autonomic nervous system activity using impedance cardiography. Biomedical Sciences Instrumentation, 37, 331-336.

Tursky, B. (1974). The indirect recording of blood pressure. In P.A. Obrist, A.H. Black, J. Brener, & L.V. DiCara (Eds.), *Cardiovascular psychophysiology*, (pp. 19-92). New York: Guilford.

Uijtdehaage, S.H.J., & Thayer, J.F. (2000). Accentuated antagonism in the control of human heart. *Clinical Autonomic Research, 10*, 107-110.

Urban, J.M., Bowers, C.A., Monday, S.D., & Morgan, Jr., B.B. (1995). Workload, team structure, and communication in team performance. *Military Psychology*, 7, 123-139.

Vallbo, A.B., Hagbarth, K., & Wallin, B.G. (2004). Microneurography: how the technique developed and its role in the investigation of the sympathetic nervous system, *Journal of Applied Physiology, 96*, 1262-1269.

Vasey, M.W., Thayer, J.F. (1987). The continuing problem of false positives in repeated measures ANOVA in psychophysiology: a multivariate solution. *Psychophysiology*, *24*, 479-486.

Von Neumann, J., Kent, R.H., Bellinson, H.R., Hart, B.I. (1941). The mean square successive difference. *The Annuals of Mathematics and Statistics, 12*, 153-162.

Wilson, G.F. (1993). Air-to-ground training missions: A psychophysiological workload analysis. *Ergonomics*, *36*, 1071-1087.

Wilson, G. F. (2002). An analysis of mental workload in pilots during flight using multiple psychophysiological measure. *The International Journal of Aviation Psychology*, *12*(1), 3–18.