Objective Neurological Measurement for Learning: A Review

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ABSTRACT

The war of cognition has become a major focus of the US military and its allies who recognize that optimizing the mind's ability to act with agility, resilience, and to manage cognitive load is of significant importance to operational effectiveness and lethality. Yet training programs continue to rely on self-report, paper-based assessment, and limited performance metrics. Further, given the extensive maturity of technology that can objectively measure various cognitive actions related to learning, it is surprising that the US military has yet to fully embrace the capabilities these apparatus can provide. Accordingly, we review the research literature to identify a) patterns of research findings and b) the gaps that should drive additional research and optimization efforts. By quantifying learning impact, defining neuro-signatures, and objectively assessing the building blocks of learning optimization, it is possible to enhance overall learning abilities in military personnel at the individual and collective levels.

Four hundred abstracts were reviewed and categorized by: Mental State, Attention, Processing, Learning, Operations, and Teaching. Major themes suggest three key observations. First, relatively few applied research studies have been conducted in the US that provide the data required to scale the use of EEG in military settings. Second, the majority of studies that used EEG outside the lab or medical setting focused on measurement and assessment rather than actionable intervention. Finally, the most recent study demonstrated a 44% improvement in learning outcomes when personalized neuro-driven feedback was compared to standardized feedback or lecture without interruption (Chae, 2020). Yet these research efforts are driven by our adversarial nations. Accordingly, this paper outlines the findings and concerns associated with the lack of robust and extensive testing of objective neuro-technology to enhance US military training, education, and operations.

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DEMAND SIGNAL

Though there are many arguments that the nature of war does not change, the advancement of technology certainly changes the way we prepare for and ultimately engage in war. It changes the way we strategize, plan, and employ our human power to these ends. More specifically, the recent evolution of technology has reduced the need for human physical power while simultaneously increasing the need for cognitive capabilities. Further, it is beginning to change the way we approach military training, progressing beyond methods that focus solely on the human to personalized training methods that incorporate sensors for human and environmental assessment as well as technology supports such as augmented reality that can enable the trainee to learn beyond his or her unaided capability. However, in order for this progression in training conceptualization to be enacted, we must first reach a level of interoperability between technologies that will allow for sensor data to be employed. Then we need to understand what has been achieved in the scientific laboratories with these sensors, what needs to be developed, and what can be applied to the operational and training environments today. Further, looking beyond military, as revenue from the online learning industry, where these data sensors will be used to drive virtual learning interventions, is expected to grow to $325 Billion by 2025 (McCue, 2018), there is a likelihood that industry will solve many micro problems and goals across the enterprise, but we will find ourselves in an abundance of solutions that lack the connection needed to ensure our warfighters are benefiting holistically from the efforts. Rather, we will, once again, find that technology access and affordability level the military battlefield globally.

Training Modernization Needs and Efforts

Several national strategies (National Defense Strategy, 2018; DoD Digital Modernization Strategy, 2019), as well as policy (DoDD 1322.18 Military Training, 2019; DoDI 1322.31 Common Military Training [CMT], 2020; DoDD 5000.59 DoD Modeling and Simulation [M&S] Management, 2018; DoDI 1322.26 Distributed Learning, 2017) have been written and enacted across the military training continuum aiming to make possible the connection of data across apparatus, training experiences, time, and location. Ultimately, the goal is to be more precise and targeted with training interventions in order to optimize not only the efficiency of training but also elevate the effectiveness of it. To accomplish the goal of interoperability, standard tagging practices must be enacted but before tagging can occur, data must be collectable. To date, the primary type of data used in military training is based on observable performance. These observations are inherently biased and more importantly, require the observer to make assumptions about underlying reasons for the behavior, motivations, beliefs, and decisions. The likelihood of inaccuracy is consequently very high.

Alternatively, sensors that measure biological and neurological processes can provide direct, objective assessment of what is happening in the mind and body of the trainee, in real-time, and provide unbiased insight. Further, these sensors can help define what the trainee needs to learn next, how much information they can learn at once, and in what fashion information should be presented to optimally engage the mind in learning. However, until recently, neurotechnology has lacked the portability and price that would realistically allow for large scale use in military environments (Walcutt, Horton, Jeyanandarajan, & Yates, 2020). Now that the shift to commercially available cost-effective units is realistic, it is necessary to understand the history of the science behind these apparatus as well as what is possible with their use. It is also recommended to consider which nations are leading the charge in furthering experimentation as well as incorporating it into their military training arsenals.

Neurotechnology Advancements and Gaps

Substantial advancements in neurotechnology have occurred over the past decade but relatively less research has focused on ruggedizing the apparatus for widespread use or on testing the impact application of the findings could have on students, military, or business professionals. It is an incredible capability to gain awareness in real-time of what is happening in the brain as a person is training, rehearsing, or applying knowledge but how to transform that data into actionable recommendations is more challenging and nearly absent from the research literature. There is an assumption that once more information and insights are created, the ability to optimize neural pathways, information flow, or even assembly line work will result but the translation of the data into recommendations for action is independently necessary to study. In 2011, the Office of Naval Research funded a large-scale review of the learning science research that drove much of the last decade of learner interventions resulting in several key methodologies and data sharing activities that are necessary to optimize learner experiences (Vogel-Walcutt, Fiorella, Malone, 2013). The question now is how has this hybrid field progressed? What lessons learned can be applied now to military training and education practices and which gaps require further research or development? Accordingly, a full-scale review of the extant literature spanning the last decade was conducted.

METHOD

The goal of this review was to determine what progress, if any, had been achieved over the last decade, specifically with regard to learning interventions. There was little doubt that the technology capabilities, validity, and reliability had improved but the use of it to drive learning decisions was less clear. To that end, electroencephalogram (EEG) was paired with four key terms of interest: Learning, Education, Training, and Military. The 100 most relevant articles in each category were reviewed. To be included in the final analysis, they had to focus on learning interventions. Primary exclusion areas included those papers that focused on classification algorithms, motor tasks, emotions, animals, or teaching how to use the EEG apparatus. In all, 81 articles were kept and reviewed more deeply (see table 1).

Table 1. Initial Review Findings

Term	Tot Review	Kept	Machine Learning/ Neural Nets/ Classification	Motor Tasks	Medical Focus	Emotions	Animals	Teaching/ Training EEG	Other	Repeat
EEG Learning	100	20	31	10	30	5	1	0	3	0
EEG Education	100	22	11	5	34	9	0	10	8	1
EEG Training	100	20	12	17	29	9	0	6	4	3
EEG Military	100	19	4	1	54	6	0	0	16	0
Total	**400**	**81**	**58**	**33**	**147**	**29**	**1**	**15**	**28**	**4**

Key Themes

Several key themes regarding available data surfaced. Specifically, it was noted that there are relatively few studies focused specifically on education and training. Given the possibility of impact, it is surprising to see that little progress has been made in the testing of which instructional strategies, interventions, scaffolding, or translation to operations the use of EEG can provide. It suggests that while the technology reliability, validity, and durability has increased, the use of it has not. More than that, interest in how it might be used has also been limited. A second finding was that the majority of useful studies focused on measurement and assessment. In other words, data is being collected but few, if any changes are made to the training environment. It is a start but entirely insufficient for satisfying the possibilities that an EEG apparatus can provide. Finally, the most commonly rejected studies focused on classification algorithms, medical issues, or emotions. Each of these can play a significant role in assessing and thus aiding in the design of support systems that promote human optimization of functioning. However, without additionally, a strong emphasis on training, EEG will be used as a supporting device rather than an enabling one.

Key Focus Areas

For those studies that did focus on learning, a deeper review was conducted. 21 labels were developed to define the focus areas but those articles that focused solely on assessment and not actionable interventions were removed during this stage (N=58). Unfortunately, with a relatively small sample size of usable articles, the number of terms needed to be reduced (see Table 2). Typically, in these situations, we do not report the more specific descriptive terms, however, given the diversity of focus and the importance of understanding what research is happening, no matter how limited, we felt that it was important to share all terms. Ultimately though, the terms were organized into six key groups: Mental state, Attention, Processing, Learning, Teaching, and Operations suggesting that the needed areas of focus are accurately being represented in the literature but with too few studies to draw clear conclusions or create actionable solutions. A summary of the retained articles is provided in Table 3.

Table 2. Term Review and Consolidation

Key Terms	All Terms
Cut	Assessment and measurement but not actionable – observational
Mental State	Stress
	Confusion
	Mental State
Attention	Attention Classification
	Workload
	Engagement
Processing	Cognitive Processing
	Neurofeedback
	Cognitive Control and Self-Regulation
	Working Memory
Learning	Learning rate variance
	Neuro-adaptation
	Training Performance
Operations	Operator Performance
	Operation Performance, Accidents
Teaching	Tutoring efficacy
	Teacher Support
	Best Practices
	Framework

	WL Management
	Automated Support

Table 3. Summary of Retained Articles

Article	Key Words	Punchline		
Yin, Z. & Zhang, J. (2017). Cross-session classification of mental workload levels using EEG and an adaptive deep learning model 2017	Learning EEG	"Evaluation of operator Mental Workload (MW) levels via ongoing electroencephalogram (EEG) is quite promising in Human-Machine (HM) collaborative task environment to alarm the temporal operator performance degradation."	Operator Performance	Operations
Liu, N., Chiang, C., & Chu, H. (2013). Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors 2013	Learning EEG	"During the learning process, whether students remain attentive throughout instruction generally influences their learning efficacy. If teachers can instantly identify whether students are attentive they can be suitably reminded to remain focused, thereby improving their learning effects. Based on the experiment results, the method proposed in this study provides a classification accuracy of up to 76.82%."	Attention Classification	Attention
Mathewson, K.E., Et al. (2012). Different slopes for different folks: Alpha and delta EEG power predict subsequent video game learning rate and improvements in cognitive control tasks	Learning EEG	"By combining these predictors, we could explain about 50% of the learning rate variance and 10%–20% of the variance in transfer to other tasks using only pretraining EEG measures. Thus, control processes, as indexed by alpha and delta EEG oscillations, can predict learning and skill improvements."	Learning rate variance	Learning
Jebelli, H., Khalili, M.M., Hwang, S., & Lee, S. (2018). A Supervised Learning-based Construction Workers' Stress Recognition Using a Wearable Electroencephalography (EEG) Device	Learning EEG	"Results yielded a high of 71.1% accuracy using SVM in recognizing workers' stress. This EEG based stress detection approach will help to enhance workplace environment and conditions as well as to improve workers' health by early detection and mitigation of the factors that cause stress."	Stress	Emotions
Siripornpanich, V. et al. (2018). Enhancing Brain Maturation Through a Mindfulness-Based Education in Elementary School Children: a Quantitative EEG Study	Education EEG	"Our results suggested that implementation of the Mind-Edu into the regular elementary school curriculum would be of benefit for enhancing maturation in brain areas involved with cognitive control and self-regulation, which might provide support for a smooth transition into the adolescence."	Cog Control & Self-Regulation	Processing
Wang, H., Li, Y, Yang, Y., Meng, Z., & Chang, K. (2013). Using EEG to Improve Massive Open Online Courses Feedback Interaction	Education EEG	"We found weak but above chance performance for using EEG to distinguish when a student is confused or not."	Confusion	Mental State
Romer, E. (2014). Measuring Cognition in Computer-Based Instruction Using an EEG: A Review of the Literature	Education EEG	"This paper provides an overview of research studies that have successfully implemented EEG in education research and computer-based instruction as a measure of different cognitive processes during the learning experience."	Cognitive Processes	Processing
Lin, F. & Kao, C. (2018). Mental effort detection using EEG data in E-learning contexts	Education EEG	"Based on Cognitive Load Theory, we built a system to capture and tag a user's mental states while s/he is watching online videos with a commercial EEG device, and used different normalization schemes and time window lengths to process EEG signals recorded from the EEG device."	Mental State	Mental State

Mostow, J., Chang, K., & Nelson, J. (2011). Toward Exploiting EEG Input in a Reading Tutor	Education EEG	"A new type of sensor for students' mental states is a single-channel EEG headset simple enough to use in schools. Better-than-chance performance shows promise for tutors to use EEG at school."	Mental State	Mental State
채연수 (2020). Adaptive Neuro-learning: A New Education Strategy using EEG-based Passive Brain-Computer Interfaces	Education EEG	"We quantitatively evaluated the educational effects of each group and our results exhibited significantly higher learning performance in the experimental group, demonstrating the feasibility and practicality of the new education strategy."	Neuro-adaptation	Learning
So, W.K.Y, Wong, S.W.H., Mak, J.N, Chan, R.H.M. (2017). An evaluation of mental workload with frontal EEG	Education EEG	"Our findings revealed that theta activity is the common EEG feature that increases with difficulty across four tasks. Meanwhile, with a short-time analysis window, the level of mental workload could be classified from EEG features with 65%–75% accuracy across subjects using a SVM model. These findings suggest that frontal EEG could be used for evaluating the dynamic changes of mental workload."	Workload	Attention
Alwedaie, S.A., Zhabbaz, H.A., Hadi, S.R., & Al-Hakim, R. (2018). EEG-Based Analysis for Learning through Virtual Reality Environment	Education EEG	"Positive emotions in a real lecture are better than positive emotions in a VR-Lecture. However, the engagement score in both classes was approximately the same."	Engagement	Attention
Amin, H.U., Ousta, F., Yusoff, M.Z., & Malik, S. (2021). Modulation of cortical activity in response to learning and long-term memory retrieval of 2D verses stereoscopic 3D educational contents: Evidence from an EEG study	Education EEG	"In conclusion, it was experimentally showed that the human brain processed the S3D contents differently by utilizing more cortical regions and neuronal networks than the traditional 2D contents, which modulates the behavior of the participants by recollecting the LTM faster in the recall task."	Cognitive Processing	Processing
Galan, F.C. & Beal, C.R. (2012). EEG Estimates of Engagement and Cognitive Workload Predict Math Problem Solving Outcomes	Education EEG	"EEG data were also correlated with students' self-report of problem difficulty. Findings suggest that relatively non-intrusive EEG technologies could be used to improve the efficacy of tutoring systems."	Tutoring efficacy	Teaching
Zoefel, B., Huster, R., Herrmann, C.S. (2010). Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance	Training EEG	"The enhancement of cognitive performance was significantly larger for the neurofeedback group than for a control group who did not receive feedback. Thus, enhanced cognitive control went along with an increased upper alpha amplitude that was found in the neurofeedback group only."	Neurofeedback	Processing
Pergher, V. et al. (2018). N-back training and transfer effects revealed by behavioral responses and EEG	Training EEG	"The application of a WM training is a promising tool for both healthy adults, and in particular for older subjects, as it showed physiological and behavioral differences in cognitive plasticity across life span and evidence of benefits in the trained task and near-/far-transfer effects to other cognitive functions."	WM	Processing
Ko, L., Lai, P., Yang, B., & Lin, C. (2015). Mobile EEG & ECG integration system for monitoring physiological states in peforming simulated war game training	Military EEG	"Through the real-time signal processing and implementing the technique on the mobile platform, we can know the player's five major physiological states such as attention, fatigue, stress, emotion and heart rates. Experimental results and demonstration are showed that the proposed integration system is feasible for understanding the military training performance in the future."	Training Performance	Learning
Ma., Q. (2014). Neural Operation Management: A New Avenue for Productive and Military Operations	Military EEG	"Thus it has become a hot field of research and practice to monitor and assess the operator's physiological and psychological states online based on neural measurement technology, and then to give real time intervention, so as to reduce the occurrence of accidents and increase the operation performance."	Operation Performance, Accidents	Operations

Kloudova, G. & Stehilk, M. (2017). The Enhancement of Training of Military Pilots Using Psychophysiological Methods	Military EEG	"For training purposes, an application was developed for the instructors to decide which of the specific tasks to focus on during follow-up training. This complex system can help instructors detect the mentally demanding parts of the flight and enhance the training of military pilots to achieve optimal performance."	Teacher Support	Teaching
Blacker, K.J., Hamilton, J., Roush, G., Pettijohn, K.A., & Biggs, A.T. (2019). Cognitive Training for Military Application: a Review of the Literature and Practical Guide	Military EEG	"Therefore, we provide a guide for best practices when conducting cognitive training research specifically in a military setting. While cognitive training has attracted much controversy in both academia and commercial markets, we argue that utilizing near transfer effects in a targeted, outcome-based approach may represent a powerful tool to improve human performance in a number of military-relevant scenarios."	Best Practices	Teaching
Shi, H., Zhao, H., Liu, Y., Gao, W., & Dou, S. (2019). Systematic Analysis of a Military Wearable Device Based on a Multi-Level Fusion Framework: Research Directions	Military EEG	"The proposed framework covers multiple types of information at a single node, including behaviors, physiology, emotions, fatigue, environments, and locations, so as to enable Soldier-BSNs to obtain sufficient evidence, decision-making ability, and information resilience under resource constraints. In addition, we systematically discuss the problems and solutions of each unit according to the frame structure to identify research directions for the development of wearable devices for the military."	Framework	Teaching
Arico, P., et al. (2016). Adaptive Automation Triggered by EEG-Based Mental Workload Index: A Passive Brain-Computer Interface Application in Realistic Air Traffic Control Environment	Military EEG	"Results demonstrated the effectiveness of the proposed pBCI system, since it enabled the AA mostly during the high-demanding conditions (i.e., overload situations) inducing a reduction of the mental workload under which the ATCOs were operating. On the contrary, as desired, the AA was not activated when workload level was under the threshold, to prevent too low demanding conditions that could bring the operator's workload level toward potentially dangerous conditions of underload."	WL Management	Attention
Kacer, J., et al. (2018). Measurement and Modelling of the Behavior of Military Pilots	Military EEG	"It is possible to determine whether the pilot needs the support of the automatic flight control system. This system can be also be used in the flight control system and can increase battle effectiveness of the deployed aircrafts."	Automated Support	Teaching

FINDINGS

General findings across the review suggest that using EEG can help optimize learning experiences because it provides an objective assessment of what is happening within the brain. It is expected that these measurements are also superior to other currently used apparatus such as eye tracking because these elements require the developers to infer from the data events in the brain, intent, and other actions or motivations. EEG, however, provides more robust, direct, clear, and expansive data. Nonetheless, while EEG data could drive training interventions, they are not, on their own, prescriptive. Rather, they are descriptive, making the current literature interesting to the extent that it justifies further investigation but insufficient for current instantiation into training events.

Though, while the majority of retained studies did not clarify usable interventions based on EEG data, six studies provided key insights and these findings warrant review. Specifically, Aricò, et al. (2016) demonstrated improved performance when workload was managed using EEG during Air Traffic Control Training. Chae, (2020) was able to improve learning with automated interventions personalized to mental state. Galán and Beal (2012) used engagement and workload from EEG data to predict the problem outcomes better than base rate of problem performance. Kloudova and Stehlik (2017) assimilated EEG and heart rate data measured during flight training tasks to aid instructors to drive training decisions. Shi, et al.

(2019) proposed a multi-level fusion framework (MLFF) based on Body Sensor Networks (BSNs) of soldiers and created a model of the deployment of heterogeneous sensor networks. Finally, Kacer, et al. (2017) reviewed current systems and methods for measuring and modeling military pilot's behavior then connected them to create a complete system able to determine a pilot's stress load, along with physical and visual load levels. Taken together these hallmark research and development projects demonstrate the possibility that EEG can provide with regard to training intervention decisions. Detailed descriptions of each are provided below.

Chae (2020): Improved learning with automated interventions personalized to mental state.
Participants were 45 undergraduate students. Based on mental state (attention, comprehension, emotions, and stress), measured by the EEG, online learning interventions were applied. For example, interventions included, "telling something interesting to liven the atmosphere when learner seems to get distracted and inattentive on learning activity, reminding of fundamental concepts when learner seems not to perfectly understand present subject, and taking a short break when learner looks tired". Results indicated a 44% better outcome than random feedback or straight lecture.

Galán & Beal (2012): ENG and WL from EEG data predict the problem outcomes better than base rate of problem performance.
During a 90-minute session (15-minute baseline), 16 participants completed eight multiple-choice SAT math problems online. Attention and workload were measured using an EEG headset. Additionally, participants self-reported perceived problem difficulty and feelings of frustration. Data was used to predict likelihood of solving the problem accurately. Findings were substantive. Results suggest 67-83% accuracy in predicting participants' answers, depending on difficulty level of problem.

Kloudova, G., & Stehlik, M. (2017): EEG and HR were measured during flight training tasks to aid instructors in measuring WL and drive training decisions.
The authors report that there is a lack of focus on mental health of pilots and the impact it has on optimizing human performance during flight. Specifically, they highlight that 80-85% of aviation accidents are caused by human error (Thomas & Russo, 2007). In response, they observed five Mi-2 and Mi-171 helicopter pilots in their first stages of training, connecting them to a 19 electrode EEG across 10 training flights (1.5 hrs) and navigation flights (2-2.5hrs), real and simulated. From these data, researchers were able to elucidate which parts of training were most cognitively taxing and accordingly make recommendations to instructors about where to focus their training efforts to achieve optimal performance at greater speed.

Shi, H., Zhao, H., Liu, Y., Gao, W., & Dou, S. C. (2019): Proposed a multi-level fusion framework (MLFF) based on Body Sensor Networks (BSNs) of soldiers and describes a model of the deployment of heterogeneous sensor networks.
Recognizing the Internet of Battlefield Things (IoBT), the authors investigated a composite of multiple sensors that, combined create a "Fatigue Detection System (FDS), an Emotion Recognition System (ERS), a Behavior-Tracking System (BTS), an Environmental Detection System (EDS), a Cooperative Localization System (CLS), and a B-level physiological parameter set". Broken down into their elements, apparatus included optical sensors, vest plate electronic systems, camera-enabled binoculars, acoustic wearable tactical systems, and mobility assisting and energy-scavenging exoskeletons. The goal of this project was not testing but rather, investigation of the art of the possible. Thus, the Multi-Level Fusion Framework (MLFF) was developed. It is a three-layer analysis tool that takes original data from each of the sensors and then cross-connects data streams to create outputs that are actionable for driving military training and operations recommendations.

Kacer, J., Kutilek, P., Krivanek, V., Doskocil, R., Smrcka, P., & Krupka, Z. (2017): Describes current systems and methods for measuring and modelling military pilot's behavior. The complete system is able to determine the pilot's stress load, along with physical and visual load levels.

24 experienced pilots were connected to an array of sensors while completing a F-16 flight simulation. Sensors included heart rate measurement, electrocardiogram (ECG), EEG, respiratory, blood pressure, pulse oximeter, eye blink and path, electromyography, temperature, galvanic skin response (GSR), perspiration, motion tracking, glucose, and electrochemical sensors for homeostasis. Combining the data allowed the authors to model the pilots' behaviors and determine their stress levels and physical and visual load levels. Based on these data, both training and operational supports were recommended.

FUTURE RESEARCH NEEDS

Given the art of the possible that would allow the military to be able to optimize both training as well as operational performance for every warfighter and the supporting data, there can be no other conclusion but that program managers need to consider writing requirements for research and development that further this area of focus. To avoid it would be to yield significant advantage to our adversaries without response. But it is not sufficient to simply focus on using more sensors or combining multiple sensors to out put large data sets. Rather, specific areas of the research need to be conducted to increase the use of these wearable devices and collection of the data in such a way that makes it prescriptive for interventions and support. Accordingly, six key areas of research focus are recommended:

1. **Learning Impact:** The level of impact on learning the use of EEG can have (at each level of cognition – time, depth of learning, and simultaneous learning) needs to be quantified across several content specialty areas. With this information, it will be possible to calculate the impact to warfighters individually but also to collectively measure readiness, time to readiness, and which interventions will be most impactful.

2. **Learning Signature:** The "signature" that demonstrates a person is learning, has learned, and/or has mastered material needs to be defined. With this information, an objective understanding of knowledge could be defined and with that, the ability to achieve knowledge superiority across the fleet would become possible.

3. **Flow Signature:** The "signature" for cognitive flow needs to be defined. With this information, optimal times for learning as well as optimal operational teams could be identified that would help optimize not only individual capabilities but multiple those capabilities across teams and larger units.

4. **Learning x Time in Flow:** Learning impact by time needs to be determined. Translated, it is necessary to be able to measure the time a person can stay in a state of flow and then use that data to determine which interventions can elongate the timeframe. Ultimately, this would allow for longer periods of heightened focus, attention, and assimilation of information.

5. **Learning Building Blocks:** The building blocks to learning (e.g., improved working memory) need to be identified and measurable signatures for each element need to be created. These data and signatures would allow for generalizable learning capabilities to be enhanced.

6. **Neuro-enhanced Learning Training:** Finally, actionable recommendations and interventions that promote each element that supports learning capabilities need to be connected to the raw data outputs and combined signatures to drive a holistic system of learning optimization based on real time cognitive and physiological scaffolding and support.

RECOMMENDATIONS

Major themes suggest three key observations. First, given the importance of this work and the significant interest from multiple disciplines to not only understand the brain but also how to optimize its use in the classroom, in training, or in operations, it is surprising to find relatively few applied research studies that provide the data required to scale the use of EEG in non-clinical settings. Second, the majority of the studies that did assess the use of EEG outside the lab or medical setting focused on measurement and assessment rather than actionable intervention. A few exceptions are noted. Specifically, six studies yielded findings particularly interesting for the educational neuro-tech community. Taken together, these limited, but robust studies, demonstrate the potential usefulness of EEG data to drive learning interventions but also suggest that a significant number of additional studies are needed.

It is therefore recommended that future research requirements focus in three key areas: Quantifying learning impact, Defining signatures, and the Building blocks of learning optimization. Replicating early lab-based studies that show positive impact on learning in applied settings is a necessary step to proving the true value of brain-based personalization. Defining learning and flow signatures that allow for objective measurement of learning will enable instructors and strategic or executive level decision makers to determine efficient interventions and pathways for improved learning outcomes. Finally, by understanding the building blocks, or elements, that can be measured, trained, and practiced, we create the ability to enhance overall learning abilities in humans. The possibilities become nearly endless.

REFERENCES

Alwedaie, S. A., Khabbaz, H. A., Hadi, S. R., & Al-Hakim, R. (2018). EEG-based analysis for learning through virtual reality environment. Journal of Biosensors and Bioelectronics, 9(1), 249.

Amin, H. U., Ousta, F., Yusoff, M. Z., & Malik, A. S. (2021). Modulation of cortical activity in response to learning and long-term memory retrieval of 2D verses stereoscopic 3D educational contents: Evidence from an EEG study. Computers in Human Behavior, 114, 106526.

Aricò, P., et al. (2016). Adaptive automation triggered by EEG-based mental workload index: a passive brain-computer interface application in realistic air traffic control environment. Frontiers in human neuroscience, 10, 539.

Blacker, K. J., Hamilton, J., Roush, G., Pettijohn, K. A., & Biggs, A. T. (2019). Cognitive training for military application: a review of the literature and practical guide. Journal of cognitive enhancement, 3(1), 30-51.

Chae, Y. (2020). Adaptive Neuro-learning: A New Education Strategy using EEG-based Passive Brain-Computer Interfaces.

Chae, Y. (2020). Adaptive Neuro-learning: A New Education Strategy using EEG-based Passive Brain-Computer Interfaces (Doctoral dissertation, 한양대학교).

DoD Digital Modernization Strategy. (2019). https://media.defense.gov/2019/Jul/12/2002156622/-1/-1/1/DOD-DIGITAL-MODERNIZATION-STRATEGY-2019.PDF

DoDD 1322.18 Military Training. (2019). https://www.esd.whs.mil/Portals/54/Documents/DD/issuances/dodd/132218p.pdf

DoDD 5000.59 DoD Modeling and Simulation (M&S) Management. (2018). https://www.esd.whs.mil/Portals/54/Documents/DD/issuances/dodd/500059p.pdf

DoDI 1322.26 Distributed Learning. (2017). https://www.esd.whs.mil/Portals/54/Documents/DD/issuances/dodi/132226_dodi_2017.pdf?ver=2017-10-05-073235-400/home_new

DoDI 1322.31Common Military Training (CMT). (2020). https://www.esd.whs.mil/Portals/54/Documents/DD/issuances/dodi/132231p.pdf?ver=2020-02-20-114040-493

Galán, F. C., & Beal, C. R. (2012, July). EEG estimates of engagement and cognitive workload predict math problem solving outcomes. In International conference on user modeling, adaptation, and personalization (pp. 51-62). Springer, Berlin, Heidelberg.

Galán, F. C., & Beal, C. R. (2012, July). EEG estimates of engagement and cognitive workload predict math problem solving outcomes. In International conference on user modeling, adaptation, and personalization (pp. 51-62). Springer, Berlin, Heidelberg.

Jebelli, H., Khalili, M. M., Hwang, S., & Lee, S. (2018, January). A supervised learning-based construction workers' stress recognition using a wearable electroencephalography (EEG) device. In Construction research congress (Vol. 2018, pp. 43-53).

Kacer, J., Kutilek, P., Krivanek, V., Doskocil, R., Smrcka, P., & Krupka, Z. (2017, October). Measurement and modelling of the behavior of military pilots. In International Workshop on Modelling and Simulation for Autonomous Systems (pp. 434-449). Springer, Cham.

Kacer, J., Kutilek, P., Krivanek, V., Doskocil, R., Smrcka, P., & Krupka, Z. (2017, October). Measurement and modelling of the behavior of military pilots. In International Workshop on Modelling and Simulation for Autonomous Systems (pp. 434-449). Springer, Cham.

Kloudova, G., & Stehlik, M. (2017). The Enhancement of Training of Military Pilots Using Psychophysiological Methods. International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering, 11, 2435-2442.

Kloudova, G., & Stehlik, M. (2017). The Enhancement of Training of Military Pilots Using Psychophysiological Methods. International Journal of Psychological and Behavioral Sciences, 11(11), 2600-2607.

Ko, L. W., Lai, P. W., Yang, B. J., & Lin, C. T. (2015, November). Mobile EEG & ECG integration system for monitoring physiological states in peforming simulated war game training. In 2015 IEEE Conference on Computational Intelligence and Games (CIG) (pp. 542-543). IEEE.

Lin, F. R., & Kao, C. M. (2018). Mental effort detection using EEG data in E-learning contexts. Computers & Education, 122, 63-79.

Liu, N. H., Chiang, C. Y., & Chu, H. C. (2013). Recognizing the degree of human attention using EEG signals from mobile sensors. sensors, 13(8), 10273-10286.

Ma, Q. G. (2015). Neural operation management: a new avenue for productive and military operations. Frontiers of Engineering Management, 1(3), 304-307.

Mathewson, K. E., Basak, C., Maclin, E. L., Low, K. A., Boot, W. R., Kramer, A. F., ... & Gratton, G. (2012). Different slopes for different folks: alpha and delta EEG power predict subsequent video game learning rate and improvements in cognitive control tasks. Psychophysiology, 49(12), 1558-1570.

McCue, T.J., 2018, E Learning Climbing To $325 Billion By 2025 UF Canvas Absorb Schoology Moodle. Forbes. Retrieved from: https://www.forbes.com/sites/tjmccue/2018/07/31/e-learning-climbing-to-325-billion-by-2025-uf-canvas-absorb-schoology-moodle/

Mostow, J., Chang, K. M., & Nelson, J. (2011, June). Toward exploiting EEG input in a reading tutor. In International conference on artificial intelligence in education (pp. 230-237). Springer, Berlin, Heidelberg.

National Defense Strategy Summary. (2018). https://dod.defense.gov/Portals/1/Documents/pubs/2018-National-Defense-Strategy-Summary.pdf

Pergher, V., Wittevrongel, B., Tournoy, J., Schoenmakers, B., & Van Hulle, M. M. (2018). N-back training and transfer effects revealed by behavioral responses and EEG. Brain and behavior, 8(11), e01136.

Romero, E. (2014, June). Measuring cognition in computer-based instruction using an EEG: A review of the literature. In EdMedia+ Innovate Learning (pp. 2487-2496). Association for the Advancement of Computing in Education (AACE).

Shi, H., Zhao, H., Liu, Y., Gao, W., & Dou, S. C. (2019). Systematic analysis of a military wearable device based on a multi-level fusion framework: research directions. Sensors, 19(12), 2651.

Shi, H., Zhao, H., Liu, Y., Gao, W., & Dou, S. C. (2019). Systematic analysis of a military wearable device based on a multi-level fusion framework: research directions. Sensors, 19(12), 2651.

Siripornpanich, V., Sampoon, K., Chaithirayanon, S., Kotchabhakdi, N., & Chutabhakdikul, N. (2018). Enhancing brain maturation through a mindfulness-based education in elementary school children: a quantitative eeg study. Mindfulness, 9(6), 1877-1884.

So, W. K., Wong, S. W., Mak, J. N., & Chan, R. H. (2017). An evaluation of mental workload with frontal EEG. PloS one, 12(4), e0174949.

Thomas, M. L., & Russo, M. B. (2007). Neurocognitive monitors: Toward the prevention of cognitive performance decrements and catastrophic failures in the operational environment. Aviation, Space, and Environmental Medicine (78), pp. 144-152.

Vogel-Walcutt, J., Fiorella, L., Malone, N., 2013. Instructional strategies framework for military training systems. Computers in Human Behavior 29: 1490-1496.

Walcutt, J.J. & Schatz, S. (2019). Modernizing Learning: Developing the Future Learning Ecosystem. Government Publishing Office. Washington, D.C.

Walcutt, J.J., Horton, C., Jeyanandarajan, D., & Yates, W. (2020). Neuro-optimization for Accelerated Learning Pace and Elevated Comprehension: Military Applications. Paper presented at I/ITSEC, Orlando, FL.

Wang, H., Li, Y., Hu, X., Yang, Y., Meng, Z., & Chang, K. M. (2013, June). Using EEG to Improve Massive Open Online Courses Feedback Interaction. In AIED Workshops.

Yin, Z., & Zhang, J. (2017). Cross-session classification of mental workload levels using EEG and an adaptive deep learning model. Biomedical Signal Processing and Control, 33, 30-47.

Zoefel, B., Huster, R. J., & Herrmann, C. S. (2011). Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. Neuroimage, 54(2), 1427-1431.