**EAI Endorsed Transactions**
**on Security and Safety**

Research Article

# Decision-making and emotions in the contested information environment

M.W. Haas[1,*], L.M. Hirshfield[4], P.V. Ponangi[2], P. Kidambi[2], D. Rao[3], N. Edala[2], E. Armbrust[5], M. Fendley[2], S. Narayanan[2]

[1]Department of Systems Engineering and Management, Air Force Institute of Technology,
2950 Hobson Way, Wright-Patterson AFB, OHIO, USA – 45433

[2]College of Engineering & Computer Science, Wright State University,
3640 Colonel Glenn Highway, Dayton, OHIO, USA – 45435

[3]Department of Computer Science & Engineering
Miami University, Oxford, OHIO, USA – 45056

[4]S.I. Newhouse School of Public Communications, Syracuse University,
215 University Place, Syracuse, NEW YORK – 13244

[5]Warfighter Interface Division, Air Force Research Laboratory
2510 5th Street, Wright-Patterson AFB, OH – 45433

## Abstract

Future conflicts will necessitate the ability to conduct effective military operations in a contested information environment. The building and maintaining of robust situational awareness, protection of decision-making effectiveness of individuals and teams, fighting through information attacks from both in, and through, the cyberspace domain, will be essential. Increasing the knowledge of the mechanisms involved in degrading task performance and decision-making during cyber attacks will enable the development of advanced human-centered defensive techniques that aid fight-through capability. In this position paper, the development and evaluation of software that simulates real-time and persistent manipulation of the information environment is discussed. Results of the evaluation indicated that the task performance of a team of decision-makers performing collaborative tasks could be degraded through real-time manipulation of cyberspace content and operation. The paper concludes with a discussion of focus and direction for future research and development. It is suggested that the building of a deeper understanding of the perceptual and cognitive factors that are significant in the relationship between information environment manipulation and reduction in task performance is required. This understanding will aid in the defence of cyberspace attacks, will aid in fight through and mission assurance, and will aid the Information Operations community.

**Keywords:** Information Operations, Decision-making, emotion, situation awareness, affective computing, adaptive interfaces

Received on 31 March 2012; accepted on 31 March 2013, published on 03 May 2013



doi: 10.4108/trans.sesa.01-06.2013.e3

* Corresponding author. Email: michael.haas@afit.edu

## 1. INVESTIGATIONS OF MALWARE IMPACTS ON COGNITIVE PROCESSES

Several recently completed experiments are indicating that decision-making, situation awareness, and emotion regulation may be impacted by the presence of malware operating on automation during task performance. These indications are seen in overall task performance as well as brain imaging studies and are described in the following three experiments.

### 1.1 Behavioural and emotional response from dyads to simulated malware

In one such study, the Human Effectiveness Directorate of the Air Force Research Laboratory led the software development of a tool to simulate, in real-time, cyberspace-based attacks on the information environment of decision-makers performing tasks and the subsequent human-in-the-loop experimental evaluation of the tool for its ability to create task performance effects. This software tool, called the Cognitive Cyber Weapon Selection Tool (CCWST), is described by Ponangi *etal*[12] and furthered detailed in a forthcoming journal article by Ponangi *et al* [11]. In summary, the initial use of the CCWST within the Human Effectiveness Directorate was to simulate attacks hypothesized to cause reductions in the ability to build and maintain situation awareness, as well as the quality of decision-making. These cognitive effects would then be observable and measurable as changes in task performance.

Each of ten teams of two participants each were asked to plan as quickly as possible a travel itinerary (for a 1 day trip to occur in 6 months) consisting of airline travel and lodging information from Columbus, Ohio to Cincinnati, Ohio, while minimizing costs. A between-team experimental design was used with 5 teams experiencing the simulated information attacks and the remaining 5 teams not experiencing any simulated information attacks. The teams were permitted to use Internet Explorer 7 and Outlook in any way they determined would best aid their completion of the task.

The dependent variables were:

- The number of e-mails exchanged.
- The total volume of e-mails exchanged.
- The number of website repetitions.
- The time to complete planning.
- Self-reported rating of confidence level.

Overall, it was shown that significant reductions in task performance were observed when the simulated cyberspace-based attacks were present relative to task performance observed without the presence of the simulated cyberspace-based attacks. Easily observable manipulation of information integrity, as well as occasional web site re-direction during task performance, significantly reduced the user's level of confidence. [12] Anecdotally, it was noted that while experiencing the simulated information attack, it was typical for the two users to begin to first suspect, then accuse, each other of making errors and that these beliefs would then precipitate anger responses from one user toward another as the attacks progressed. The level and veracity of the anger appeared to vary across teams. This finding was not expected prior to the experiment and has begun to shape our belief that emotion is a cognitive state that can significantly be affected by operating while under information attack and that uncertainty, as well as emotion, may drive decision-making effects while under the threat of an information attack.

### 1.2 Malware and Working Memory.

In other laboratories, a range of studies measuring cognitive load in the brain with functional near infrared spectroscopy have recently been completed [5,7,8,9,13,14]. Two of these studies are particularly relevant to decision-making and the building and maintaining of situation awareness in a contested information environment and are described in the following paragraphs.

The fNIRS device used in this study was an ISS OxyplexTS frequency-domain tissue spectrometer with two probes. Each probe had a detector and four light sources. Each light source produces near infrared light at two wavelengths (690nm and 830nm) which are pulsed intermittently in time. This results in 2 probes x 4 light sources x 2 wavelengths resulting in 16 readings at each time point.

For the experiment, benchmark tasks from the cognition literature shown to vary the load place on working memory were utilized. These tasks are collectively known as *nback* tasks with each lasting roughly 30 seconds. Research shows that the working memory load of the 0back task is less than that of the 1back task, which is less than the working memory load of the 2back task [15-17].

Two disruptions were incorporated into the system operation while participants were working with the 1back task. The two disruptions were:

- Pop up manipulation—an internet pop-up was used to disrupt users at predefined points throughout the experiment while performing the 1back task.
- Dropped keystroke manipulation—During predefined points throughout the experiment the participant's keyboard was disabled (during a 30 second task, the keyboard would be inactive for .8 seconds out of every 5 seconds.

The 5 conditions used in this experiment are listed below:

- Set of 0back tasks (benchmark low workload)
- Set of 1back tasks (benchmark medium workload)
- Set of 2back tasks (benchmark high workload)

- Set of 1back tasks with a pop up in each 30 second task (unknown workload)
- Set of 1back tasks with dropped keystrokes in each 30 second task (unknown workload)

Six participants (3 female, 3 male) completed the experiment. Participants were all Tufts undergraduate students. A randomized block design with eight trials was used in this experiment. Therefore, there were 5 conditions * 8 trials = 40 thirty-second long tasks throughout the experiment. Each task was separated by a 20 second rest period, allowing participants' brains to return to a resting, or baseline, state. By choosing the benchmark nback tasks, it was possible to acquire known patterns of brain activity relating to workload for each participant. This enabled the comparison of brain activity of the benchmark tasks, and the brain activity associated with the disruptions. When participants completed 0, 1, and 2back tasks, their patterns of brain activity associated with low (0back), medium (1back), and high (2back) workload conditions were acquired. Once participants' brain activity was analyzed under these various workload demands, it was possible to look at participants' brain data while being disrupted to see if the data was similar, or different from, the low (0back), medium (1back), or high (2back) tasks. If a disruption had no effect on users' mental workload, the brain activity during that task would be similar to the participant's brain activity during benchmark 1back tasks.

Hierarchical clustering was computed on each condition, for each participant. Similarities were identified between the disruptions and the 0back, 1back, and 2back control conditions. Being closely associated with 0back suggested a decrease in workload. This could be due to the participant losing track or 'giving up' because the condition was too difficult. Being associated with the 1back suggested that the disruption had no effect on the working memory load of the participant. Being associated with the 2back condition suggested that the disruption caused a noticeable increase in the participant's working memory load.

For 67% of participants, the pop up condition was most similar to the 2back benchmark condition, suggesting that the pop ups increased participant's workload. The data for one participant showed the tightest clustering between the 0back and the pop up condition. This implied that this participant had a lower working memory load when the pop up occurred. Since this participant had the lowest accuracy out of all participants during the pop up condition, it is probable that this participant gave up during the pop up tasks, which would explain the low accuracy and low workload during that time period.

Qualitative observations suggested that participants did not notice that the dropped keystrokes were occurring. They simply continued working on their task without noticing that some of their keys were not being recorded on the screen. Clustering results support this observation. The brain data for 83% of participants indicated that the dropped keystroke condition was most closely related to the 1back condition, indicating that there was no change in mental workload during this condition. Therefore, since participants' accuracy was significantly lower during the dropped keystroke condition and their brain data suggested no change in workload during this condition, we can conclude that participants' accuracy was affected by this disruption, although they never became aware that the disruption was occurring.

### 1.3 Brain Imaging of Changes to Cognitive Processing and Situation Awareness

The Air Force's updated version of the Multi-Attribute Task Battery (AF_MATB) [18] was used in an experiment designed to study how situation awareness may be observable in brain images. Detailed information about AF_MATB can be found in [18]. In pilot studies, a difficulty level that would result in the majority, if not all of the participants, having difficulty doing everything perfectly was selected. This selection would force the participants to multi-task, prioritize, and accept that while their performance would likely be imperfect, they needed to keep from becoming frustrated in order to complete the AF_MATB scenario. Eight participants completed this experiment. After providing informed consent, participants completed a Trail Making Test aptitude test, as well as a visual perception and scanning aptitude test. Participants completed two experimental conditions, and repeated these conditions 5 times. The conditions consisted of 2 minutes of working with the AF_MATB, and then 2 minutes while making similar mouse movements as those caused by the AF_MATB (control condition).

The detailed performance data output by AF_MATB was collected and analyzed. The top 3 performers were selected as the high situation awareness group. The rest of the participants were included in our average situation awareness group.

A Pearson Product Correlation was conducted on the visual scanning data and the total score data, as well as on the Trail Making Test data and the total score data. There was not a strong correlation between visual scanning test scores and the final score, but there was a strong relationship (-.69) between one's score on the Trail Making Test and their overall score. Thus, it seems that the same high level resources that caused one to be superior at the Trail Making Test were recruited to aid performance during the AF_MATB task.

fNIRS data were collected using the Hitachi ETG-4000 device. Participants wore a cap with 52 channels that take measurements every quarter of a second. This technique is non-invasive and allows for data monitoring in real-time. As fNIRS equipment is sensitive to movement, participants were placed at a comfortable distance from the keyboard and mouse and were asked to minimize movement throughout the experiment. Prior research has shown that this minimal movement does not corrupt the fNIRS signal with motion artifacts[19].

The NIRS_SPM Matlab suite of tools was used to analyze the fNIRS data [20]. The raw light intensity data were converted into relative changes of oxygenated (HbO) and de-oxygenated[21] hemoglobin(Hb) concentrations. All data were then processed using a band-pass filter (between .1 and .01 Hz) to remove noise and motion artifacts. Further analyses were conducted on only the HbO data, as those types of data usually correlate most directly with increased brain activation. A general linear model (GLM) was used to fit the fNIRS data. By incorporating the GLM with the p-value calculation, NIRS-SPM not only enables calculation of activation maps of HbO, Hb, or total haemoglobin, but also allows for spatial localization, that is not possible using conventional analysis tools. Figure 1.3.1 shows the results obtained by visualizing the statistically significant HbO data summed across participants. Tsuzuki's 3D-digitizer-free method for the virtual registration of NIRS channels onto the stereotactic brain coordinate system was used. This method allows the placing of a virtual optode holder on the scalp by simulating the holder's deformation and by registering optodes and channels onto reference brains in place of a participant's brain [21]. Participants were grouped based on their task performance (high and average SA groups). Figure 1.3.1 shows the imaging results utilizing data obtained from operating the AF_MATB tasks that were significantly different from the movement control condition using a 95% confidence interval. Thus, the resulting figure shows the brain regions that were activated for each group while operating the AF_MATB task.

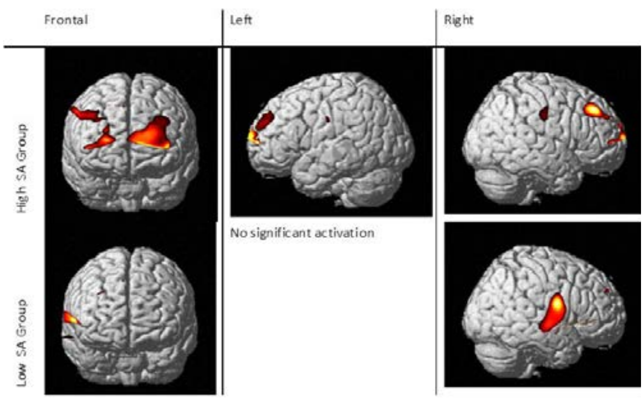


Figure 1.3.1: Comparison of Significant Brain Activation between High and Low SA Groups

The brain activation occurring in the frontal view indicates that the high SA group had more brain activation in areas directly responsible for cognitive load processing (i.e., concentrating and thinking) than the average SA group. These results dovetail nicely with the recent neural efficiency research that suggests that high performing participants elicit more brain activity than their peers when undergoing highly complex tasks [22]. In particular, the activation on the left side view of the High SA group corresponds with Brodmans area 10, also known as the anterior prefrontal, rostral prefrontal cortex and frontopolar prefrontal cortex. These regions correspond with executive functioning, memory, and planning and coordinating activities. The left side of the High SA groups' brain also shows activation in Brodman's area 9, or the dorsolateral prefrontal cortex (DLPFC). The DLPFC region is the area responsible for motor planning, organization, and regulation. In particular, the DLPFC is responsible for emotion regulation. It is possible that the high SA group may have been expending cognitive effort to regulate their emotions, keeping them from becoming stressed by the demands of the AF_MATB task. Using emotion regulation to control one's level of stress during a challenging task is an important aspect of maintaining SA. Average SA participants did not show this activation in the DLPFC, and may have become more easily overwhelmed by the stressful nature of the task. On the right side of the brain, the high SA group and the average SA group had activation in the Superior Frontal Sulcus, which is heavily involved in working memory, but the high SA group had a good deal more activation than the average SA group in that region. The activation on the right side of the brain of the high SA group also has some overlap with regions responsible for prospection. Prospection involves thinking into the future about upcoming events and situations. It is interesting to note that high SA users may have been predicting future events in the task, which is a key element of Endsley's SA stage 3. This is in line with prior research showing that people with higher IQ's spend more cognitive resources 'planning ahead' than their average IQ counterparts when doing the same task[23].

## 2. CONCLUSIONS GUIDING FUTURE RESEARCH

Maintaining decision-making quality and timeliness is critical for operations performed in, and through, the contested information domain of cyberspace. There are many factors which impact decision-making outcomes such as how the decision is framed, the likelihood of potential outcomes, and the emotional state of the decision-maker. This is illustrated in the dissertation by Hyung-il Ahn from the Affective Computing Group at MIT [6]. Ahn presents an investigation of the impact of emotion on decision-making and embodies the empirical results into a computational modelling framework. Ahn also incorporates other factors, such as uncertainty of decision outcomes and likelihood of gain in the resultant computational framework, in the research Ahn's Affective-Cognition Model is shown in Figure 2.1.

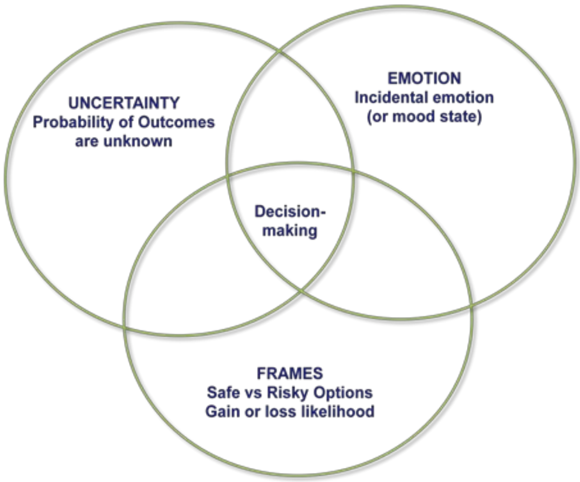


**Figure 2.1.** Ahn's Affective-Cognition Model [6]

Many of the factors which impact decision-making, as well as those factors impacting global measures such as situation awareness, can be purposefully manipulated through information operations. These information attacks can put task performance at risk and can ultimately erode system's-level capabilities.

Research regarding the emotional response and emotional regulation processing occurring while performing complex tasks under information attack, as well as associated impacts to decision-making and task performance, is sparse at best. The number of research efforts in this area is less than the number of research efforts investigating other factors having an impact on decision-making. Documented research results do seem to indicate that negative affect combined with high arousal increases the probability of performance or judgment error [10].

It appears that increasing the knowledge regarding emotion's role in impacting decision-making and task performance in a contested information environment is an overarching need. Understanding the interactions between operator traits, cognitive state, and potential information attack options would enhance the weaponeering of cyberspace-based information operations as well as increasing options for defensive actions against those same attacks. There are several threads of research that necessarily spin from this overarching need and associated technical challenges that enable the focusing of future research and development efforts.

If we speculate that attacks on the information environment can drive emotional transitions of users performing tasks in the contested information environment, a significant research need is to understand the relationships between information manipulations, emotional responses, influences on decision-making, and their associated changes in task performance. The emotional response and emotional regulation capabilities may well be very individualized and a function of the users traits, as well as being a function of task characteristics, environmental factors, and the current cognitive state (including emotional state) of the user. Capturing this fundamental understanding in a response model capable of predicting quantitatively accurate and reliable emotional response, as well as influences on decision-making and task performance, is a potential product of this thread of research that would be of use for the Information Operations community.

Additionally, it may be the case that there is an "optimal" emotional state that is individualized and a function of task and environmental factors. Developing a process by which the "optimal" emotional state can be maintained in a user performing tasks can be thought of as an adaptive emotional interface which must measure, and drive, emotional state in an individual in a feedback control loop. There exists a scientific literature base covering the past 25 years regarding the development and utilization of automation and feedback control loops operating as adaptive interfaces. This literature involves dynamic task allocation as well as dynamic multi-modal human interface modulation based on the combination of environmental factors and operator state. Much of this literature is focused on fundamental issues involving the design and operation of adaptive interfaces and a significant portion is focused on aircraft crew stations as a domain of application. For examples of these, see Hettinger *etal* [1], Haas[2], Hudlicka[3], and Klein [4].

Understanding how well emotion can be measured in a quantitatively accurate, reliable, and repeatable manner is essential. Understanding the characteristics and limitations of measuring emotion, and the multi-modal stimuli needed to elicit emotional state transitions, is a required research need and a prerequisite for implementing defensive techniques to protect an individual's, or team's, decision-making and task performance capabilities while operating in a contested information environment.

Individual differences in one's ability to interpret, to respond, and to convey emotion may exist, be significant, and may be a function of many innate and/or experiential factors. It may also be the case that there are significant differences between individuals in their abilities to transition between emotional states temporally and these differences may be a function of current state (level of SA, level of cognitive workload), modality and content of the stimulation factors, i.e. one individual responds optimally to specific musical passages while another responds optimally to olfactory stimulation of specific aromas. Needed levels of the understanding of individual differences in emotional ability and capability goes well beyond results obtainable from typical emotional intelligence appraisal techniques, but is needed to accurately and reliably transition an individual from one emotional state to another. Essentially, this research would entail the building of understanding necessary to predict an individual's emotional response to multi-modal stimuli intended to elicit emotional transitions. Building a process which could create an individual's predictive emotional "signature" would be necessary to purposefully influence a user's task performance both accurately and reliably.

### Acknowledgements

The authors wish to gratefully acknowledge the research support provided by Dr. Robert Herklotz, Program Manager for Information Operations and Security, Air Force Office of Scientific Research, Air Force Research Laboratory.

## References

**[1]** Hettinger, L.J. & Haas, M.W. (Eds.) (2003) Virtual and Adaptive Environments-Applications, Implications, and Human Performance Issues. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

**[2]** Haas, M.W. & Hettinger, L.J. (Eds.) (2001). *The International Journal of Aviation Psychology Special Issue: Current Research in Adaptive Interfaces*. Volume 11, Number 2, Mahwah, NJ: Lawrence Erlbaum Associates.

**[3]** Hudlicka, E. and D. McNeese (2002), 'Assessment of user affective and belief states for interface adaptation: Application to an Air Force pilot task'. *User Modeling and User-Adapted Interaction* **12** (1), 1-47.

**[4]** Klein, J., Y. Moon and R. Picard (2002), 'This computer responds to user frustration – Theory, design, and results'. *Interacting with Computers* **14** (2), 119-140.

**[5]** Hirshfield, L.M., et al. Human-Computer Interaction and Brain Measurement Using Functional Near-Infrared Spectroscopy. in Symposium on User Interface Software and Technology: Poster Paper. 2007: ACM Press.

**[6]** Ahn, H., "Modeling and Analysis of Affective Influences on Human Experience, Prediction, Decision Making, and Behaviour", Massachusetts Institute of Technology, Ph.D. Dissertation, Cambridge, MA, 02139.

**[7]** Hirshfield, L., et al. This is your brain on interfaces: enhancing usability testing with functional near infrared spectroscopy. in SIGCHI. 2011: ACM.

**[8]** Hirshfield, L.M., et al. Combining Electroencephalograph and Near Infrared Spectroscopy to Explore Users' Mental Workload States. in HCI International. 2009: Springer.

**[9]** Sassaroli, A., et al., Discrimination of mental workload levels in human subjects with functional near-infrared spectroscopy. accepted in the Journal of Innovative Optical Health Sciences, 2009.

**[10]** Kleider, H; Parrott, D and King, T (2010). Shooting Behavior: How Working Memory and Negative Emotionality Influence Police Officer Shoot Decisions. *Applied Cognitive Psychology 24*, 707-717.

**[11]** Ponangi, P. "Cognitive Cyber Weapon Selection Tool Empirical Evaluation", Unpublished thesis, Wright State University, College of Engineering and Computer Science, Dayton, Ohio, 45435, 2011. http://etd.ohiolink.edu/view.cgi/Ponangi%20Preethi%20Vinayak.pdf?wright1303229011

**[12]** Ponangi, P., Kidambi, P., Rao, D., Edala, N., Fendley, M., Haas, M., Narayanan, S., "Influencing Cognitive Behavioral Changes Using a Suite of Cyber Weapons", In *Proceedings of the 2012 International Conference on Applied & Theoretical Information Systems Research*, Taipei, Taiwan, February 10-12, 2012.

**[13]** Hirshfield, L.M., Enhancing Usabiltiy Testing with Functional Near Infrared Spectroscopy, in Computer Science. 2009, Tufts University: Medford, MA.

**[14]** Girouard, A., et al. Distinguishing Difficulty Levels with Non-invasive Brain Activity Measurements. in Proc. INTERACT Conference. 2009.

**[15]** Leung, H., et al., Load Response Functions in the Human Spatial Working Memory Circuit during Location Memory Updating. NeuroImage, 2007. 35.

**[16]** Gevins, A., et al., High-Resolution EEG Mapping of Cortical Activation Related to Working Memory: Effects of Task Difficulty, Type of Processing, and Practice. Cerebral Cortex, 1997.

**[17]** Smith, E. and J. Jonides, Storage and Executive Processes n the Frontal Lobes. Science, 1999. 283.

**[18]** Miller, W., The U.S. Air Force-developed Adaptation of the Multi-Attribute Task Battery for the Assessment of Human Operator Workload and Strategic Behaviour. AFRL-RH-WP-TR-2010-0133, 2010.

**[19]** Solovey, E., et al. Using fNIRS Brain Sensing in Realistic HCI Settings: Experiments and Guidelines. in ACM UIST Symposium on User Interface Software and Technology. 2009: ACM Press.

**[20]** Ye, J.C., et al., NIRS-SPM: Statistical parametric mapping for near-infrared spectroscopy. Neuroimage., 2009. 44(2): p. 428–447.

**[21]** Tsuzuki, D., et al., Virtual spatial registration of stand-alone functional NIRS data to MNI space. NeuroImage, 2007. 34: p. 1506-1518.

**[22]** Roland H. Grabnera, Aljoscha C. Neubauera, and E. Sternb, Superior performance and neural efficiency: The impact of intelligence and expertise. Brain Research Bulletin, Science Direct, 2006. 69(4): p. 422–439.

**[23]** Graham, S., et al., IQ-Related fMRI Differences during Cognitive Set Shifting. Oxford Journals, Life Sciences & Medicine, Cerebral Cortex, 2010. 20(3): p. 641-649.