Neurocognitive engineering for systems development

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Abstract

The complexity of the current and future security environment presents significant challenges for the warfighter. Advances in information and communications technologies are widely believed to provide a path forward for meeting those challenges, but will also impose new and potentially significant demands on soldier cognitive capabilities. In this paper, we discuss an approach to materiel development, neurocognitive engineering, which seeks to design systems that work in ways that are consistent with the function of the human brain. Neurocognitive systems would both augment the capabilities of the human brain to compensate for and overcome limitations, and capitalize on inherent neurocognitive strengths in those domains where effective technological solutions cannot be attained. The design of such systems will require new understandings of how the brain underlies soldier cognitive performance. We argue that traditional approaches to systems development will not be able to provide such understandings to meet the increased cognitive needs of future systems, and that adopting tools and approaches from the neurosciences provides opportunities to demonstrably improve systems designs.

Key words: materiel development, neuroscience, neurotechnology, cognition, information dominance

Today, our nation faces a security environment that is more complicated than ever, imposing new and ever-changing demands and challenges on our personnel. Recent analyses by the Office of the Chairman of the Joint Chiefs of Staff has pointed to three key aspects of the security environment that will drive the development of operational capabilities and concepts needed to ensure success on the battlefield now and into the future: a wider variety of adversaries, a more complex and distributed battlespace, and increased technology diffusion and access (1). Successful future human-system materiel development will depend on an approach that is able to account for the complex interactions of these critical aspects of the environment, as well as the numerous other environmental, task, and personnel factors that impact performance. For example, imagine a leader in an unpredictable, dynamic, stressful situation; it could be a military commander in charge of a platoon or a transportation officer in charge of a security team at an airport. What factors will affect their performance? Some factors will be external to them and will be out of their control, such as the size of the enemy force, the time of day, or the effectiveness of their security systems. Other factors will be internal, such as their

ability to communicate and lead their personnel, their personalities, and their fatigue levels. Importantly, an individual's cognitive functioning, or how they think about the situation and the information presented to them and how they translate that thinking into effective behaviors, will be critical to their performance. However, as will be discussed, ensuring adequate levels and sustainment of cognitive performance needed for mission success is non-trivial and will depend on the development and integration of advanced technologies and understandings of human neurocognitive behavior that lead to the effective design of socio-technical systems (i.e., complex systems accounting for both people and technology).

The potential impact of environmental complexity on cognitive function can be seen in the analysis of those military and industrial disasters where decision makers needed to interact with equipment and personnel in a stressful, dynamic, and uncertain environment. Analysis of the shooting down of Iran Air flight 655 by the USS Vincennes in 1988, and the partial core meltdown of the nuclear reactor on Three Mile Island in 1979, revealed that cognitive aspects of complex human–system inter-

actions can have dramatic and unexpected consequences (2). One of the primary contributors in these and similar incidents was the highly dynamic and information-rich environment enabled by advances in computer and information technologies (see below for further discussion). Similarly, contributors to the complexity of future socio-technical interactions are likely to include: the increasingly dynamic and nonlinear nature of the battlespace; the adoption by the adversary of advanced information technologies, such as the Internet, cellular telephones, GPS devices; non-traditional approaches to warfare, such as the widespread use of improvised explosive devices and suicide bombings; the high level of interactions between our forces and the local populations and political leaders; and the envisioned nature and demands of future warfare, which will involve reduced manpower, greater availability of information, greater reliance on technology, including robotic assets, and full functionality under sub-optimal conditions (3). These challenges will fundamentally alter the balance and nature of the socio-technical interactions in the emerging operating environment such that meeting the *cognitive demands* posed by these environments will necessitate the change from a model that primarily relies on personnel to one that involves a balance between personnel and system. While such a shift may be necessary to provide the capabilities needed on the future battlefield, it can also lead to new patterns of errors (4) and imposes new demands on systems developers.

From the materiel development perspective, the complexity of the aforementioned security environment presents significant difficulties. It is widely believed that the profound advances in computing, information and communications' technologies will provide a path forward towards meeting those demands. Underlying how such capabilities can be realized, however, is the need for the research and development community to understand the impact that the complexity of the operational environment has on behavior in order to develop and implement systems that will best provide the capabilities required to work in harmony with our personnel. More specifically, we believe that systems should be designed to work in ways that are consistent with the function of the human brain, augmenting its capabilities to compensate for and overcome limitations, and capitalizing on inherent neurocognitive strengths in those domains where effective technological solutions cannot be attained. In this way, human-system performance can be maximized to meet the challenges of a complex, dynamic, and ever-changing security environment.

In this paper, we discuss an approach to materiel development utilizing cognitive engineering supported by neuroscience, viz., *neurocognitive engineering*. We use as an example the problem space of the information-intensive security environment and the widely-accepted approach to addressing its challenges, namely, decision superiority and information dominance that can be enabled through advanced information networks. Within this context, we argue that traditional approaches to addressing the cognitive needs of systems development will not be met by traditional methods, and that adopting tools and approaches from neuroscience provides opportunities to enable neurocognitive engineering to demonstrably improve systems designs. Finally, we discuss several challenges wherein a neurocognitive engineering approach has the potential for improving soldier, system, and integrative soldier-system performance.

The information-intensive security environment

As discussed above, the current and future security environment poses more complex and diverse challenges to our warfighters than ever before. To address these challenges, it has become widely believed that information and its use on the battlefield is vital to the success of our armed forces; that is, that "superiority in the generation, manipulation, and use of information," or "information dominance," is critical to enabling military dominance (5). Winters and Giffin assume an even more aggressive position, defining information dominance as a qualitative, rather than simply quantitative, superiority that provides "overmatch" for all operational possibilities, while at the same time denying our adversaries equivalent capabilities (6). As reported in Endsley and Jones, each of the major branches of the armed forces has embraced the critical importance of information dominance on the future battlefield (7).

A more recent elaboration on the concept of information dominance is the notion of "decision superiority": the process of making decisions better and faster than our adversaries (1). Decision superiority is one of the seven critical characteristics of the future joint force (1). It rests upon a paradigm of information dominance to provide the capabilities to acquire, process, display, and disseminate information to decision-makers at every echelon across the force.

The capabilities of the information age

Over the past 40 years, our technological capabilities to process, store, transmit, and produce information have increased remarkably. As reported by Chandresekhar and Ghosh (8), progress in information and communications technologies over the past 40 years has been truly remarkable. For example, between the early 1970s and late 1990s there was a greater than 10,000-fold increase in the number of transistors that could be placed on a computer chip; a 5,000-fold decrease in the cost of computing power; a 4,000-fold decrease in the cost of data storage, and a 1,000,000-fold decrease in the cost to transmit information. Other authors have produced similar, but varying, estimates of the growth and impact of information and communications technologies (9,10), as well as predictions of the continued growth in such technologies in the near and mid-range future (11,12). This growth has, in turn, stimulated the development and availability of devices that have revolutionized the ability to produce, acquire, organize, retrieve, display, manipulate, and disseminate information at levels that have been historically unprecedented. Lyman et al. estimate that worldwide production of original information in 2002 was between 3.4 and 5.6 exabytes (1 exabyte = 10^{18} bytes of information) (13). The authors provide some context: 5 exabytes of information is equivalent to about 37,000 times the size of the 17-million-book collection of the US Library of Congress, or about 2,500 times the size of all of the US academic research libraries combined. The amount of information transmitted across various modes of electronic communication (i.e., radio, television, telephone, and the Internet) — 18 exabytes — is even more striking.

It is widely maintained that the complexity of the current and future battlespace can be addressed through the development and use of information and related computer technologies, and thus, these technologies are considered vital for national security at the highest political and scientific levels (14,15). Specifically, it is envisioned that decision superiority and information dominance can be realized through the development and effective utilization of advanced information networks (16). Indeed, the *National Military Strategy* discusses the development of a Global Information Grid (GIG), which would facilitate "information sharing, effective synergistic planning, and execution of simultaneous, overlapping operations (1)." According to this analysis, the GIG "has the potential to be the single most important enabler of information and decision superiority." Similarly, proposals for the Army's future forces also rely heavily upon an advanced battlefield network to provide superior battlespace awareness and strategic and tactical advantages by providing precise and timely information of enemy and friendly positions, capabilities, activities, and intentions (1). Such information is intended, in turn, to make flexible, adaptive planning possible in the face of a complex, dynamic security environment. The belief that information and communications technologies can support increased operational capabilities appears to be both clear and pervasive, although alternative perspectives have been expressed (17).

Information intensity and consequences for human performance

While the technological capabilities for collecting, processing, displaying, and disseminating information have dramatically increased over the past several decades, human information processing capabilities have not increased in the same manner. The human brain, despite its vast complexity, is capacity-limited, and such limitations are widely noted (18, 24). These limitations of human cognitive capabilities will have obvious and significant consequences for performance in the face of an increasingly complex and information-intensive operational environment when considering a paradigm of information dominance. This may be especially true when the demands of a task (or set of tasks) exceed an operator's capacity (i.e., under conditions of mental or cognitive overload) (25).

Performance suffers under overload conditions. Numerous studies have shown the negative performance effects of increased information load on task performance across a range of human performance, including driving (26), simulated flight control (27), production management and scheduling (28), and business and consumer decision-making (29). For example, Jentsch and colleagues have found that increased task and information load leads to losses in situational awareness (SA) among flight crew members, resulting in poor task performance(30). These researchers analyzed 300 civilian air traffic incidents, and found that pilots were more likely to lose SA when at the controls of the aircraft than when their co-pilot was at the controls; a finding that was valid regardless of aircraft type, flight segment (e.g., takeoff, approach), or weather conditions.

The significance of the detrimental effects of information load and the potential for substantial deficits of soldier-system performance has also been well acknowledged

within the defense community (16, 31, 32). Leahy discusses two examples in which information overload has had serious, and sometimes disastrous, effects (33). During "Operation Desert Storm," a 1,000-page, computerized listing of all Coalition air operations, the Air Tasking Order (ATO), was produced every day. With limited time to read and process this amount of data, the result was that tactical air planning staffs focused only on information pertaining to their specific missions, and were "often unaware of other missions in the same area," though that information may have been available in the ATO. In 1988, the *USS Vincennes* mistakenly classified Iran Air Flight 655 as an enemy F-14 fighter jet, shooting it down and killing 290 civilian passengers and crew. In his analysis, "No Time for Decision Making," Gruner pointed out that investigators concluded that the ship's information systems "functioned as designed," but that bad decisions on the part of the captain and crew were due to information overload, among other factors, during a time-critical operation (34). He states: "Simply put, the rate at which the brain can comprehend information is too slow under fast-paced action. It has neither the time to understand all the inputs it receives, nor the ability to effectively perform all the other function [sic] it would be capable of in a less harried environment." Acknowledging these issues, several conceptual and empirical efforts have examined the issues of information and cognitive task load and its effects on human performance in military and defense-related domains (32, 35, 36), and have explored potential solutions that could mitigate these effects (37-39).

The negative impact of cognitive and information load incurs additional effects beyond task performance. As Kirsh reported, a survey of middle and senior managers in the United Kingdom, Australia, Hong Kong, and Singapore, revealed delays and deficits in making important decisions, but also showed loss of job satisfaction, ill health, and negative effects on personal relationships, as a consequence of the stress associated with information overload (40). In another study, Kinman conducted a survey of 2,000 academic and academic-related staff in the United Kingdom (41), and found that 61% of respondents cited information overload as a cause for stress related to time management, and 66% reported that time management pressures forced them to compromise on the quality of their work. This result is consistent with Cooper and Jackson's contention that the increased prevalence of information technology has resulted in information overload and an accelerated pace of work (42). Similarly, Cotton has argued that the proliferation of information on

the battlefield would increase stress on warfighters across the joint force, with the need for "faster access to information, quicker decision cycles, increased productivity, and measurable improvements," while at the same time producing unintended, but significant negative psychological, cardiovascular, and other health-relevant consequences (16).

Systems design and cognitive performance

In the previous sections, we have discussed the challenges imposed by the increased complexity of the current and future security environment, the belief that solutions based on information and communications technologies can meet those challenges, and the detrimental effects of information and cognitive load on human performance. Given that the human brain's finite cognitive capacities and limited information processing capabilities are a major limitation to soldier-system performance, one of the major goals of technology developers should be to design systems that can work in ways that are consistent with human brain function(s). Such an approach would exploit the unique capabilities of the human nervous system, while accounting for its limitations, to maximize soldier-system performance.

Unfortunately, the general model for technological development has not taken this approach. Instead, the standard has been to allow technologies to advance essentially unfettered, and to depend upon the capabilities of the human operator to adapt to the latest innovations. Consider, for example, the current prevalence of navigation and route-guidance systems and/or information and entertainment systems in automobiles. These systems are intended to improve safety and convenience for drivers, but they also add additional tasks — some of which can be information intensive (e.g., searching through a list of restaurants or songs— to the primary driving task (43). Green has reported that the use of such in-vehicle systems (44): 1) is a contributing factor in accidents, 2) causes drivers to lose awareness of their primary driving task, and 3) is associated with accidents that happen during good driving conditions, suggesting that such accidents are distraction-related occurrences (rather than alcohol-related or fatigue-related). And while some states have recently moved to limit cell phone use while driving, regulation of the installation and use of most in-vehicle information systems is still lacking (45). So, while systems-design approaches that rely upon the adaptive capacities of the human nervous system have been generally successful, it

is important to note that as technologies are increasingly inserted into the systems in use, new approaches to integrating these systems and mitigating information overload will be necessary.

Neurocognitive approaches to system design

Designing systems that can work in ways that are consistent with human brain function is non-trivial when considering the factors that influence human neural activity. For example, substantial evidence points to inter-individual differences in neural function; adaptation of neural function as a function of training, experience, and transfer effects; and changes in brain state due to stress, fatigue, and the use of various pharmacological and even nutritional agents. These factors point to a systems engineering approach that examines, not only the use of the system itself, but: 1) the impact of environmental stressors, training and experience with the system and other related technologies, and 2) the capabilities of users at various levels of skill and experience. Perhaps the most critical aspect of such an approach is to first enhance our understanding of cognitive function in operationally relevant contexts.

Assessment in operational environments

Previously, traditional cognitive psychology, human factors, and engineering approaches have often been successful in addressing some of the cognitive-based needs of technology development. However, increased information intensity of the current and future battlefield, as discussed, is likely to challenge soldiers in ways not previously considered. Given the importance of cognitive performance in facing these challenges, we believe that systems that are not harmonized to human neural information processing will diminish the potential impact of our investments in technology. More importantly, this would lead to deficits in soldier-system performance on the battlefield, endangering soldier sustainability, survivability and mission success.

Understanding the impact of an increasingly complex and information-intense operational environment on cognitive performance is a fundamental step towards developing approaches to systems design that can mitigate the negative consequences of cognitive and information overload. We contend that, to provide systems developers with the knowledge of human (i.e., warfighter) cognition needed to make critical design and development decisions, such understandings must be objective, non-intrusive, high-

resolution, and operationally-relevant. Real-time assessments of warfighter cognitive capabilities and limitations would provide the further potential for systems research, development test and evaluation (RDTE) that can integrate online knowledge of soldier functional state and adapt system behavior to suit the operator's current operational needs and abilities.

Unfortunately, traditional methods of cognitive performance evaluation alone cannot provide an understanding of the mechanisms and technical approaches required. Here again, we consider the concept of cognitive or information workload. Generally, there are four traditional techniques for assessing workload: performance measures, subjective ratings, physiological measurement, and subject matter expert opinion. Performance measures such as reaction time or response time are used extensively in psychological and human factors research on simple tasks. However, as Veltman and Galliard suggest, performance measures often cannot be used to index workload in complex task environments (27). This is especially true when assessing workload for subtasks, as changing task priorities make it impossible to determine whether such measures accurately reflect specific subtask performance. Even if such subtask evaluation(s) were possible, there is not a formalized methodology for combining scores on different tasks into a single score to adequately reflect overall task performance. Operators will also adapt to increasing task demands by "exerting additional effort" (For a discussion, see: Sarter M, Gehring WJ, Kozak R. More attention must be paid: The neurobiology of attentional effort (46)), which may lead to equivalent assessments of task and cognitive performance when assessed through task outcome measures alone, even though cognitive workload has increased. This means that performance-based measures can only provide information on workload when some estimate of the operator's effort can also be indexed.

Rating scales, which are based upon post-hoc, subjective reports of perceived workload, might provide such estimates. Several instruments (e.g., NASA Task Load Index (TLX), Subjective Workload Assessment Technique (SWAT), Workload Profile) have been extensively used in previous research (27, 47-53) and have been shown to be effective in assessing subjective workload associated with performance on routine laboratory tasks (49). However, it has also been argued, to the contrary, that individuals do not always report their current psychological, mental, or emotional status accurately (54). Veltman and Gaillard

posit that rating scales are limited by the effect of participants' memory, perception, and biases (27). For example, participants appear to be unable to discriminate between task demands and their effort invested in task performance. As well, subjective rating scales are not well-suited for online estimation of workload, as they often require significant task interruptions, imposing at least some cost(s) to performance due to task switching (28, 55).

Measurement of physiological function and state offers a third approach to assessing cognitive processing. Central and peripheral physiological measures can provide a more objective means of assessment than can be obtained via traditional performance and rating scale methods, and numerous different measures have been related to cognitive performance, including: heart rate, heart rate variability, blood pressure, respiration rate, skin temperature, pupillary responses, and galvanic skin response (52, 56, 57). Unfortunately, physiological measures taken in isolation from central nervous system activity do not seem to have a high degree of sensitivity to cognitive performance across different task and environmental conditions.

Barandiaran and Moreno conceptualize this problem from an evolutionary perspective (58): biological systems are intrinsically purposeful in terms of their self-sustaining nature, which is the result of their internal, metabolic organization. At the most fundamental level, this is the source of what we refer to as intentionality. The evolution of the nervous system enabled organisms to actively modify their relationship with the external environment (e.g., by enabling the organism to move to different locations within the geographic space) in order to satisfy biologically-defined constraints. In the case of systems that are distinctly cognitive, however, constraint satisfaction and metabolically-driven intentionality do not seem to be able to fully explain the phenomenology of cognition (e.g., behavior that does not seem to be solely in response to metabolic needs). The authors suggest that the nervous system can be considered to be "de-coupled" from the metabolic (and constructive) processes of the organism such that the interactions of the nervous system that underlie cognitive state are no longer explicitly governed by the metabolic organization that supports the nervous system's architecture. A significant implication of such a perspective is that the local states of metabolic systems (i.e., the physiological states of the heart, lungs, kidneys, etc.) alone will not be able to predict the dynamic behavior and states of the nervous system.

Given the shortcomings of traditional approaches to cognitive assessment, it is unlikely that incremental improvements in our knowledge based upon these approaches alone can (or will) provide the necessary understandings of cognitive function that would be needed to address the challenges of systems design for the current and future security environment. However, recent progress in the neurosciences has expanded our knowledge of how brain function underlies human cognitive performance. Increasingly, the connection between human experience and its bases in nervous system function are considered to be the foundation for understanding how we sense, perceive, and interact with the external world. In particular, the advancement of noninvasive neuroimaging technologies has provided new windows into our understanding of the human brain (59).

However, much of the recent knowledge of human brain function has been gained from the highly-controlled environments of the laboratory, with tasks that often are not representative of those that humans perform in real-world scenarios. Such experimental conditions are required both to minimize motion as much as possible to maximize measurement fidelity (e.g., in functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG)), and to control for the effects of potentially confounding variables that could affect the interpretation of experimental data. The dynamic, complex nature of military operational tasks and environments, by contrast, is likely to affect the human nervous system, and its functioning, in ways that are significantly different than the tasks and environments traditionally employed in laboratory studies. It is clear that not only do different individual process information differently (see below), but the same individuals may engage different brain regions to cognitively process information in ways that are dependent on context (59). Thus, assessing the cognitive demands of human operators during the performance of real-world tasks in real-world environments will be critical for understanding how we really process information, integrate neural function, and behave (60) (i.e., ecological validity). Such an understanding is vital for generalizing results of laboratory studies to more naturalistic behaviors and environments (i.e., external validity).

Towards this end, several research groups have advanced the use of electroencephalography (EEG) within environments previously thought to be unapproachable (61-63). EEG, as a direct measure of the electrical activity of the brain detected at the scalp, provides an objective measure

that is more closely associated with cognitive function than other psychophysiological measures (e.g., heart rate or respiration). EEG also provides measurement at very high temporal resolution, enabling observation and analysis at time scales (~ 1 ms) that are relevant to the dynamic behavior of the brain, unlike performance measures or rating scales. And while current technologies are still fairly cumbersome to use (e.g., requiring significant setup time and the application of electrolytic gels), technological advances hold the promise of nearly non-invasive, zero-preparation EEG recording (64-66). Progress in computational power and data analytic techniques have also enabled the development and application of novel signal analysis and decomposition methods (67, 68), as well as advanced data mining techniques (69) for data processing and knowledge discovery in highly-multidimensional data in ways that have clearly surpassed our previous capabilities. These advances have great potential to improve EEG technology, enhancing its spatial resolution relative to the current state-of-the-art in neuroimaging technologies (i.e., fMRI) and moving neuroscience-based cognitive assessment into the operational realm.

While further technological advances and methodological developments are still needed, the current tools of neuroscience, when integrated with complementary approaches of more traditional methods, can provide more complete characterizations and understandings of cognitive (or somewhat more specifically, neurocognitive) performance in operational environments. This is critical not only for systems engineers who are developing systems to meet the challenges of the current and future security environment, but also for cognitive systems engineers who aim to facilitate performance by focusing on the "thinking" aspects within such socio-technical systems (70). In the following section, we discuss an important issue — individual differences — in which a neurocognitive engineering approach may have significant potential for enhancing systems design.

Differences in operator capabilities

One of the most common, yet more difficult systems engineering issues is the need to account for the individual difference in operator capabilities. Cognitive research has revealed that people not only differ in classical categories of mental function, such as intelligence, skill set, or relating to past experience, but they also differ on a more fundamental level in how they think (i.e., cognitive styles, abilities, and strategies). These differences arise from

many factors, including inherent characteristics of the operators and how operators are affected by stressors, such as emotionality and fatigue. A growing body of evidence suggests that individual differences in cognition, behavior, and performance of skilled tasks are rooted, at least to some extent, in differences in neural function and/or structure (59). This has been supported by the association of genetic markers with variability in brain size, shape, and regional structure (71); elucidation of differences in nervous system connectivity that relate to different patterns of cognitive activity (72, 73); and demonstrating variability in individual patterns of brain activity (74-76). These findings suggest the need for, and perhaps the basis of, plausible engineering solutions that are directed at developing integrated systems that accommodate and maximize individual structure-function relationships in the brain.

Training, expertise, and exposure

Individual differences between operators, such as those associated with the related factors of training, expertise, and exposure, can change how an individual processes information and makes decisions. An example of this is how people "naturally" envision force and motion. Research has indicated that people who have formal education in Newtonian physics can understand motion differently than neophyte physics students, who generally have a naïve "impetus" view of motion (77, 78). The concept appears to be related to differences in the neural processing involved with learned knowledge versus simple "beliefs" about physics (79). From this example, one can see the potential for different system designs to alter the cognitive processing associated with performance; if the system is inconsistent with the operator's view of the world, different and perhaps increased neural resources will be required to complete tasks. This possibility has been supported by research showing distinct neural and time factors involved in skill acquisition (80, 81, 82). Further, these studies provide insights into the ways that future systems might employ neuroscience-based technologies to assess and adapt to how an operator "naturally" interacts with the system.

Both training and expertise are related, in part, to exposure. Many national security technologies are envisioned that may have unique aspects to which operators have not been previously exposed. Thus, while they may have been trained on related technologies, even with extensive exposure, many operators may never achieve expert lev-

els of performance with new technology. It is known that exposure to an enriched environment produces changes in synaptic growth, brain morphology, neurochemistry, as well as behavior (for a review, see van Praag H, Kempermann G, Gage FH. Neural consequences of environmental enrichment (83). Studies have shown positive effects of exposure to multiple channels of stimuli (e.g., audio, visual, and tactile, as compared to unimodal stimuli) in the performance of single tasks (84, 85). However, unintended and interference effects of multi-modal stimuli have also been shown (86).This latter finding highlights a possible negative effect of learning: the strength of past events may influence future perceptions when conditions are sufficiently similar. This illustrates that an operator's expected exposure to a given technology must be considered in system design, and gives insights into potential system designs that might be utilized to predict operator perceptual biases over time, and to adapt to and eliminate these potentially negative effects.

Future applications and considerations

To be sure, recent advances in neurotechnology are enabling understandings of neurocognitive functioning in ways, and within environments, that are highly-relevant to national security. This is prompting neurocognitive engineering approaches to materiel development that has the potential to revolutionize human-system design(s). One of the primary capabilities afforded by these advances is the leveraging of insights into nervous system function, with particular attention to individual differences, so as to design systems that are consistent with "natural" patterns of information processing in the human brain. In this light, one could imagine designs that allow presenting information in a manner that limits the neural resources required for processing, and thereby increases the speed of perception and performance by accessing, facilitating and/or augmenting the cognitive style and abilities of an individual operator. Insights into the neural basis of performance also allow detection of real-time, moment-to-moment changes in neural activity that can be fed back into an adaptive system (87). Such information could be used to develop laboratory systems that use EEG classification technologies to interpret when an operator has seen a militarily-significant target (88). Current efforts are underway to further measure and classify perceptual states and to improve signal-to-noise ratio and detection accuracy. Ultimately, it is envisioned that this type of technology could be merged with automated target recognition systems and operator behavior to improve the overall accuracy and speed of overall soldier-system target detection (59).

Of equal importance, insight into the neural basis of performance is leading to an ability to predict future operator capability. Recently, applications of neural decoding techniques to spatial patterns of activity measured with fMRI (89, 90) and high resolution temporal patterns of neural activity within EEG (91) have been shown to predict performance in a dual task target detection paradigm. Such results, when taken together with advanced neurophysiological measurement technologies, suggest the potential to not only monitor ongoing neurocognitive activity, but to use such measurements to predict possible performance failures, giving systems engineers an opportunity to design systems that can mitigate the detrimental effect(s) of such errors, and thereby enhance soldier survivability and mission success.

In summary, rapid advancements in technology coupled with the dynamic, complex nature of the national security environment creates novel challenges for the materiel developer. The information-intensive environment and widely-accepted approach of decision superiority and information dominance force the creation of socio-technical systems that share the cognitive burden between personnel and the systems with which they interact. A neurocognitive engineering approach is posited to offer insights into developing such systems, from designing more effective displays to systems that adapt to the state of the operator. Any such approach must take into account traditional cognitive engineering issues such as the changing capabilities of the operator, the environments under which the systems will be used, and the different potential tasks the operator-system may attempt to undertake. Furthermore, as neuroscience (and its constituent and allied fields) rapidly advance, it is expected that the neurocognitive engineering approach will advance, as well. In this way, future progress not only involves the direct employment of neurotechnology (e.g., moment-to-moment brain-computer interface (BCI) (92), but will likely be fortified by the use of nutriceuticals and pharmaceuticals that work in tandem with any such technology and insights to enhance individual capabilities (93-95).

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Disclaimer

The findings in this report are those of the authors and are not to be construed as an official Department of the Army position unless so designated by other authorized documents. Kelvin Oie is a US Government employee and this manuscript was written as part of his official duties as an employee of the US Government

Competing interests

The authors declare that they have no competing interests.

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