Situational States Influence on Team Workload Demands in Cyber Defense Exercise

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Abstract. Cyber operations are increasingly automated processes that can occur at computational speed with the intent of reducing, or denying time for good decision making or time to ground communication between human agents. There is a lack of performance measures and metrics in cyber operation settings. One potential setting describing human performance could be emotional stability under stress. Measures of higher individual affective variability indicate more emotional adaptability and allows for measuring individuals as dynamic systems. Previous research in other security-sensitive high-stake situations has shown that individuals with less emotional adaptability display maladaptive behaviors while individuals with more emotional adaptability can adapt more efficiently to changing situations, show more confidence in their own abilities and skills, and display better performance. We hypothesized that measurements of affective variability during a cyber defense exercise will be associated with team workload demands. Data was collected from 13 cadets during the Norwegian Defence Cyber Academy's annual Cyber Defense Exercise. Three indicators of individual affective variability were measured daily with the Self-Assessment Manikin and compared to scores on the Team Workload Questionnaire. We found that affective variability was negatively associated with team workload demands. Participants with higher affective variability, as measured by the Self-Assessment Manikin, will impose less workload demands on the team, which can lead to better outcomes. This is the first study to assess how individual emotional adaptability affects team dynamics in a cyber defense setting. Future research should include variable measurements as they may have better explanatory power for performance measurements.

Keywords: affective states, team workload demands, cyber defense exercise.

1 Introduction

Cyber operations are increasingly automated processes that can occur at computational speed with the intent of reducing, or denying time for good decision making or time to ground communication between human agents. One of the most persistent issues in studying cyber defense individuals and teams is that there is a general lack of performance metrics and measures in such a setting. In recent years, there has been an increase in research evaluating the performance of cyber defenders in teams, but few studies have looked at individual aspects that may influence team performance [1].

Cyber operations are high-stake situations and COs are under heavy cognitive load for prolonged periods of time. Security Operations Centers (SOCs) consist of teams that work around the clock to prevent, detect, and respond to cyber threats and incidents [2]. SOC teams monitor large and continuous streams of network data to detect potential threats. Operative cyber personnel (Cyber Operators; COs) make up the technical staff of SOC teams and are responsible for threat detection, data analysis, digital forensics, network security and cyber intelligence, as well as communicating with SOC decision-makers and clients. Thus, the task-environment that COs are working within spans the cyber, physical, and social domain [3] and creates a complex socio-technical system (STS)[4] where humans and machines interact to maintain cyber resilience in civil and military sectors.

The cognitive challenges SOC teams face while operating in a STS span a wide range of domains from complex problem-solving, to asset prioritization and protection, intra- and inter-team communication, decision-making based on high uncertainty, leadership efficiency, collaboration and coordination efficiency, constant acquisition of technical and threat competence, updating situational awareness, risk management, problem detection, and information seeking, and more [3]. Developing applicable solutions to these challenges such that SOC team performance can be improved will require scientific approaches at both the team- [3] and individual level [3, 5].

Communication problems are listed as one of the main challenges facing SOC teams [6] but individual factors that affect communication and coordination in cyber teams are poorly understood. Due to the cognitive load associated with cyber operations, the ability to adaptively regulate stress and emotions may serve as relevant individual level indicators of performance.

1.1 The relationship between affective states and adaptive performance

Higher affective variability (RMSSD)[7] is defined as "relatively short-term changes that are construed as more or less reversible and that occur more rapidly" [8]. Indices of affective variability allows for the measurement of individuals as dynamic systems where neither trait nor state measurements are able to access changes during specific situations [9] and has been shown to predict higher maladaptive behaviors [10] and higher variability in perceived control predicted earlier mortality [11].

Interpreting stress reactions and tension has effects on perceiving one's state and adaptation ability [12, 13]. Research has shown that positive moods improved confidence [14], while despondent moods decreased feelings of self-efficacy [15, 16]. Research on affective states and their influence on behaviors in cyber security is scarce. Research in other domains has shown that affective states can influence performance [17, 18] and this could lead to targeted interventions to help learning [18].

Situational stressors, whether environmental, emotional, or cognitive, increase physiological arousal to prepare the individual to adapt to the environment, and all stressor categories essentially work on the same biological systems to activate the individual for action. Theories for optimal arousal suggest that there is an individual sweet spot for every person where arousal levels matched to a task maximizes performance, and arousal levels below or above this sweet spot is an impediment to performance (Yerkes-Dodson law [19, 20]). Arousal levels change with shifts in attention but are dependent on the emotional valence of stimuli [21] and optimal attention-allocation for task-related performance appears to be associated with proxies for regulation of arousal that are also associated with affective variability [22]. This suggests that the neural components responsible for regulating affective states are intertwined with performance-related factors associated with attention and arousal. Cognitive- and behavioral neuroscience approaches to problems facing the field of cybersecurity are currently under-explored. To fully appreciate why the regulation of affective states can be important for cyber team performance, it is necessary to first understand the central and peripheral psychophysiological correlates of affective regulation, communication and coordination, and complex problem solving, and how these abilities rely on the same neural systems. Thus, in the three following sections we will detail the underlying neural components of these abilities and how they are related.

1.2 Neural correlates of affective control and variability and relationships with regulation of physiological arousal

The primary neural structure that is responsible for an individual's ability to regulate their own affective states is the prefrontal cortex (PFC). The PFC exerts top-down control on emotional states in part via a prefrontal sub-structure called the dorsolateral PFC (DLPFC) which is involved in regulating both neutral and negative emotions [23]. In addition to affective regulation, the DLPFC also plays an important role in other executive functions such as planning and attention control. During conscious regulation of one's own affective states, activity in the DLPFC increases while activity in the Amygdala, a structure associated with arousal and negative affect, decreases along with self-reports of negative affect [23, 24].

For an individual to consciously regulate their own affective states, the DLPFC must first be engaged to allocate attention to the individual's emotional state then decide how to regulate it. The role of the DLPFC in affective regulation is lateralized, with the left DLPFC (lDLPFC) being involved in affective regulation while increased right DLPFC (rDLPFC) activity is associated with affective dysregulation and deficits in emotional attention regulation [25, 26]. The PFC receives signals about emotional- and physiological arousal through a process called interoception (sensing the activity in your organs; gut feelings)[27] and the PFC integrates this information when deciding how to regulate affective states.

The DLPFC regulates physiological- and emotional arousal in part by (1) increasing activity in the vagal branch of the autonomic nervous system (ANS), and (2) inhibiting activity in the sympathetic branch of the ANS [28-30]. Both branches of the ANS innervate all the organs of the body, and this DLPFC-to-ANS pathway of stimulation will lead to reduced arousal, characterized by decreased activity in organs such as the heart and lower heart rate. As opposed to the constant and high heart rate resulting from sympathetic input to the heart, the increased DLPFC modulated vagal input to the heart causes the length and variations in the intervals between each heart beat to increase, increasing heart rate variability (HRV). This mechanism is what allows the DLPFC to aid the individual in adapting their emotional and stress responses to situations with varying levels of stress [31]. Higher vagally mediated HRV (vmHRV) reflects higher vagal input to the heart at rest, lower heart rate, and higher affective variability, while lower vmHRV reflects lower vagal input to the heart at rest, higher heart rate, and lower affective variability. Higher affective variability means higher regulatory range thus higher capacity for adaptive emotional responding, while lower affective variability means lower regulatory range thus lower capacity for adaptive emotional responding.

Evidence for top-down control of the PFC on stress- and emotional arousal was found in a study where transcranial direct current stimulation (tDCS) to the left DLPFC reduced was associated with increased vmHRV, higher mood scores, and reduced levels of cortisol, the latter being a hormonal biomarker of stress [28]. Further evidence for the coupling of cognitive function, affective variability, and physiological adaptive ability was demonstrated in a study showing that cognitive flexibility along with higher vmHRV predicted ability to regulate arousal during prolonged stressors [32]. As COs operating in teams can be exposed to heavy stress and cognitive load for long periods of time [5, 33] it suggests that affective regulation capacity can be vital to cyber team performance. Furthermore, affective regulation ability is related to the degree individuals can emotionally detach from work-related stress, with lower affective regulation ability being associated with lower ability to detach, indicated by higher levels of work-related perseverative cognitions [34]. The temporal intensity of affective states may increase allocation of attentional resources to attentional states resulting in perseverative cognition [35]. Given the tendency for SOC team members to work 12-hour shifts [2], the ability to detach from work may be important to reduce work-stress load on COs, although our previous research show that indicators of affective intensity are not related to perseverative cognitions in cyber officer cadets [36]. This may suggest that the selection process for COs result in cognitive and emotional profiles that differ from the general population, which in turn could downplay the effect of affective variability on cyber team dynamics.

1.3 Neural correlates of affective variability and control overlaps with neural correlates of social coherence, coordination, and communication

vmHRV and its relation to affective regulation is suggested to be important for interpersonal functioning [37] arguing for its relevance in collaborative settings such as cybersecurity. Studies on socio-emotional problems in children suggest that they co-occur with communication problems [38] and continuous measures of vmHRV suggest that reduced affective and arousal regulation is associated with communication problems in adults [39]. Moreover, vmHRV is associated with proxies of social cognitions. This includes personal indicators of ability to adapt to the environment in the face of adverse conditions such as feelings of trust and social relatedness among adolescents and young adults [40] as well as social orientation values in male adults such as preference for cooperation [41]. Being able to regulate one’s own affective states during social interactions may result in experiencing social interactions as low-stress, thus, for individuals working in high-stress social settings and in teams, affective regulatory capacity could possibly aid cooperation by facilitating pro-social cognitions.

A wide range of data from various settings suggest that for humans to coordinate and communicate successfully in dyads and in groups, it requires the synchronization of various physiological systems in both the central and peripheral nervous system [42-51]. One simple example of how disruptive asynchrony can be to communication is if you are trying to maintain a conversation with someone who is shouting when you are talking calmly or if they are not walking at your pace. The same is true for affective states and physiological arousal, indicated by studies assessing vmHRV synchrony with respect to social coherence and communication [39, 48]. Coordinating and communicating with an individual that is in a different and perhaps unpredictable affective state compared to one's own can be challenging during exposure to prolonged stressors.

Communication is a complex social interaction, with contextually guided predictions and mental models of speakers and listeners contributing to message comprehension as much as the actual words that are shared. In studies using functional magnetic resonance imaging, spatial and temporal neural coupling (brain-to-brain synchrony) between speaker and listener is important for the success of communication with respect to whether the listener comprehends what the speaker is trying to convey [47, 51]. Both mirroring and predictive synchronous activity was observed in the listener with respect to the brain activity of the speaker, with greater neural coupling being related to greater understanding of the conveyed message. In naturalistic studies of groups of high-school students, attentional effort appears to be a determinant of brain-to-brain synchrony [44]. A recent review found that optimizing attentional efforts for task-related processing is positively associated with vmHRV [22].

The pupil of the eye has been used as a physiological system to study synchrony with respect to communication [52]. Pupil dilation is under control of the sympathetic nervous system, with reduced sympathetic activity resulting in wider pupil diameter [53, 54]. Under constant luminance conditions, pupil dilation is positively associated with emotional arousal, cognitive load, mental effort, conflict processing, and emotion regulation efforts [55-57]. tDCS of the DLPFC during processing of emotional stimuli has opposite effects on pupil diameter depending on whether the lDLPFC or rDLPFC is stimulated, with tDCS of the lDLPFC being associated with increased pupil diameter [58]. Similarly, chronic vagus nerve stimulation, a safe treatment for affective dysregulation, increases resting pupil diameter without affecting light reflexes [59]. Spontaneously synchronized pupil dilation patterns across individuals (speaker-and-listener dyads) has been shown to be a marker of joint attention, with higher pupillary synchrony occurring during emotional peaks in communication [52]. Individual factors such as level of expressiveness in the speaker and level of empathy in the listener is positively associated with degree of synchrony, thus greater brain-to-brain coupling. For high-school students, silent gazing into a randomized peer's eyes for 2 minutes prior to class predicted greater brain-to-brain synchrony during class, as measured with electroencephalogram [44]. Together, the above data suggest that the neural mechanisms responsible for successful affective regulation is, at least in part, responsible for successful coordination and communication.

1.4 Neural correlates of affective variability and control overlaps with neural correlates of complex problem-solving

Being involved in executive functioning, the DLPFC is also a central structure involved in working memory [60, 61] which is a resource with limited capacity that individuals use for problem solving. In line with this notion, complex problem solving is dependent brain networks where the DLPFC is a central component in breaking the problem up in individual tasks [62-64], representing contextual task-demands [65], and cognitive control of perceptual information during loss of situational awareness [66]. Taken together with the fact that optimal allocation of attention to task-related stimuli is associated with psychophysiological proxies of DLPFC functioning and affective variability [22], this can potentially have important implications for cyber operations. If cybersecurity personnel are simultaneously exposed to (1) complex technical problem solving, (2) stressors that require conscious regulation of affective states, and (3) challenges related to communication, this will arguably tax the DLPFC and plausibly result in a conflict of information processing that can affect priorities and be detrimental to team performance.

Together, the above studies suggest that there is a significant overlap in the neural substrates that affect success in both communication and affective control as well as problem solving. If DLPFC task-load reaches an individual's capacity threshold in one domain (e.g. affective regulation), functioning in the other domains (problems solving or communication) may break down. Thus, measures of indicators of affective variability at the level of the individual may provide important performance metrics related to inter-individual cooperation and coordination in collaborative settings such as cyber defense.

1.5 How affective states may relate to the Hybrid Space framework and the Orienting, Locating, Bridging (OLB) model

As the challenges that COs face span the cyber, physical, and social realm, COs must skillfully apply a wide range of cognitive abilities to flexibly transition between these contexts. To conceptualize the cognitive complexity and communicative challenges that COs face, work conducted in collaboration with our lab proposed the Hybrid Space (HS) framework [3]. The HS framework is based on cognitive engineering and focuses on the interconnectedness between cyber- and physical space, and the tension between tactical and strategic goals in decision-making to illustrate the cognitive landscape that COs must navigate (Figure 1, a). Knowing where you are in the HS requires the ability to observe your own mental state, termed metacognitive awareness, and to move within the HS requires cognitive agility (Figure 1, b)[5]. When individuals such as team members or superordinates and subordinates are located in different quadrants of the HS, competencies, goals, and proximity to situational stressors may differ between them, making the nature of communication more difficult thus increasing the cognitive load on COs (Figure 1, c)[33]. When information is relayed back and forth across individuals with different locations in the HS, cognitive complexity increases (Figure 1, d)[33] and may require constant re-adjustment of message content and mental representation of the recipient. During prolonged high-stress cyber threat situations, increased efforts to regulate affective arousal may also be necessary. Knowing how to navigate and communicate in hierarchical social structures requires an accurate model of one's own position in the social network relative to others. Recent fMRI studies on accurate neural representation of social network position (e.g. social distance between individuals) show that these representations occur spontaneously in the brain when an individual enters a social context (e.g. is shown a picture of a peer) [67] and that this encoding rely on prefrontal structures involved in affective regulation [30]. If affective variability is an indicator of prefrontal cortical function, then lower affective variability may indicate reduced prefrontal functioning thus ability to accurately represent one's own position in a social setting which may be detrimental to social cohesion.

To accurately locate other individuals in the HS requires perspective taking [68, 69]. Taking the perspective of other individuals is partly dependent on empathy. Empathy is reliant on PFC structures [70], is positively associated with psychophysiological proxies of affective regulation such as vmHRV [41] and may in part explain some of the ways the PFC aids the individual in navigating a social network.

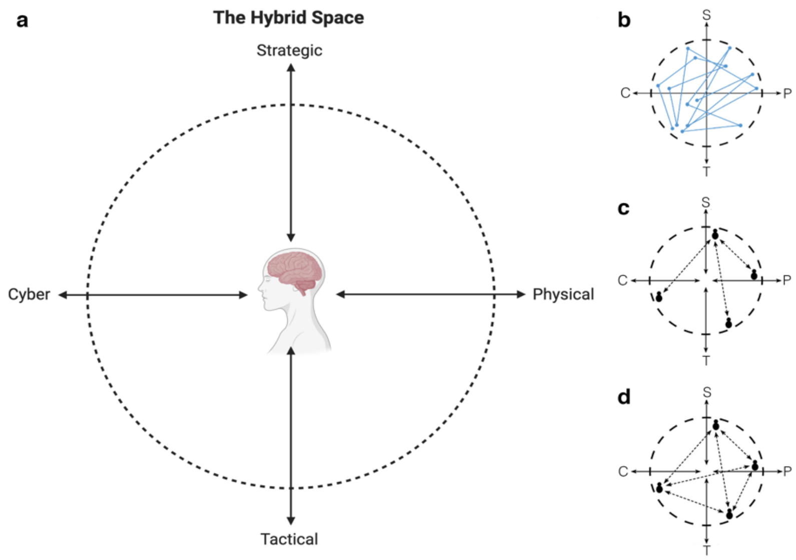

Fig. 1. The Hybrid Space framework conceptualizing the cognitive and communicative challenges of cyber operations [3, 5, 33]. **a** The Hybrid Space. Created with BioRender.com. **b** Cognitive agility. **c** Hierarchical structure, complicated relations. **d** Hierarchical structure, complex relations.

Our lab recently proposed the Orienting, Locating, Bridging (OLB) model [68], a three-stage pedagogic tool to foster metacognitive awareness for improved communication flow in the HS. The OLB model explicates the steps an individual must take to facilitate communication and coordination across levels of expertise, hierarchical layers, and professional backgrounds. First, an individual must apply metacognition to find their own location in the HS (Orienting), then the individual must apply perspective taking to find the communication partner's location in the HS (Locating), then the individual must adapt their communication style and content to the partner depending on their own and the partner's location in the HS (Bridging).

Affective dysregulation could potentially prevent successful OLB-ing, either by forcing the individual to allocate attentional resources to their own affective states thus preventing them from engaging in model application (or communication in general), or at individual stages of the model depending on the timing of situational and affective challenges. For example, affective dysregulation could lead to problems with:

1. Orienting, via conflicts or deficits in shared mechanisms that relate affective regulation to metacognition [71] or deficits in neurocognitive processing related to self-regulation such as being aware of and aligning emotional responses, cognitions, and behaviors to goals [72]. If you are not aware of whether your mental state is aligned with your goals then, arguably, you may not successfully self-locate in the HS. Your goals may be oriented towards the cyber operation, but your affective and cognitive states and behaviors may be focused on your arousal levels in the physical and social domains.
2. Locating, for example by disturbances in perspective taking due to suboptimal development of self-other representations [73-75] or via reduced capacity for maintaining a stable model of other people's mental states and emotions with empathy [41].
3. Bridging, via affective mechanisms related to communication and coordination through social coherence [39, 48, 52].

Although numerous studies link affective variability to cooperative proxies and optimal social interactions, how this translates to collaboration in a cyber operation setting has yet to be explored.

1.6 Aim

We argue that multiple affective measurements taken during an exercise would be associated with team workload demands. Being able to measure how individual variable affective states influence team performance would give a better understanding of how to develop better interventions to increase metacognition, thus having better situational awareness and helping team performance. Research has shown that metacognition has positive influences on situational awareness and performance [76]. Thus, in this paper we examine the relationship between affective variability and team workload demands.

2 Methods

2.1 Participants and Procedure

Data was collected during the Norwegian Defense Cyber Academy's (NDCA) annual Cyber Defense Exercise (CDX). This arena facilitates the opportunity for students to train in tactics, techniques and procedures for handling various types of cyberattacks. The exercise contributes to improving appreciation for the human and technical competences necessary to establish, manage and defend a military digital information infrastructure under simulated operational conditions. The exercise lasted five days. Before each day, the participants were asked to rate their affective states. At the end of the day the participants were asked to assess team performance. A total of 13 cadets participated in the research.

2.2 Measurements

The Self-assessment Manikin (SAM;[77]**)** was used to measure affective states. The SAM is a 3-item 9-point Likert-scale (1 to 9) that measures mood (negative to positive), physiological activation (PA; little to much), and control (little to much). The SAM is a validated culture- and language independent visual scale that is used in performance [18] research in different domains and populations including cyber environments [77-79].

Both mean and variability scores were computed. Affective variability was computed for the three aspects of the SAM using the formula:

$$RMSSD = \sqrt{\frac{1}{(N-1)} \sum_{j=0}^{n} \left(RR_{j+1} - \overline{RR}\right)}$$

where N is the total number of R peaks, RR $_j$ is the jth RR interval, RR is the mean of the RR intervals, $_j$ denotes the average of the RR intervals up to the jth. This resulted in three independent variables: Mood, Activation and Control. Higher mood indicates more positive mood, higher activation indicates more arousal, and higher control indicates higher self-efficacy.

For this study, the SAM showed good reliability for each subscale (Mood Cronbach’s a= .633; Activation Cronbach’s a = .891; Control Cronbach’s a = .928).

The Team Workload Questionnaire (TWLQ)[80] was used to assess the workload demand in team tasks. Items are scored on an 11-point Likert scale (range: very low – very high) with high scores indicating higher levels of subjective workload. Average scores for team workload performance were computed on the subscales of the two dimensions, the Teamwork component (communication, coordination, team performance monitoring) and Task-Team component (time-share, team emotion, team support).

The TWLQ has shown good reliability on all subscales (Cronbach’s a >.70) [80] and also for this research (Teamwork Cronbach’s a = .847; Task-team Cronbach’s a = .624).

2.3 Ethical considerations

The study conformed to institutional guidelines and was eligible for automatic approval by the Norwegian Social Science Data Services’ (NSD) ethical guidelines for experimental studies. Participants gave their informed consent verbally prior to the study and were informed that they could withdraw from participation at any time and without any consequences.

2.4 Data Analysis

Statistical analysis was done with JASP version .14.1 [81]. All variables were centered and standardized for analysis. Alpha levels for hypothesis testing were set at the 0.05 level. A multiple linear regression was computed with affective state measures (SAM) entered as predictors and the subscales of the TWLQ as criterion variables.

3 Results

Descriptive statistics and correlations among the variables are given in Table 1. From the initial correlation analysis, separate regressions were computed on each of the relevant TWLQ subscales.

Table 1: Descriptive Statistics and Correlations (*N*=13)

	Scale	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1	Mood	6.38	.75	—											
2	Activation	4.36	1.44	-.428	—										
3	Control	5.65	1.31	.238	-.412	—									
4	R-Mood	1.38	.54	-.569**	.241	.245	—								
5	R-Activation	1.37	.73	-.460	.158	-.202	.251	—							
6	R-Control	1.07	.44	-.019	-.300	.334	.132	.301	—						
7	TWLS Communication	5.60	.70	.010	.133	-.195	.144	.274	.237	—					
8	TWLS Coordination	5.16	.92	.367	.364	-.036	-.117	.046	-.082	.675*	—				
9	TWLS TPM	4.04	1.06	-.161	.828***	-.337	.124	-.056	-.558**	-.114	.218	—			
10	TWLS TSD	4.12	1.26	.366	-.019	-.295	-.450	-.592*	-.290	.187	.346	.067	—		
11	TWLS Team Emotion	2.91	1.08	-.315	.295	-.163	-.187	.118	-.374	-.320	.066	.193	.177	—	
12	TWLS Team Support	3.86	1.24	.201	-.331	-.372	-.538**	-.488*	-.473	-.144	-.264	-.050	.604*	.128	—

R: RMSSD (variability); TWLQ: Team Workload Questionnaire; TPM: Team Performance Monitoring; TSD: Time Share Demand

*p <.1, ** p < .05, *** p < .01,

Only the SAM Activation average score had any association with teamwork components of the TWLQ (Team Performance Monitoring; r = .828, p < .01) but not with any of the Team-task components.

For calculated variability SAM scores for workload demands focusing on Teamwork aspects; communication, coordination and performance monitoring workloads, only higher variable control was associated with less team performance monitoring (β = -.558, p =.048, R^2 = .311, F = 4.96).

For calculated variability SAM scores for team workload demands focusing on Tasks-team workloads, higher mood variability (β = -.322) and higher activation (more aroused; β =-.511) predicted less team support demands (R^2 = .448, F = 4.058, p = .026 1-tailed).

Higher variability for mood (β = -.423), activation (β = -.282), and control (β = -.323) predicted less team support demands (R^2 = .523, F = 3.29, p = .036 1-tailed). For team emotional support, higher variable control was associated with lower team emotional support but this was not significant (r = -.473, p = .051 1-tailed)

4 Discussion and Conclusion

Recent research indicated that there is a scarcity of studies in cybersecurity that simultaneously assess team and individual factors [1]. In this study, we set out to assess the association between individual measurements of affective variability (Mood, Physiological Activation, and Control) on team workload demands (teamwork demands, task-team demands).

We found that higher affective variability could predict better teamwork behaviors (team performance monitoring) as well as decreasing the task-team workload demands. Participants with higher affective variability, as measured by the Self-Assessment Manikin, will impose less workload demands on the team, which can lead to better outcomes [7, 82]. Previous studies showed that more flexible intra-individual psychological processes (i.e. variable self-efficacy) could predict better team outcomes [82].

On a neurological level, while being important for regulating affective states [23], the DLPFC is also important for complex and technical problem solving such as understanding computer code [63, 64] and perceptual tasks such as sorting through perceptual stimuli [83, 84]. Moreover, psychophysiological proxies for DLPFC functioning are associated with a sense of mastery as an adaptive individual trait [40]. In our study, we found that higher variable Control, an indicator of self-efficacy, was associated with less performance monitoring and less team support demands. In previous research, we showed that interoceptive ability, an indicator related to the cognitive perceptions of emotions and arousal, was moderated by self-efficacy during counterintuitive decision-making in officer cadets [85]. Self-efficacy may facilitate better cyber oriented decision-making in certain situations [86] and is negatively associated with stress arousal during task-engagement [87]. Higher Control variability in our sample may be indicative of the level of expertise among COs, and recent research seems to suggest that cybersecurity experts need less intra-team communication and coordination compared to novices [88, 89].

A previous study suggested that increasing cybersecurity alerts were associated with drops in team performance [90]. The authors suggested that team dynamics were affected at the structural level with communication breaking down due to cognitive fatigue. As lower affective variability is due to limited capacity of prefrontal structures such as the DLPFC to exert top-down control on emotional states [23] then it is possible that the (1) arousal was higher than participants were comfortable with (i.e. past optimal arousal levels) such that attention was focused inwards, (2) that affective states were competing with problem solving (3) and sorting between task-related perceptual stimuli to maintain situation awareness [66]. Thus, lower affective variability in our sample may reflect reduced capacity for situational load thus higher team support demands.

Inability to regulate one's own affective states will also affect the capacity to help regulate other individual's affective states due to low tolerance for cognitive-emotional load [91, 92]. If an individual must spend cognitive effort on regulating their own stress- and affective arousal, less cognitive capacity can be allocated to help handle other people's stress levels. If communication dyads are significantly stressed without capacity to down-regulate their own arousal, this may result in a positive feedback loop elevating arousal-related conflict levels during communication [39]. A recent preliminary report on US army computer network defense teams participating in a CDX reported that arguing in cyber defense teams was negatively associated with team performance [93]. The authors reported that frequent arguing was negatively associated with two performance measures: (1) the time between start of an inject to returned rapport approval by team controller, and (2) the percentage of category of injects correctly identified by the blue team. The study did, however, not report p-values for this relationship. This can have major consequences in high-stress, high time-pressure social settings such as cyber threat situations. The relationship between affective variability, characteristics of communication among cyber team members, and performance in a CDX should be assessed in future studies.

This is the first study to assess how individual emotional adaptability affects team dynamics in a cyber defense setting. Our findings suggest avenues for metacognitive training on self-regulation strategies as well as advocating the need for neuroergonomic approaches to understanding how the interrelatedness between different domains of challenge to individual CO performance might affect team performance in cybersecurity.

4.1 Limitations

There are several limitations for the study. An a priori power analysis (G*Power [94]) showed that the minimum number of participants needed ($N = 17$) to achieve medium effect sizes ($f^2 = .25$), our study only had 13, but was the full cohort of the group. This, alongside that the study is correlational in nature and all variables are self-reported, meaning the results need to be interpreted with caution as type I and II error may occur since several results were near significance levels.

4.2 Conclusion

Future research on team performance in cybersecurity should include variable measurements of individual factors as they are more sensitive and may have better explanatory power for performance measurements than team-level measures alone.

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