Neural Activity Mapping of Army Aviation Flight Task Performance

Dr. Christina K. Parker	LT Nick Armendariz	Dr. JJ Walcutt	Dr. Dhiraj Jeyanandarajan	Dr. Leonard Momeny
Christina.parker.9@us.af.mil	Nicholas.j.armendariz@health.mil	drjjwalcutt@claystrategicdesigns.com	djey@qneuro.com	Leonard.s.momeny.mil@army.mil

ABSTRACT

The following paper explores how Army Aviation could leverage the neural pattern mapping of cognitive activity during flight task performance for curriculum design as well as learning and performance modernization that directly supports multi-domain operational environments. This study introduced a commercial-of-the-shelf (COTS), eight (8) non-contact node EEG device into a cap and through iterative exploratory research methods sought to establish and confirm both learning and learned neural activity patterns for the performance of nine (9) selected rotary-wing flight tasks. This initial research, as a technology review, collected performance data regarding the interface between the EEG device and Army Aviation Flight Simulators. The first step of the analysis, using device-specific machine learning analysis, was compared to establish differences and baselines of learned (control) and learning (experimental) flight task performance neural activity patterns while also monitoring device or simulation 'noise' interruptions to the data collected. As gateway research, the data collected in this research opens doors to greater opportunities for multi-branch studies that address cognitive load, attention, and other brain-based influences and impacts on learning and mission performance. The data serves to improve understanding of when learning occurs and knowing how to adjust curriculum design to be immediately responsive to performance needs. It acts as a trigger for future research that informs organizational education structures, occupational proficiency, and mission readiness that ultimately enhance wartime readiness under Large-scale Combat Operations.

ABOUT THE AUTHORS

Christina K. Parker, Ed.D. U.S. Air Force, is a Department of the Air Force civilian since 2023 and serves at the Special Operations Command at Hurlburt Field AFB, FL as the Chief Learning Officer. Christina previously served as a Department of the Army civilian since 2003. She holds degrees from the University of South Alabama and her doctorate from Indiana University. She has served as an adjunct professor for Southern Illinois University for 14 years and with Indiana University since 2020.

LT Nick Armendariz Former Marine training and education (T&E) expert who a holds master's degrees in education and cognitive science. During his tenure with the Marines, he was focused on T&E innovation for the Training and Education Command. He later helped lead research and policy for the Advanced Distributed Learning Initiative under the Office of the Secretary of Defense. LT. Armendariz currently serves as an Aerospace Experimental Psychologist in the US Navy working to continue to improve training through human systems integration. He has extensive DoD experience and expertise regarding insights on curriculum development, testing, and evaluation, and acquisitions.

JJ Walcutt, Ph.D. Former Director of Innovation for the Advanced Distributed Learning (ADL) Initiative under the Office of the Secretary of Defense. She is also a form Human Innovation Fellow under the Office of Personnel Management focused on using design thinking to promote Federal Government transformation. Dr. Vogel-Walcutt has 20 years of experience in research and development for training and education with specific interests in applying instructional techniques to improve the effectiveness and efficiency of cognition and educational development.

Dhiraj Jeyanandarajan, M.D., M.B.A. Board-certified neurologist with fellowship training in neurophysiology. He was a former clinical instructor of neurology at the University of Southern California Keck School of Medicine. He has 13 years of specialty experience in the application of neuromonitoring to measure the integrity of the nervous system during spine and brain surgery for improved outcomes. He is the founder of Qneuro, which applies similar neuromonitoring technology used in the medical space to applications for education and performance enhancement.

Leonard S. Momeny, Ed.D. U.S. Army is a Chief Warrant Officer 5 at the Warrant Officer Career College, Fort Novosel, AL. Dr. Momeny currently serves as Chair for the Department of Military History. Leonard holds degrees from Central Texas College, Southwestern College Kansas, American Military University, and Liberty University where he completed his doctorate. Leonard has served as adjunct faculty for Central Liberty University since 2021.

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INTRODUCTION

The future of learning can no longer be ignored nor held back, as advances in sensor development, computing power, AI, and other areas have made abundantly clear to both education and government professionals alike. This is especially true in the realm of many standard Department of Defense educational or instructional institutions. The reality remains that there is a failure to optimize the potential of the mind throughout the educational experience or to put in military parlance to apply cognitive weaponry (Walcutt, 2019). Whether through the deliberate omission or inclusion of wearables equipped for cognitive data collection (Walcutt et al., 2020) or the neglect to fully include opportunities in augmented reality, many struggle to create the training or education necessary to effectively complement the experience so richly deserved by the nature of the future battlefield (Parker & Momeny, 2021; Parker et al., 2022). What propagates this struggle? Perhaps there are insufficient infrastructures to support the advanced implementation of rapidly evolving and extending technologies throughout the learning and performance space. It is easy to estimate that many personnel lack both exposure and experience with advanced technologies that could revolutionize educational tools available to the DoD. Such lack of exposure and experience with both cutting-edge technology and educational science can easily contribute to rampant resistance to change across all echelons of training and training support organizations.

New doctrine and concepts surrounding the future of modern warfare would seem to imply that if the technology used by service members is not met with comparable advances in the application of educational science, then the future success of the services is at risk (FM 3-0). For instance, initial training for aviators, in many cases, remains comparable to what others experienced in years passed while their avionics, elements of the user interface, and eventual application in combat have grown exponentially in complexity. Readiness rates for line units are also impacted by the growing complexity of both war and technology, especially with respect to end-user readiness of high-priced military systems, e.g., aircraft, as both individual operator and unit performance require constant assessment. A real challenge to all of this remains the cost. And whether for initial training or readiness, the cost to operate either a simulator or actual aircraft/vehicle remains exceedingly high.

What is required to begin moving in the right direction is an optimization of education and tailoring of individual educational experience. Efficiencies can be found in moving past the subjective assessment of often undertrained instructors locked in dated instructional methods (Parker et al., 2022) and embracing the promise of tech-enabled cognitive science. For example, imagine the potential savings in both time and resources should someone be able to measure cognitive load drop-off through simple and lightweight worn EEGs on aviators performing duties in simulators or collective training devices. An instructor pilot could identify when learning occurred during training and consider observed task proficiency, thereby being able to move on in training rather than following mandatory subjective flight time requirements. Or simply put, tailor flight experience and training to individual proficiency instead of wasting both time and resources on unnecessary iterations based upon objective data that learning has occurred. Modern training can gain incredible efficiencies through the optimization of cognitive weapons available to instructors. The power of knowing when learning has occurred and the provision of freedom to accelerate a student through individually tailored flight training has the potential to be major cost-savings for the greater DoD.

PURPOSE

The purpose of this research is to begin to delve into the practical application and integrative nature of the aforementioned technologies. The authors seek to explore the learning and performance environment within the highly technical field of Army Aviation. Through limited experimentation in an LUH-72 simulator, and using device-specific machine learning analysis, the authors seek to establish and compare differences and baselines of learned (control) and learning (experimental) during flight task performance. It is hypothesized that mapping of neural activity patterns during simulated flight task performance, while also monitoring device or simulation 'noise' interruptions to the data collected, can reveal moments of objective identification of a learned task through measurement of brain activity. Such measurements, when coupled with complementary observations from an instructor pilot, can confirm the occurrence of task confidence and competence and thereby allow the trainer to move the student along at the right moment rather than arbitrarily according to generalized and prescribed time allotments for task training. Successful analysis of data will allow the authors to advise on how such neuro-mapping may effectively be integrated within both existing and conceptualized future educational systems and platforms through a greater view of the workings of the brain, thereby advancing the application of identified moments of cognition during learning and development to better impact student mission performance. The first task for these authors was to determine technological compatibility between existing flight simulators and the neurotechnology devices.

LITERATURE REVIEW

EEG and Learning

EEG (electroencephalography) and learning in the context of integrating new learning technologies explores the potential of EEG-based techniques to enhance learning experiences. EEG measures the electrical activity of the brain, offering insights into cognitive processes during learning. This may provide key indices of stressors in human performance which could help improve learning outcomes.

Research in this field has shown promising results. EEG-based techniques, such as brain-computer interfaces (BCIs) and neurofeedback provide real-time information about learners' brain states enabling personalized and adaptive learning experiences. For instance, BCIs can be used to detect learners' attention levels and engagement, allowing learning technologies to dynamically adjust content delivery (Nam, et.al., 2018). Moreover, neurofeedback training using EEG has been found to improve attention, memory, and cognitive control, leading to enhanced learning outcomes (Guger, et.al., 2014). By providing learners with real-time feedback on their brain activity, they can learn to self-regulate their cognitive processes and optimize their learning experiences.

However, challenges exist in the integration of EEG and learning technologies. EEG data analysis and interpretation require expertise, and the development of user-friendly interfaces and algorithms is essential to make EEG-based technologies accessible and practical for widespread educational use. The potential of EEG and its applications in enhancing learning experiences through personalized and adaptive approaches is emerging, but further research is needed to refine EEG-based techniques, improve usability, and explore the long-term effects of integrating EEG with learning technologies on learning outcomes.

Cognitive Load and Learning

Cognitive load refers to the amount of mental effort required to perform a task or complete a given objective. It refers to the mental effort required to process information, while learning involves acquiring and integrating new knowledge and skills. Cognitive load can be categorized into three main types: intrinsic, extraneous, and germane load. Intrinsic load represents the inherent difficulty of a task, extraneous load refers to the additional cognitive effort required to process irrelevant information, and germane load is the cognitive effort required to process relevant information. The measurement of cognitive load is important in understanding human performance and behavior. One way to measure cognitive load is through the analysis of brain activity, specifically in the theta, alpha, and beta frequency bands which will be described in an upcoming section within this article.

Cognitive load and learning in the context of integrating new learning technologies explores the impact of these technologies on learners' cognitive processes and the potential benefits and challenges they present. Several studies have investigated how learning technologies influence cognitive load. Sweller's cognitive load theory (Sweller, 1988) suggests that well-designed technologies can reduce cognitive load by providing interactive and multimedia-based learning experiences that cater to learners' individual needs and preferences. For instance, virtual reality and simulation-based environments offer immersive and engaging experiences, enhancing understanding and retention of complex concepts (Wu et al., 2020). Further, the ability to utilize these training aids in a simulated (safe) environment may enhance cognitive load availability (Walcutt, Armendariz, & Jeyanandarajan, 2022).

However, the integration of new learning technologies can also pose challenges. In the DoD, acquisitions can be an unnecessary hurdle if not planned for, but also if creators do not consider how the tool will be integrated (Armendariz, et.al., 2017). Poorly designed or overly complex interfaces may overwhelm learners, increasing their cognitive load and hindering learning outcomes. Furthermore, the presence of multiple technological tools and platforms may lead to cognitive overload, as learners must navigate and adapt to different interfaces and functionalities (Paas et al., 2003).

The literature emphasizes the importance of instructional design in mitigating cognitive load. Strategies such as chunking information, providing clear and concise instructions, and scaffolding learning activities can help learners manage their cognitive load effectively (Mayer & Moreno, 2003). Additionally, adaptive learning technologies that personalize content delivery based on learners' abilities and prior knowledge can optimize cognitive resources and facilitate learning. Careful consideration must be given to design principles and instructional strategies to ensure that these technologies effectively support learning and minimize cognitive overload. Further research is needed to explore optimal methods of integrating new learning technologies and to assess their long-term effects on cognitive load and learning outcomes.

Understanding Theta, Alpha, and Beta Frequencies as they relate to Cognitive Load

In layman's terms, brain waves are electrical patterns produced by the brain that can be measured using electroencephalography (EEG) during different mental states and activities. EEG measures the frequency of brain waves in terms of oscillations per second or Hertz (Hz). These brain waves are measured in terms of frequency, with different frequencies corresponding to different mental states. Theta, alpha, and beta frequencies are three of the most well-known brain waves. The results of these three frequencies establish the foundation by which the authors determine technology efficacy during flight task performance in a simulated environment. In recent years, researchers have been studying the relationship between these frequencies and cognitive load, which is the amount of mental effort required to perform a task.

Theta Frequency is a type of brain wave that has a frequency range of 4-8 Hz. Theta waves are typically associated with states of drowsiness, daydreaming, deep relaxation and cognitive processes such as attention, memory, and learning. Recent studies have suggested that theta waves may also be an indicator of cognitive load. For example, a study conducted by Zhang et al. (2021) found that theta power was positively correlated with task difficulty during a working memory task. Zhang suggested that *increased theta power* may reflect the increased cognitive effort required to perform the task. In other words, as task difficulty increases, theta activity increases in the frontal and parietal regions of the brain.

Alpha Frequency has a frequency range of 8-12 Hz. Alpha waves are typically associated with states of relaxation and calmness, and are often observed when a person is closing their eyes or meditating. Recent studies found that alpha power was negatively correlated with cognitive load during a visual working memory task. These studies suggested that *decreased alpha power* may reflect the increased cognitive effort required to perform the task.

Beta Frequency has a frequency range of 12-30 Hz. Beta waves are typically associated with states of arousal and alertness and cognitive processes such as attention, inhibition, and decision making. They are often observed when a person is engaged in a task that requires concentration and focus. Recent studies have found that beta power was positively correlated with cognitive load during a visual working memory task in that *increased beta power* may reflect the increased cognitive effort required to perform the task.

Neurostate Assessment to Support Data-Driven Training Decisions

Strategic initiatives (e.g., Army Modernization Strategic Plan, Digital Transformation Strategy) are demanding that training practices evolve to meet the needs of the future contested and data-overloaded environment (Armendariz & Walcutt, 2023[2]). The expectation of training efficiency and specificity will grow substantially over the next decade. Data-driven insights will allow for enhanced training pathways, improved focus on key training elements, and ultimately increase lethality while decreasing time-to-train. However, in order to make sense of and use data, the capture of data is an obvious requirement. Nonetheless, we have largely limited our data capture activities to subjective behavioral observations. These are not only inherently asystematic and influenced by personal bias, but they are nearly impossible to analyze at the individual or collective level. Data from technology will need to be collected in all forms for the future soldier to meet the expectations of the future complex fight (Armendariz & Walcutt, 2023[1]). Accordingly, this project looked at the feasibility of using neuro-state assessment capabilities to determine if these data can be captured during training, without interfering with electromagnetic waves or other technology.

The expectation of training efficiency and specificity will grow exponentially over the next decade. Data-driven insights will allow for enhanced training pathways, improved focus on key training elements, and ultimately increase lethality while decreasing time-to-train. With the confirmation of this, neuro-state assessment has the propensity to provide the data needed to: (1) accelerate learning, (2) improve long-term retention, (3) synergize high-performance teams, and (4) personalize learning. Integrating neurotech hardware/software during training can allow us to actively monitor brain state through electroencephalography (EEG) to track cognitive load and engagement. This gathering and analyzing of individual as well as aggregated data can help identify and prescribe training interventions for students, instructors, and learning systems such as aircraft, simulators, virtual and extended reality devices, and synthetic training environments. The data can also be useful in determining enterprise augmentations to training pathways, focus areas, and timing of training for both individuals and cohorts when used to inform intentional learning structures and curriculum design (Parker, 2020; Parker & Momeny, 2021, Parker et.al., 2022). Ultimately, a neurotechnology-based system can work to inform and influence cognitive load (CL) by responding and adjusting training parameters within a 3D virtual reality training simulator to keep the operator in their optimal CL zone for learning new skills.

METHODOLOGY

Data collection occurred over the course of two consecutive periods in a UH72A full-motion flight simulator at the U.S. Army Aviation Center of Excellence at Fort Novosel, Alabama. The UH72A Lakota rotary wing aircraft is the designated training aircraft for all Initial Entry Rotary Wing Common Core (IERWCC) students. As this was a technology review to determine the suitability of the use of neurotechnology with existing flight simulation devices, pre-IERWCC students did not participate in the data collection. Rather, two of the five researchers and one volunteer expert UH72A Instructor Pilot (IP) wore the EEG device during the performance of 9 selected flight tasks that are instructed and assessed during the IERW (Initial Entry Rotary Wing) course.

Aviator #1 was a non-researcher in this study. He was a rated rotary wing aviator with extensive experience as a UH72A Instructor Pilot. Aviator #2 was a researcher for this study. He was a rated rotary wing aviator with no experience in the UH72A. Aviator #3 was a researcher for this study. He was a rated fixed-wing aviator with no experience in the UH72A or rotary-wing aircraft in general. Though specifically a technology demonstration for exploring the rotary-wing applications of the EEG device, and limited in participants, Aviators 1 through 3 provided excellent stratification of experience from which to collect data. From instructor pilot to experienced helicopter pilot without airframe-specific experience, to finally the helicopter novice, the sample promises to provide valuable data with respect to different circumstances in learning and their associated experience with cognitive load.

Two EEG headsets were provided by Quantum Neuromonitoring Corporation (Qneuro). The rigid frame headset was used for recordings due to the soft form factor headset being damaged during transport. After collecting baseline data that consisted of the participant maintaining one minute of eyes open/relaxed and one-minute of eyes closed/relaxed, the recordings began for specific task performance. The nine (9) recorded tasks were as follows:

Task 1	Hover day VMC[1]
Task 2	Hover day IMC[2]
Task 3	Hover night VMC
Task 4	Hover night IMC
Task 5	Flying pattern day VMC[3]
Task 6	Flying pattern day IMC
Task 7	Flying pattern night VMC
Task 8	Flying pattern night IMC
Task 9	Flying pattern night VMC EP[4]

Triggered events were labeled 'Activity 01' by the software. Simultaneously notes were taken by the EEG equipment operator noting times and descriptions of events as they occurred and referencing time markers displayed by the EEG recording software and the Simulator clock. Similar notes were also recorded by two additional researchers in this study in order to triangulate the data.

On Day 1, the simulator was not enabled for full motion, as the intent was to establish the nine tasks to serve as a baseline for the technology feasibility evaluations. The hard form factor EEG monitoring tool was adjusted for each participant to

[1] VMC stands for Visual Meteorological Conditions, equating to excellent visibility for the pilot of the aircraft, thus lower stress and cognitive load.
[2] IMC stands for Instrument Meteorological Conditions, equating to poor visibility for the pilot of the aircraft, thus higher stress and cognitive load.
[3] Pattern indicates the act of flying upwind, or on runway heading, turning either right or left, paralleling the runway heading on a downwind and then finally turning to land back at the heliport or airfield on the initial runway heading.
[4] EP stands for Emergency Procedure, a simulated problem with the aircraft requiring the pilot to immediately respond with corrective action. This is typically point of higher stress for the pilot.

ensure appropriate readings and then measured during each of the nine tasks. The nine tasks were flown by the participant in the right seat with a non-participant in the left seat. Those collecting data were at the console and able to monitor both the EEG readings and the flight instruments during each task. These personnel were supported by Army simulator staff and observing psychologist.

Baseline data was established for Aviator 1, the UH72 Instructor Pilot, and all 9 base tasks were performed. This data was thought to serve as a baseline of comparison for the other two aviators, as it is assumed the Instructor Pilot will experience far less cognitive load than the other two participants given the frequency of his routine performance of tasks in the aircraft. Once complete, Aviator 3 was equipped, achieved a baseline measure, and then proceeded to fly the aforementioned tasks.

On Day 2, Aviator 2, the experienced helicopter pilot with no time in the UH72 was again equipped with the rigid system, achieved a baseline measure, and then completed the 9 base tasks. In addition to data collection with the rigid harness, the soft form factor EEG was also checked for recording integrity along with testing during full motion flight simulation conditions to determine if this added any additional artifact to the EEG recording or if the full motion created a hinderance to the data collected. Aviator 1 wore the soft form EEG device and will appear as the fourth subject in the figures and data presented below.

Preliminary data collection was successfully recorded for all 3 aviators on both days of recording. Signal quality was considered good for real-time analysis when run through filters and noise reduction algorithms. Unfiltered, raw EEG data were also recorded for all sessions and will be used as a reference for environmental impact on the recording (motion, electrical noise). Once data is organized according to task, a comparison to baseline for each individual will be run using spectral analysis protocols, referencing markers of interest such as upper alpha, theta to beta, alpha to theta, SMR and cognitive load, engagement, and attention markers.

DATA ANALYSIS

The instruments utilized to ascertain the neuroactivity of the participants were both the rigid and soft configuration devices made by Qneuro. The neurotechnology (Qneuro) headset used 8 channels of EEG data at the following locations based on the international 10/20 system of electrode placement: Fp1, Fp2, FC3, FC4, O1, O2, Fz and Cz. The electrodes are active non-contact electrodes worn over hair and without any gel or electrolyte solution to increase conductivity. Data were collected at a sampling frequency of 250 samples per second for each channel. All data (including calibration data) were collected within the UH72 simulator. Pre-processing of data included filtering and artifact removal.

The data analysis was not conducted in real-time within the simulator. Instead, all readings were analyzed following the data collection event using the MATLAB program (Walcutt et al., 2020). Presented in the following summary of the data analysis are the sample graphs that best represent the following points:

1) Figure 1 demonstrates the EEG device is able to record the full spectrum of brain activity typically recorded by more standard EEG devices. The discriminating condition important to this technology review/application study is that data was directly recorded within the target environment of a full-motion rotary-wing simulator. The data demonstrates that a full complement of EEG signals was collected without incident and in no way detracted from the performance of flight tasks by participants. All the other graphs demonstrate this as well but for more targeted/specific frequencies, so this graph is the best for a broader overview.
2) Figure 2 demonstrates the trend of three of our more important frequencies (theta, alpha, and beta) across the range of different tasks.
3) Figure 3, 4, and 5 are individual trend representations of the different frequencies as they varied across the different tasks.
4) Figure 6 demonstrates the trend of more commonly used metrics as calculated by ratios of the base frequency powers. An example of one of these metrics is cognitive workload which correlates with one or more of the calculated ratio trends.
5) Figure 7 demonstrates one of these ratios that correspond with the cognitive load of the individual as they vary across tasks for the different channels.
6) Figure 8 demonstrates another ratio that corresponds with cognitive load.
7) Figure 9 demonstrates the trend observed with cognitive load numerically for the different tasks for one of the subjects.

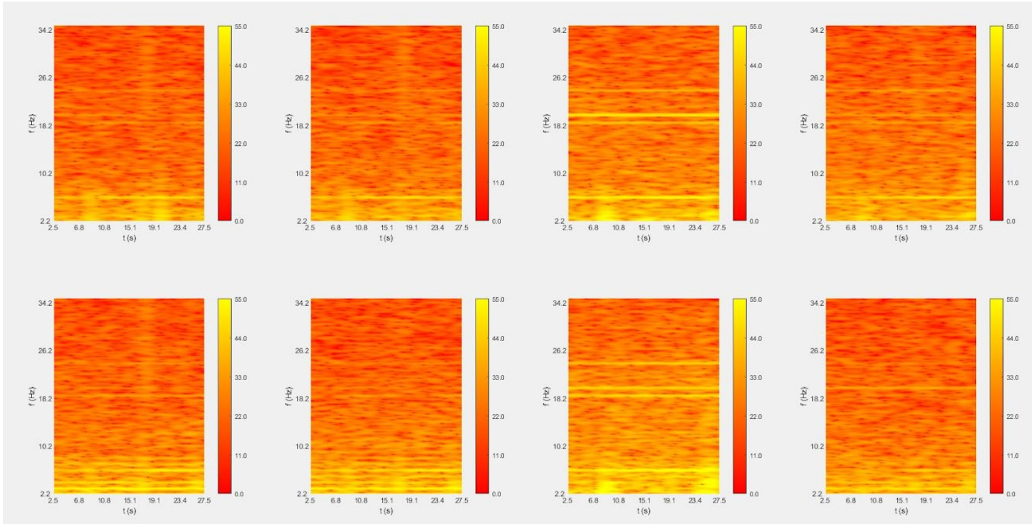

Figure 1: Spectrogram

Subject 1 was recorded within the simulator. Recorded data across frequency bands from 2-35Hz present and recorded from a portable EEG device. Data suggests that typical EEG frequencies are able to be recorded in this environment. There are some noted high power bands more suggestive of environmental causes in the high Beta range approximately around 25Hz that are stronger on certain channels (FC3) than others. This might affect further analysis if there are changes of interest for our analysis that are within those bands. This warrants further exploration in subsequent testing to reduce or eliminate the observed artifact using mechanical or software compensation. The data recorded even without this fine-tuning provided more than enough spectral data for analysis.

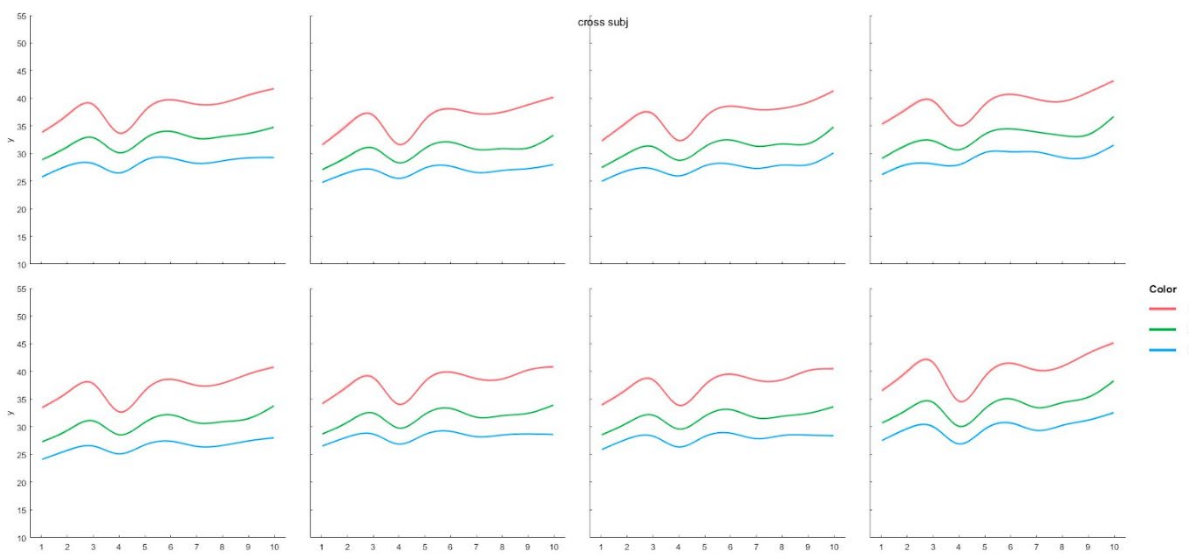

Figure 2: Cross-subject trend data for theta (1), alpha (2), and beta (3) frequencies across the different tasks.

It is notable to see there appears to be an observable trend line with increasing task difficulty (10>1). Using only three subjects without control data does not allow us to draw any substantive conclusions, but the preliminary data analysis does indicate that more detailed study is warranted to explore this observable trending.

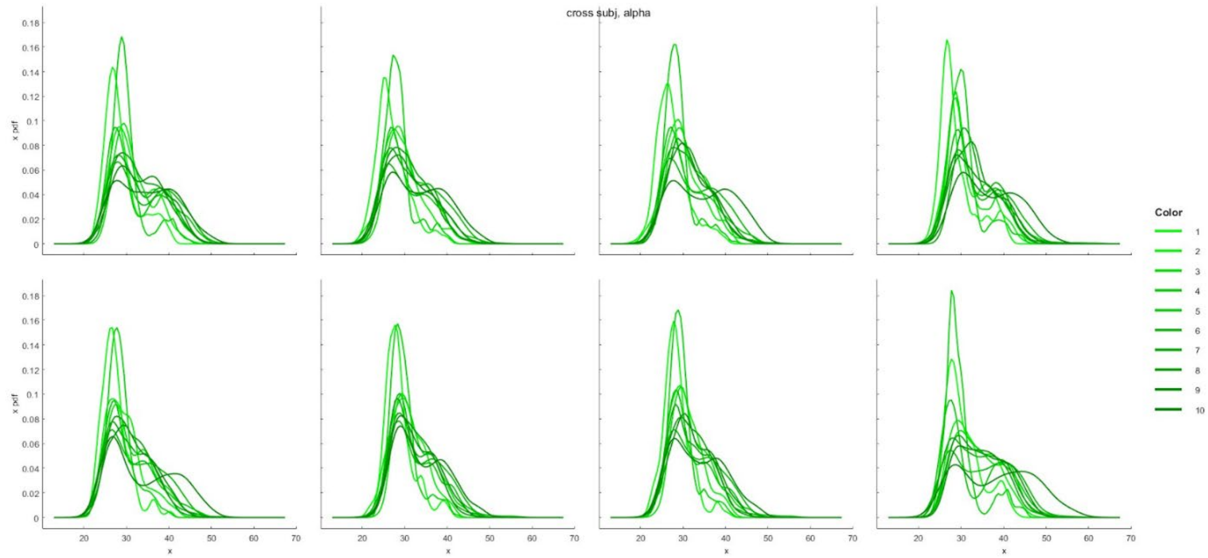

Figure 3: Cross-Subject Alpha

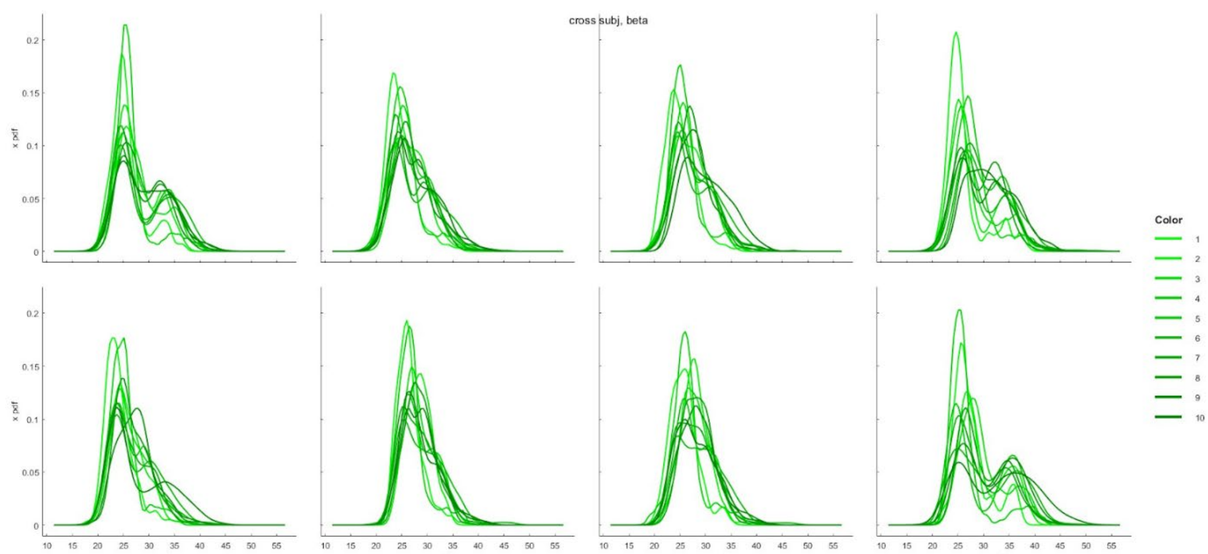

Figure 4: Cross-Subject Beta

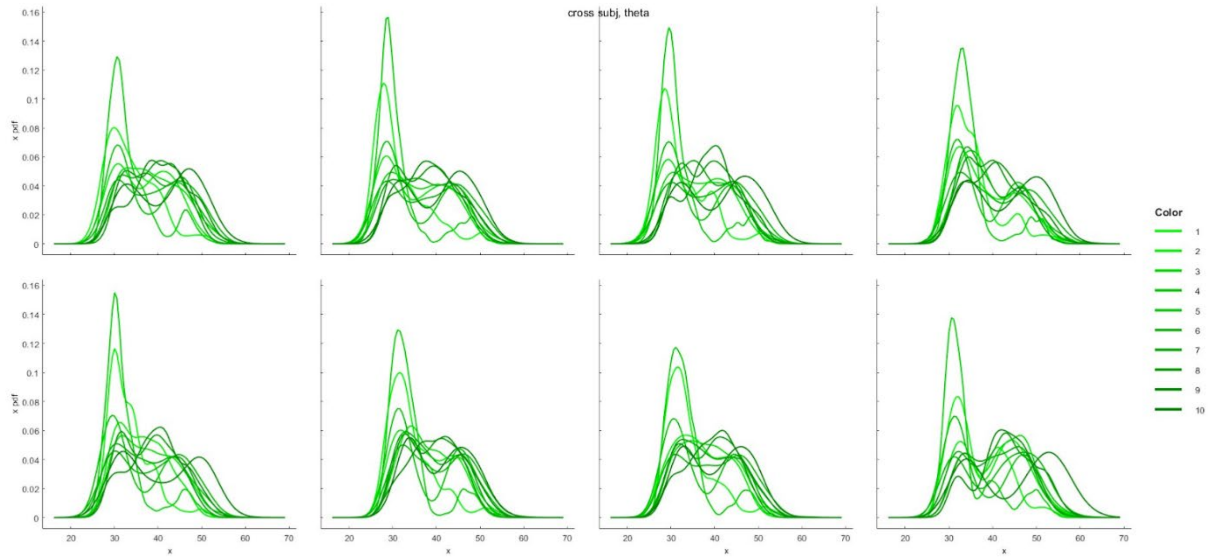

Figure 5: Cross-Subject Theta

Trend data for three of the main frequencies of interest: theta (4=8 Hz); Alpha (8-12 Hz); Beta (12-18 Hz). Tasks labeled 1-10.

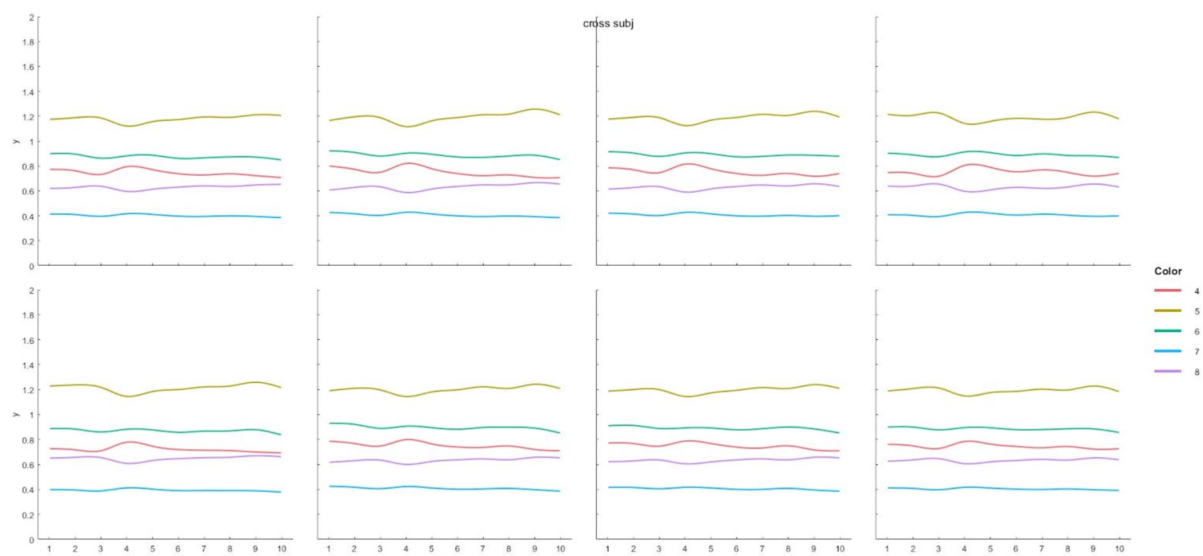

Figure 6: Cross-subject trend data of more commonly used EEG metrics: beta/theta; theta/alpha; beta/alpha; beta/(alpha+theta); theta/(alpha+beta).

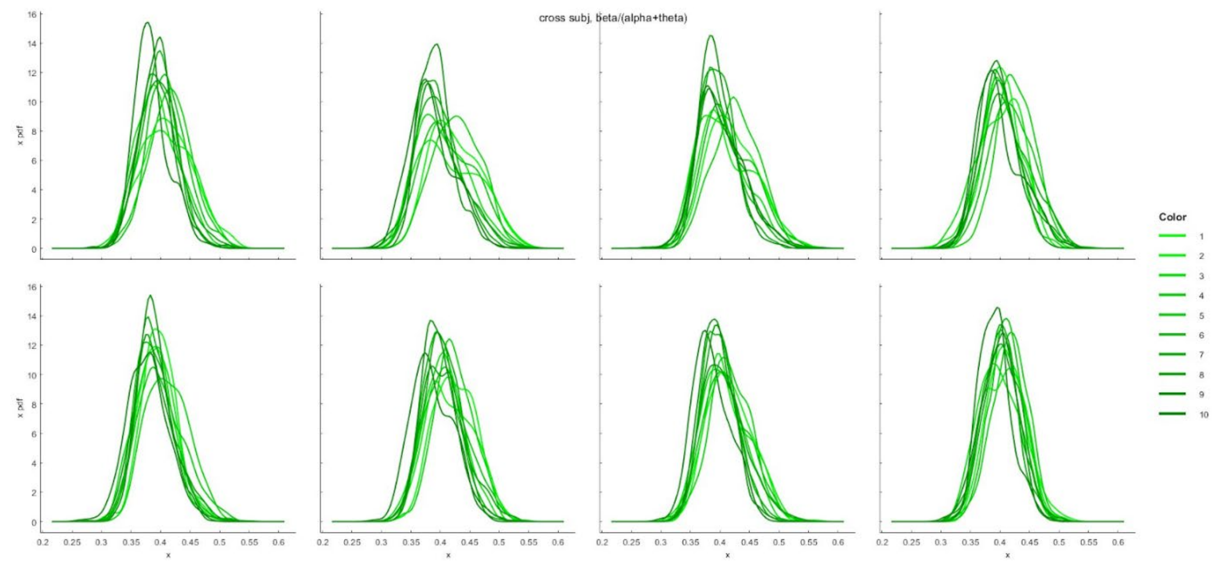

Figure 7: Cross Subject Beta/(Alpha+Theta)

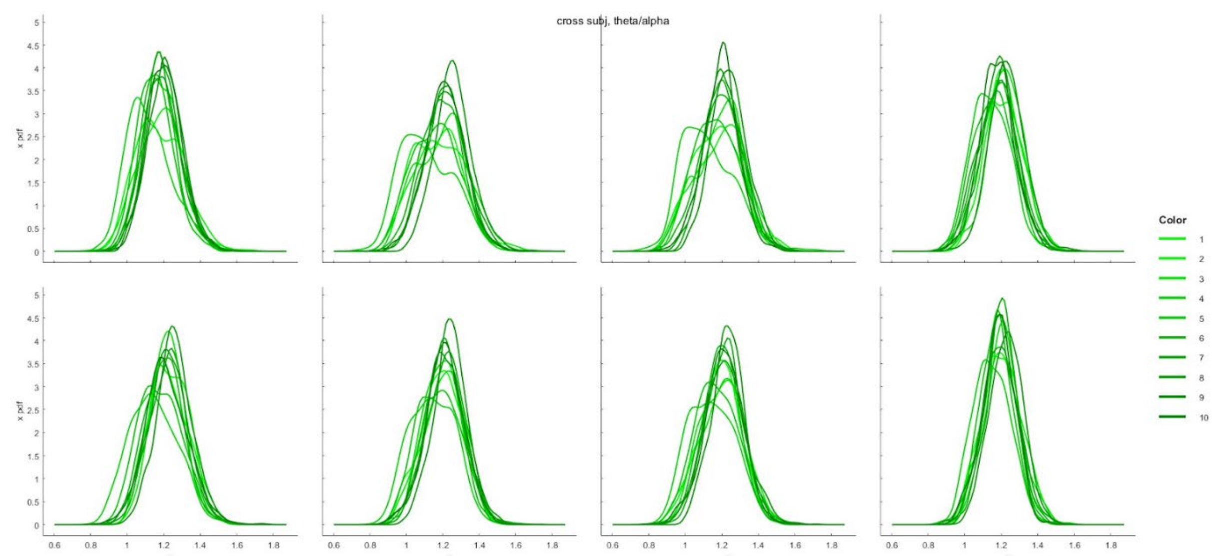

Figure 8: Cross-Subject Theta/Alpha

Activity Number (Duration)	Cognitive Load Index (Theta/Alpha)	Cognitive Load Index (1/Alpha)
1 (73s)	1.359716 (0.371318)	0.01651 (0.00414)
2 (98s)	1.070639 (0.439549)	0.015777 (0.006422)

3 (210s)	0.656788 (0.568297)	0.018576 (0.0171)
4 (70s)	1.342209 (0.4414)	0.022816 (0.008031)
5 (51s)	1.393683 (0.489078)	0.017972 (0.005533)
6 (247s)	1.030528 (0.281208)	0.014993 (0.004218)
7 (337s)	1.232244 (0.435951)	0.01697 (0.005148)
8 (329s)	1.335811 (0.537479)	0.017388 (0.007299)
9 (285s)	1.609615 (0.684026)	0.01909 (0.007047)

Figure 9: Cognitive load index

The cognitive load index was calculated using a bandpass filter (0.5 to 40 Hz), notch filter (60Hz), artifact subspace reconstruction method for artifact removal, and independent component analysis for eye blink removal, using Fp1, Fp2, O1, and O2 channels. Power spectral densities were calculated from these channels and the average power sum of theta from frontal channels and alpha from occipital channels was used to calculate the cognitive load.

FINDINGS AND DISCUSSION

This study focused on a feasibility evaluation of the neurotechnology efficacy within existing Army Aviation flight simulation devices. Far too often with technology integration, there are well-founded fears of whether the tool will work, first of all, and second – if there will be usable data collected. It is encouraging to note that the data collected was usable and exceeded expectations regarding the primary purpose of the study for seeing whether the EEG system will work in recording data in the simulator.

All figures created from collected data demonstrate an ability to utilize neurotechnology to identify both relevant EEG-related readings to moments of elevated concentration and the like to the eventual synthesis of a CL scale. There are aggregated differences visible across participants 1 through 3. It is important to recall, all figures have 4 data sets displayed and positions 1 and 4 belong to Aviator 1, the UH72 Instructor Pilot who was first measured in the rigid and then soft device configuration. There are distinct differences in the presentation of the readings from the instructor pilot, positions 1 and 4 of each figure, and that of the Aviator 2 and 3, who have varying levels of experience and thus present different wave patterns to that of the Instructor Pilot, or Aviator 1. Such pattern discrimination can imply the ability to read, measure, collect, and analyze CL and other elements of neural activity across differing experience levels during critical and often costly training.

A unique point of discussion is identified in Figure 2, as cross-subject trend data for theta (1), alpha (2), and beta (3) frequencies across the different tasks seem to demonstrate an observable trend line with increasing task difficulty (10>1). Thus, preliminary data analysis indicates that a more detailed study is warranted to explore this observable trend. Such trending is to be expected, as aviators performing tasks increasing in difficulty are not simply performing mechanical activities akin to just muscle memory but are also constantly dealing with spatial reasoning-oriented problems in a dynamic environment that can be experiencing conditional change from moment to moment. Finally, Figures 4, 5, 7, and 8 present stark differences in presentation at the various levels of wave measurement for Aviators 2 and 3 when compared to the experienced Instructor Pilot.

Given the presented assessment of data, the authors assert that, at a minimum, neurotechnology efficacy has been established with respect to its place in simulations in support of dynamic aviation training and continuing education research for a more effective future force. Future research is critical moving forward and should look more definitively toward conclusive data regarding differences between individuals, cohorts, or varying tasks. Coming study designs will need to be intentionally prescribed to collect performance and demographic data on rated aviators as the control group and not yet rated aviators, or aviation students awaiting the IERW course as the experimental group. With such a potential research pool researchers could compare and establish differences between baselines of learned (control) and learning (experimental) flight task performance via analysis of neural activity patterns in aviators. Learning pattern baselines could consider 1) what learning neural patterns looked like in comparison to the learned neural patterns and 2) the time it takes to progress from learning patterns to learned patterns. With that type of quantification, qualification, and analysis, education could be streamlined and more individually tailored and adaptive.

FUTURE RESEARCH

The importance of cognitive research and learning technology tools that can measure cognitive performance becomes particularly evident in the context of training aviators in simulators. Aviation training demands a high level of cognitive abilities, including spatial awareness, decision-making, multitasking, and situational awareness. Understanding and optimizing these cognitive processes can significantly improve the performance and safety of aviators. Cognitive research provides valuable insights into the specific cognitive skills required for successful aviation operations. By studying the cognitive demands of flight scenarios, researchers can identify key areas where aviators may encounter challenges or potential errors (Warm, et.al., 1997). These findings can inform the development of tailored learning technology tools, such as flight simulators, that replicate realistic aviation environments. Advanced flight simulators equipped with sophisticated learning technology tools can measure and assess an aviator cognitive performance during simulated flights. These tools can track eye movements, response times, decision-making patterns, and other cognitive indicators. By analyzing this data, instructors and trainees can gain a comprehensive understanding of an aviator’s strengths and weaknesses, enabling targeted training interventions. Moreover, learning technology tools in aviation training can offer adaptive learning experiences, adjusting the difficulty and complexity of simulated scenarios based on the aviator’s performance. This personalized approach optimizes the training process, allowing aviators to focus on specific areas that need improvement while reinforcing their strengths.

Key next steps in future research require greater analysis of the currently collected data against more qualitative assessments that could be provided via the insight of a qualified instructor pilot. Such a detailed qualitative assessment conducted in conjunction with the research team’s neurologist could provide more insight into the difference in measuring neural activity between learners in a more static environment and those in a dynamic flight environment (Walcutt et al., 2020). While learning will always be learning, sorting through the additional noise found in specific wave patterns as a byproduct of spatial problem-solving continuously occurring in the mind of the aviator would be necessary if to identify exactly when learning occurs, e.g., CL drop-off.

Summary

Neural activity patterning can be a useful tool for instructional design purposes and warrants further research. By studying the patterns of neural activity that occur during the learning process, instructional designers can gain a better understanding of how the brain processes information and uses it to for memories and make decisions, particularly under high stress, high information input multi-domain operational environments. Identifying neural patterns for complex task performance can be used to design learning experiences that are optimized for the way the brain works best by collective, by individual, by environment.

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