Cognitive Engagement Profiling of Pilots in High-Speed, High-Threat Scenarios

Matthew D'Alessandro; Ryan Mackie; Tom Berger; Carl Ott; Christopher Sullivan; James Barnett III; Ian Curry

INTRODUCTION: This study investigated pilot cognitive engagement patterns across diverse flight conditions using electroencephalography (EEG)-based measurements in a high-fidelity rotary-wing simulation environment.

METHODS: A total of 8 experienced U.S. Army test pilots completed 24 flights across 3 distinct route designs using the National Aeronautics and Space Administration Ames Vertical Motion Simulator, with airspeeds ranging from 120 to 240 kn. Analysis focused on EEG Beta/(Alpha + Theta) ratios as indicators of changing cognitive engagement over time.

RESULTS: Analyses revealed distinct cognitive engagement patterns across routes: highly variable individual responses in routes with changing navigation demands, more consistent cognitive engagement in systematic route designs, and intermediate variability in mixed-demand routes. Airspeed effects on cognitive engagement became particularly pronounced above 200 kn, though these effects varied significantly by route and individual pilot. Temporal analysis demonstrated evolving patterns of cognitive adaptation, with routes eliciting different progression patterns over extended flight periods. Regression analysis showed that EEG Beta/(Alpha+Theta) values increased significantly during all three routes, with mean increases ranging from 0.0051–0.0146.

DISCUSSION: These findings provide quantifiable metrics for optimizing route design, developing personalized training approaches, and implementing real-time monitoring systems for enhanced aviation safety and performance.

KEYWORDS: cognitive engagement, aviation, simulated flight.

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The integration of neurophysiological measurements in aviation research has revolutionized our understanding of pilot cognitive workload and performance during complex flight operations.[1] While traditional studies have relied on behavioral metrics, electroencephalography (EEG)-based measurements offer valuable insights into the real-time cognitive demands placed on pilots during flight.[2,3] These neurophysiological indicators provide a window into the subtle variations in mental workload that may not be apparent through conventional performance measures alone.

Previous research has established the importance of understanding cognitive workload variations in aviation, particularly regarding route characteristics and airspeed conditions.[4,5] However, the complex interplay of these factors at the high airspeeds not yet attainable by current military rotorcraft remains unknown due to the lack of such capabilities and the inherent risks. The U.S. Army Combat Capabilities Development Command Aviation & Missile Center (DEVCOM AvMC) has developed a Future Vertical Lift (FVL) simulation capability to explore design trade studies and inform requirements which leverages a generic tiltrotor flight dynamics model and full flight envelope flight control system.[6] The model was integrated into the NASA Ames Vertical Motion Simulator (VMS), which provides the capability to simulate flight at the full operational envelopes of advanced aircraft configurations via its unparalleled reproduction of realistic flight dynamics, extensive vertical motion range, and acceleration cues. Using this advanced

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facility, we investigated three distinct route designs under airspeed conditions ranging from 120 to 240 kn. The simulator's unique capabilities enabled simultaneous, time-synchronized capture of EEG measurements and flight performance metrics while pilots experienced authentic physical sensations of flight, bridging the gap between laboratory studies and real-world operations. This information is critical for the development of the U.S. Army's aviation modernization priorities of the FVL program which will achieve advanced flight capabilities. The current investigation employed the EEG Beta/(Alpha+Theta) (BAT) ratio as a primary metric for cognitive engagement, building upon established research in aviation neurophysiology and human factors.[2,3] This specific ratio has proven particularly sensitive to changes in mental engagement during complex cognitive tasks, making it an ideal measure for understanding the demands of different flight conditions.[7,8] By tracking the BAT neurophysiological indicator across time and flight conditions, we were able to identify patterns of cognitive adaptation and potential areas of increased mental demand.

The current study's design incorporates multiple flights per condition, allowing for detailed analysis of both immediate responses to changing conditions and longer-term adaptation patterns. This approach enabled us to examine not only the overall impact of route and airspeed variations, but also individual differences in cognitive strategies and adaptation mechanisms. Understanding these individual variations is crucial for developing more effective training protocols and route design guidelines that can accommodate different cognitive processing styles while maintaining high safety standards. By combining precise experimental design with advanced neurophysiological measurements, this research aims to provide practical insights that can inform and optimize automated flight route planning tools, pilot training protocols, and aviation safety systems. The findings have potential implications for real-time monitoring systems, adaptive automation, and the development of more sophisticated approaches to route classification and pilot workload management.

METHODS

Subjects

Eight experienced U.S. Army test pilots with a minimum 1500 flight hours participated in the study. All pilots were U.S. Army-trained and current on operational requirements. The experimental protocol was approved by the DEVCOM AvMC Human Research Protection Program (HRPP) #23-016.

Procedure

Pilots in this study conducted high-speed flight simulations using the NASA Ames VMS at Moffett Field, CA—a facility renowned for its unmatched motion range and dynamic fidelity. The VMS replicates real-world flight dynamics through a 60-ft vertical motion envelope, expansive horizontal range, and precise acceleration cues that closely replicate the physical sensations of actual flight. Its advanced computational systems simulate aircraft behavior across speeds spanning 120 to 240 kn, a critical threshold for the U.S. Army's FVL program, which aims to develop next-generation rotorcraft capable of unprecedented performance. By testing at 240 kn—a speed representative of FVL capabilities and well above typical operational terrain flight speeds—the VMS provides the capability to gain insight to unique cognitive workload demands under extreme conditions, providing the potential to directly inform FVL design and safety protocols.

The tiltrotor aircraft flight model used in the testing was developed by the Army's DEVCOM AvMC and was representative of the size and performance capabilities of the FVL aircraft.[6] The simulator's integrated data acquisition systems enable the ability to capture pilot performance metrics, physiological data (including EEG), and flight dynamics, enabling researchers to bridge controlled experimentation with real-world operational demands. This synergy of high-fidelity simulation and multidimensional data analysis offers actionable insights into adaptive decision making and workload management in complex aviation environments. During all simulated flights, continuous wireless EEG was recorded using the B-Alert ×24 system, consisting of 20 EEG channels based on the International 10-20 system. All 20 channels were recorded during simulated flights, but only the frontal channels were used to calculate the EEG BAT ratio.

Three distinct flight routes were developed to explore different operational contexts, enabling a comprehensive assessment of aircrew capabilities across the aircraft's designed mission set. Although each route was constrained to approximately 20 miles in length—considerably shorter than typical operational missions—and maintained at constant speed, they effectively generated the data required for this research effort. The routes presented here are for simulation purposes only and do not represent actual Army operational scenarios. The routes incorporated varying degrees of flight maneuvering allowances, which produced a spectrum of pilot aggressiveness and workload conditions. To maintain operational relevance, evaluate perceived workload, and assess pilot responses to threats, three radar-guided threats were incorporated into each route. The Air Force's Advanced Framework for Simulation, Integration, and Modeling software was used to model the threats. Subject matter experts helped determine threat locations using various templates, which were modified across the routes to provide aircrews with diverse tactical challenges.

Route 1, "Narrow Corridor," simulated a large-scale air assault operation requiring 10 aircraft to fly over flat to rolling terrain. The tactical scenario established a narrow air corridor that permitted the air assault to proceed. Due to the narrow corridor constraints and the presence of nine simulated aircraft following in formation behind the test aircraft, strict maneuvering limitations were imposed, restricting aircraft to a maximum angle of bank of ±15°, but allowed for the pilots to vary the altitudes flown. These limitations effectively prevented aircrews from executing maneuvers to avoid radar detection or engagement, requiring them to maintain precise speed control and route adherence with minimal deviation from the established

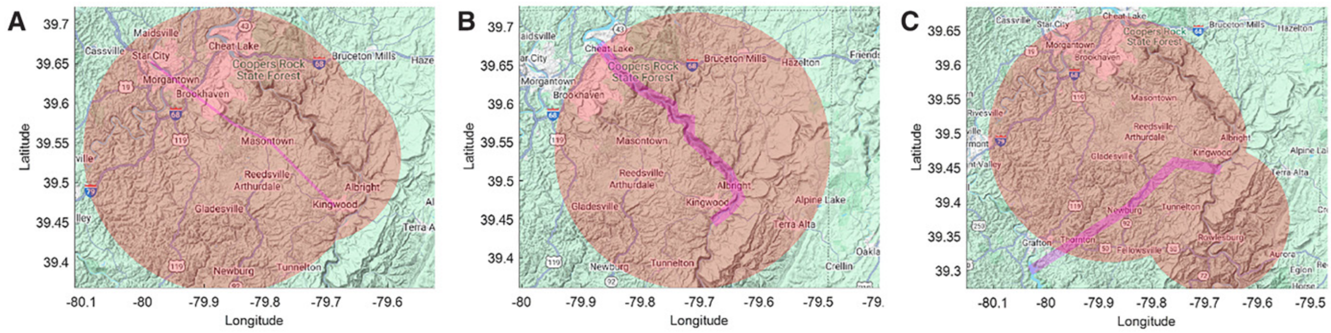

Fig. 1. Mission routes. A) Route 1 (Narrow Corridor). B) Route 2 (Deep River Valley). C) Route 3 (Wide Corridor). Mission routes are further described in the Methods/Flight Routes section of this manuscript. Scenarios are for simulation purposes only and do not represent actual operational Army scenarios.

centerline. The mission route terminated upon crossing the designated release point (**Fig. 1A**).

Route 2, "Deep River Valley," simulated a flight mission involving two aircraft navigating primarily through a deep river valley. The valley's topography offered radar detection protection when the aircraft maintained altitude below the valley rim. The test aircraft led with a simulated trail aircraft in free cruise formation, allowing pilots to employ aggressive maneuvering capabilities (up to 45° of bank and 800-m deviations from the course line) while maintaining the prescribed airspeed. These parameters enabled pilots to optimize their position within the river valley. The route concluded upon reaching the designated release point (**Fig. 1B**).

Route 3, "Wide Corridor," replicated a two-aircraft deep insertion mission conducted within a wide corridor over flat to rolling terrain. With the simulated trail aircraft in free cruise formation, pilots were authorized to maneuver within 800 m of the centerline to maximize terrain masking opportunities. The route parameters permitted aggressive maneuvering up to 45° of bank while maintaining constant airspeed. This route uniquely required pilots to not only cross a release point, but also to execute an approach to establish a 50-ft hover over a designated hover point (**Fig. 1C**).

Statistical Analysis

Each route was flown under four airspeed conditions: 120, 160, 200, and 240 kn. Pilots were instructed to maintain constant airspeed as much as possible during flights. Each pilot completed two flights per airspeed and route for a total of 24 flights (eight flights per route across three routes). The order of route presentation was randomized between pilots, but airspeed was not. Pilots completed all flights for a given route, starting with 120-kn flights, increasing to 240 kn. All 24 flights were completed by 7 pilots. Pilot 26 was not able to complete 1 flight (the Deep River Valley route at 240 kn) due to time constraints using the flight simulator. Pilots were assigned different numbers for deidentification purposes.

The time to complete simulated flights ranged from approximately 4.5 to 11.5 min depending on the route and airspeed. To facilitate statistical analysis of EEG data of varying duration, each flight was divided into four segments (further referred to as flight segments). The Narrow Corridor and Deep River Valley flights were divided into four equal segments. The Wide Corridor flight route required pilots to decelerate to a hover at the end of the route. Therefore, flight segment 4 for the Wide Corridor flights was defined as the time when deceleration began until the end of the flight. Flight segments 1–3 for the Wide Corridor flights were defined as equal thirds of the flight before deceleration.

B-Alert Live software was used to automatically remove common EEG artifacts and calculate power spectral density (PSD) values in 1-s intervals. For each EEG channel, the B-Alert Live software calculated PSD values for common frequency bands, including theta (3–7 Hz), alpha (8–13 Hz), and beta (13–30 Hz). PSD values for each frequency band were averaged across all frontal EEG channels (fp1, fp2, f3, f4, f7, f8, and fz). Mean frontal PSD values were then used to calculate the BAT ratio. BAT values were then averaged over each flight segment to produce four mean BAT values for each flight. These BAT values were used for all regression analyses detailed below. As baseline EEG levels can vary day-to-day and between individuals, the data presented in **Fig. 2**, **Fig. 3**, and **Fig. 4** show the change in BAT values relative to flight segment 1 (these values are further referred to as delta BAT values). The shaded regions in panel A for each of these figures illustrate the range of delta BAT values for each pilot, airspeed, and flight segment. Panel A for each figure also shows the mean delta BAT value as points. These figures additionally show the mean delta BAT values combined across all airspeeds for each pilot (panel B) and combined across all pilots for each airspeed (panel C). Supplemental **Table AI**, **Table AII**, **Table AIII**, **Table AIV**, **Table AV**, and **Table AVI** (all found in the online version of this article) provide summary statistics for the mean delta BAT values.

All statistical analyses were performed using R and R Studio with the following packages: tidyverse, lmerTest, emmeans, and rstatix. All statistical tests were evaluated at a significance level of 0.05. To analyze average changes in BAT values while accounting for individual EEG baselines between pilots, BAT values for each route were analyzed separately using mixed-effects linear regression models. Each regression model consisted of fixed categorical effects for airspeed (four levels) and flight segment (four levels), a fixed interaction effect between airspeed and flight segment, and a random intercept for each

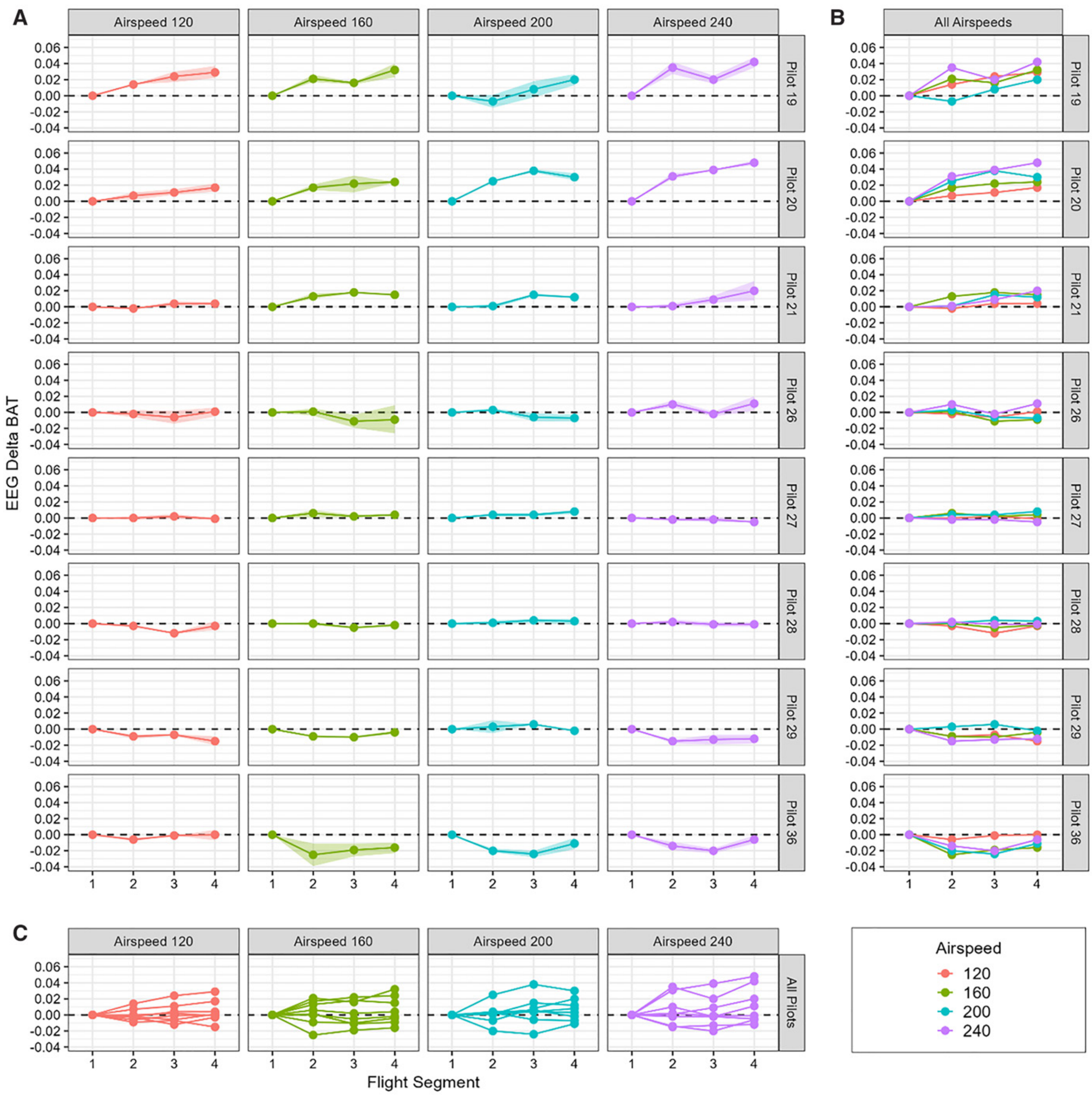

Fig. 2. Route 1 (Narrow Corridor) mean EEG delta BAT values. A) Mean delta values for duplicate flights by each pilot and airspeed. Shaded regions show range of mean delta values from individual flights. B) Mean delta values by pilot for all airspeeds. C) Mean delta values by airspeed for all pilots.

pilot. Statistical assumptions of the regression model were checked by confirming that the residuals followed a normal distribution with equal variance across the range of data. Omnibus Type III analysis of variance tests were used to determine if any main effects in the regression models reached overall statistical significance. Significant results were followed up with appropriate pairwise comparisons. All *P*-values for pairwise comparisons were adjusted using the Benjamini-Hochberg method to control the false discovery rate and balance controlling for Type 1 and Type 2 errors. For significant effects of flight segments, pairwise comparisons were limited to comparisons against the first flight segment.

RESULTS

Analysis of EEG frontal BAT ratios across the three routes revealed distinct patterns of cognitive engagement changes across airspeeds, flight segments, and individual pilots. For the Narrow Corridor flights, the data demonstrated substantial

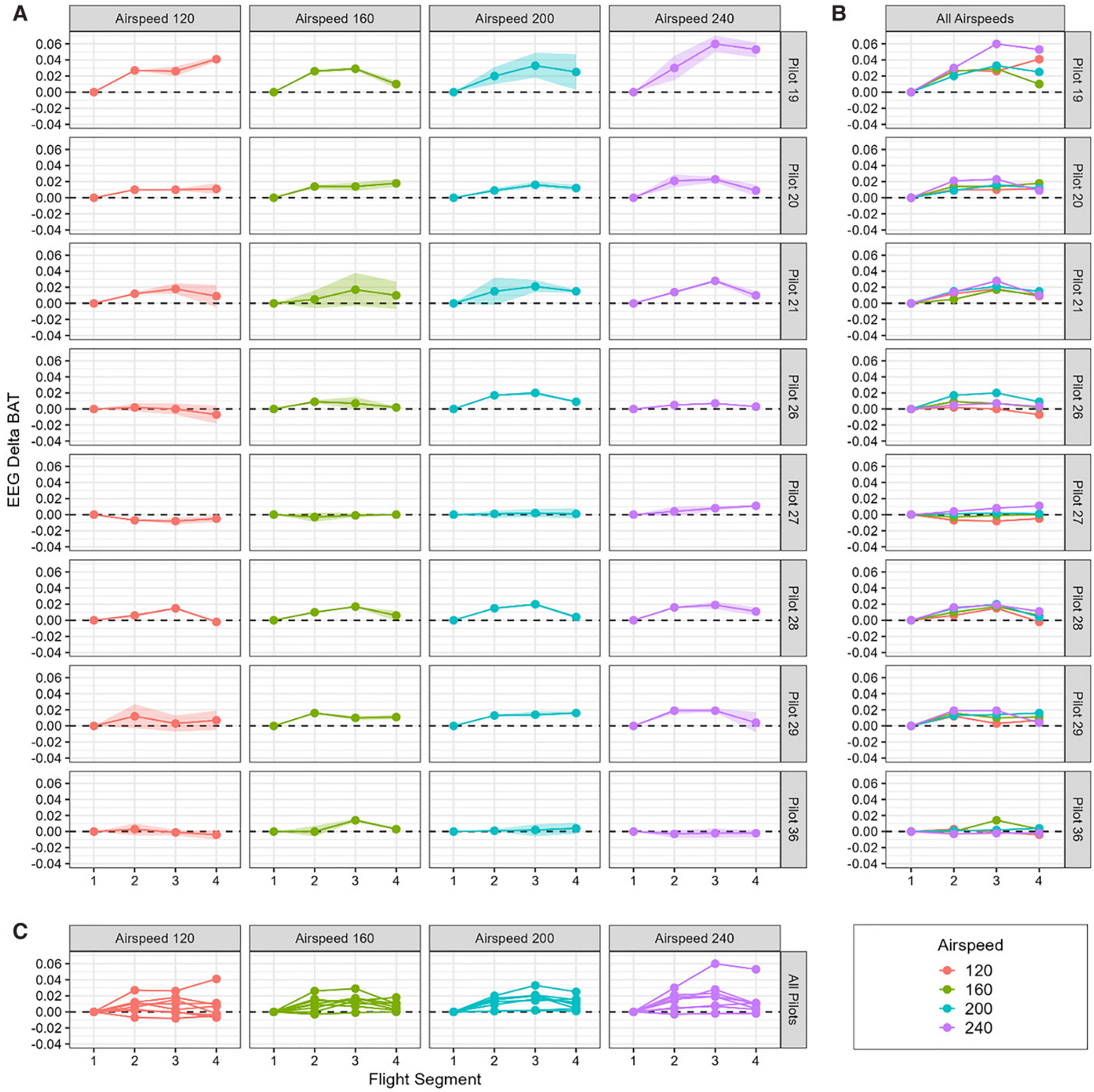

Fig. 3. Route 2 (Deep River Valley) mean EEG delta BAT values. A) Mean delta values for duplicate flights by each pilot and airspeed. Shaded regions show range of mean delta values from individual flights. B) Mean delta values by pilot for all airspeeds. C) Mean delta values by airspeed for all pilots.

interindividual variability in delta BAT patterns, reflecting different approaches to task management across flight conditions (Fig. 2 and supplemental Table AI and Table AII, found in the online version of this article). At the individual level, pilots 19 and 20 exhibited predominantly positive changes in BAT ratios that varied with airspeed, reaching mean delta values of 0.042 and 0.048, respectively, at 240 kn during flight segment 4. Pilots 27 and 28 maintained relatively stable delta BAT ratios near baseline across conditions. Pilots 21, 26, 29, and 36 demonstrated both positive and negative changes in delta BAT ratios across conditions, with mean values ranging from −0.025–0.020, suggesting varying cognitive strategies in response to task demands.

Temporal analysis for the Narrow Corridor flights revealed evolving patterns of changing cognitive engagement. During the early phase (flight segment 2), mean delta values ranged from −0.025–0.035, with the greatest variability observed in high-speed conditions. The midsegments showed more consistent patterns across pilots, with mean delta values ranging from −0.024–0.039 and increased variability compared to the

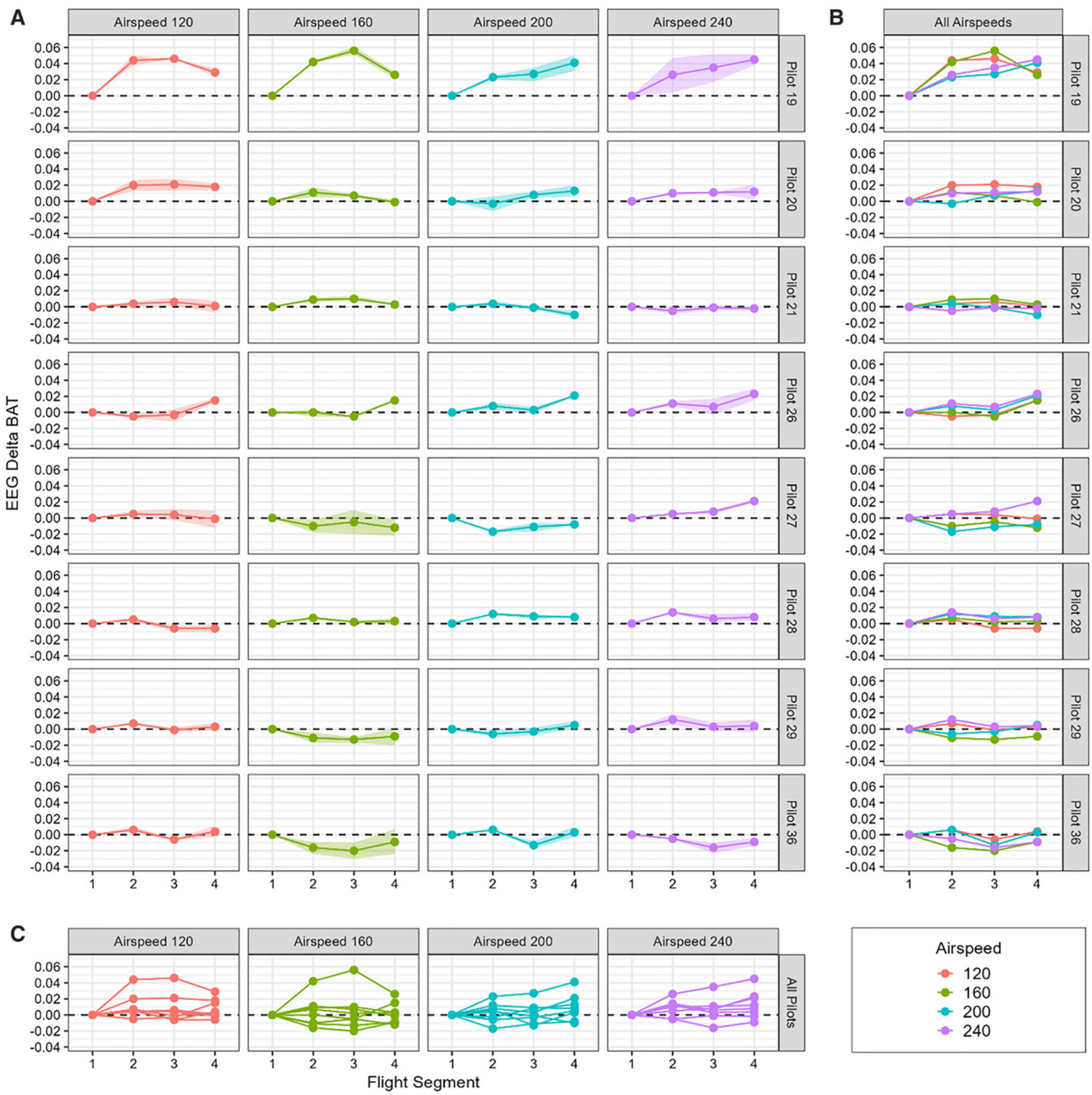

Fig. 4. Route 3 (Wide Corridor) mean EEG delta BAT values. A) Mean delta values for duplicate flights by each pilot and airspeed. Shaded regions show range of mean delta values from individual flights. B) Mean delta values by pilot for all airspeeds. C) Mean delta values by airspeed for all pilots.

early phase. The late segments exhibited the broadest range of mean delta BAT ratios, ranging from −0.016–0.048, suggesting diverse cognitive strategies among pilots during extended flight periods.

Airspeed conditions in the Narrow Corridor flights produced systematic changes in cognitive engagement measures. At 120 kn, mean delta BAT ratios ranged from −0.015–0.029 with minimal variability (SD = 0.007–0.013). As airspeed increased to 160 kn, increased variability emerged (SD = 0.015–0.017) with mean delta ratios ranging from −0.025–0.032, suggesting a transition point in cognitive engagement. At 200 kn, mean delta ratios ranged from −0.024–0.038, with individual differences becoming more apparent. The 240–kn condition showed the widest range of responses, with mean delta ratios from −0.020 –0.048 and the highest variability (SD = 0.019–0.023).

Statistical results from the regression model for the Narrow Corridor flights revealed a significant effect of flight segment [$F(3, 233) = 5.35$, $P = 0.001$], predicting an increase in the mean BAT ratio over time (supplemental **Fig. A1**, found in the online version of this article). Pairwise comparisons showed a significant increase in mean BAT values from flight segments 1 to 4 [$t(233) = 3.96$, $P < 0.001$]. The airspeed main effect [$F(3, 233) = 1.19$, $P = 0.32$] and the interaction effect between airspeed and flight segment [$F(9, 233) = 0.59$, $P = 0.81$] were not significant.

The Deep River Valley flight analysis revealed more consistent trends compared to the Narrow Corridor flights, though still demonstrating substantial interindividual variability in delta BAT patterns at the individual level (Fig. 3 and supplemental Table AIII and Table AIV, found in the online version of this article). Pilot 19 demonstrated notably high delta BAT ratios, particularly at higher airspeeds, with mean delta BAT values reaching 0.060 at 240 kn during flight segment 3. Pilot 20 maintained more moderate and consistent mean delta BAT ratios across conditions, ranging from 0.009–0.023, suggesting a more stable cognitive engagement pattern. The remaining pilots displayed diverse response patterns, with some showing predominantly positive delta ratios (Pilot 28) and others showing both positive and negative values (Pilot 36).

The temporal progression in the Deep River Valley flights showed distinct patterns across flight segments. The early phase demonstrated mean delta values ranging from −0.007–0.030, with moderate variability (SD = 0.007–0.011). The midphase showed slightly higher overall means (−0.008–0.060) with increased variability (SD up to 0.019), while the late phase demonstrated the most variable responses, with means ranging from −0.007–0.053 and standard deviations up to 0.017.

Airspeed conditions produced systematic changes, beginning with relatively low mean delta BAT ratios at 120 kn (−0.008–0.041) and moderate variability (SD = 0.010–0.016). As airspeed increased to 160 kn, slightly higher means emerged (−0.003–0.029) with similar variability (SD = 0.006–0.009). At 200 knots, means remained consistent (0.001–0.033) with moderate variability (SD = 0.007–0.010), while the 240-kn condition demonstrated the highest mean delta ratios (−0.003 – 0.060) and greatest variability (SD = 0.011 – 0.019).

Regression analysis for the Deep River Valley flights revealed a significant effect of flight segment [$F(3, 229) = 29.37$, $P < 0.001$], predicting an increase in the mean BAT ratio from flight segment 1–3, and a decrease from flight segment 3–4 (supplemental **Fig. A2** found in the online version of this article). Pairwise comparisons showed that mean BAT ratios were significantly different between flight segment 1 and segments 2, 3, and 4 [2: $t(229) = 6.62$, $P < 0.001$; 3: $t(229) = 9.04$, $P < 0.001$; 4: $t(229) = 5.82$, $P < 0.001$]. The airspeed main effect [$F(3, 229) = 2.04$, $P = 0.22$] and the interaction effect [$F(9, 229) = 1.00$, $P = 0.44$] were not significant.

The Wide Corridor route analysis revealed distinct patterns that differed notably from the previous routes (Fig. 4 and supplemental Table AV and Table AVI). At the individual level, pilot 19 maintained consistently high mean delta BAT ratios across conditions, with changes ranging from 0.023–0.056, particularly during flight segment 3 at 160 kn. Pilot 20 demonstrated moderate delta BAT ratios that generally decreased with increasing airspeed, ranging from 0.021 at 120 kn to −0.003 at 200 kn. Pilot 21 showed relatively stable but low delta BAT ratios across conditions, ranging from −0.010–0.010. The remaining pilots exhibited more variable patterns, with pilot 36 showing predominantly negative delta ratios (−0.020–0.006) and pilot 28 maintaining relatively stable positive delta ratios (−0.006–0.014).

Temporal analysis for the Wide Corridor flights showed evolving patterns, with the early phase displaying mean delta values ranging from −0.017–0.044 and moderate variability (SD = 0.010–0.018). The midphase showed similar means (−0.020–0.056), but with increased variability (SD up to 0.023), while the late phase demonstrated relatively consistent means (−0.012–0.045) with moderate variability (SD = 0.012–0.017).

Airspeed conditions produced less systematic changes compared to the other routes, with mean delta BAT ratios ranging from −0.006–0.046 at 120 kn with moderate variability (SD = 0.008–0.011). At 160 kn, means were lower (−0.020–0.056) with higher variability (SD = 0.013–0.023), while the 200-kn condition showed similar means (−0.017–0.041) with moderate variability (SD = 0.012–0.016). At 240 kn, means increased slightly (−0.016–0.045) with consistent variability (SD = 0.010–0.017).

Regression analysis for the Wide Corridor flights revealed a significant effect of flight segment [$F(3, 233) = 5.42$, $P = 0.001$], predicting an increase in the mean BAT ratio over time (supplemental **Fig. A3**, found in the online version of this article). Pairwise comparisons showed that mean BAT ratios were significantly different between flight segment 1 and segments 2, 3, and 4 [2: $t(233) = 3.10$, $P = 0.003$; 3: $t(233) = 2.41$, $P = 0.017$; 4: $t(233) = 3.78$, $P < 0.001$]. The airspeed main effect [$F(3, 233) = 0.68$, $P = 0.57$] and the interaction effect [$F(9, 233) = 0.75$, $P = 0.66$] were not significant.

Together, the findings across all three routes demonstrate that changes in cognitive engagement, as measured by delta BAT ratios, show both temporal progression and considerable individual variation, with pilots employing different cognitive strategies across conditions while successfully completing their assigned missions.

DISCUSSION

Analysis of BAT ratios across pilots, routes, airspeeds, and flight segments provided valuable insights into the cognitive demands placed on pilots, building upon existing research in aviation neurophysiology and human factors. The observed variations in BAT ratios provided important information for optimizing flight paths and understanding pilot cognitive engagement. A comparative analysis across the three routes revealed distinct patterns in several key areas. Looking at individual differences, the Narrow Corridor route exhibited high variability in individual responses with clear adaptation patterns. The Deep River Valley route demonstrated more consistent individual responses and clearer relationships with task demands. The Wide Corridor route fell somewhere in the middle, showing intermediate variability with fewer systematic patterns compared to the other routes.

When examining airspeed effects, each route displayed unique characteristics. The Narrow Corridor route exhibited an increase in cognitive engagement with airspeed, particularly above 200 kn. The Deep River Valley route demonstrated the strongest relationship between airspeed and delta BAT ratios, while the Wide Corridor route showed less systematic airspeed-related changes, suggesting different task demands were at play. Temporal patterns also varied significantly across the routes. The Narrow Corridor route showed increasing variability across flight segments, while the Deep River Valley route maintained more consistent patterns across time. The Wide Corridor route demonstrated moderate variability with less clear temporal progression. In terms of overall cognitive engagement, the Deep River Valley route generally elicited higher delta BAT ratios across conditions, while the Narrow Corridor route showed moderate but variable cognitive engagement levels. The Wide Corridor route demonstrated lower overall delta BAT ratios with less systematic variations.

These findings suggest that each route posed unique cognitive demands. The Deep River Valley route appeared to impose the most systematic cognitive engagement patterns, while the Wide Corridor route showed less airspeed-dependent variation. The Narrow Corridor route demonstrated intermediate patterns with clear individual differences in adaptation. The variations across routes likely reflect differences in navigational complexity, task demands, and required pilot strategies, with the Deep River Valley route potentially requiring the most consistent cognitive engagement across conditions. The airspeed-dependent variations in cognitive engagement, particularly evident in the Narrow Corridor and Deep River Valley routes, show that airspeeds exceeding 200 kn led to increased cognitive demands, suggesting a threshold where pilot workload management becomes more challenging. The Deep River Valley route, in particular, became more difficult to fly at higher speeds during some segments because of the challenging winding river canyon topography.

These findings align with Di Stasi et al.'s findings on attention allocation during actual flight. These insights could inform airspeed restrictions and optimal cruise airspeed recommendations for different route segments.[4] Moreover, individual differences in pilot responses emphasize the need for flexible route design that accommodate various cognitive strategies. This variability aligns with Dehais et al.'s work on individual differences in pilot cognitive states during flight operations.[5] The observed adaptation patterns, particularly evident in the Narrow Corridor route, suggest that pilots develop individual approaches to managing workload over time, supporting Hancock and Matthews' theory of cognitive resource management in complex environments.[9]

The temporal evolution of cognitive engagement across all routes indicates dynamic changes in mental resource allocation during flight. These findings parallel Rosa et al.'s research on fatigue and attention management in extended flight operations.[10] The implications for route design suggest the importance of considering both airspeed and navigational complexity when planning routes, particularly for extended operations where sustained attention demands may impact pilot performance. The BAT ratio patterns observed in this study provide quantifiable metrics for assessing cognitive demands, building upon the U.S. Army Aeromedical Research Laboratory's (USAARL) previous work on EEG-based cognitive engagement assessment in aviation.[2,3] The higher variability in the Narrow Corridor route compared to the Deep River Valley route suggests that predictable task demands might facilitate more efficient cognitive resource allocation, supporting theories of cognitive load management in complex task environments.

The integration of neurophysiological metrics with automated flight route planning protocols presents opportunities for enhanced route optimization. Arico et al.'s comprehensive review of neurometric data integration in automated flight systems provide a foundational framework for such applications.[11] Our findings suggest that incorporating cognitive engagement parameters into route planning algorithms could facilitate the development of neuroadaptive navigation protocols, particularly in high-density airspace where cognitive demands present great challenges. The observed correlation between airspeed parameters and cognitive engagement metrics provides significant implications for next-generation aircraft design and automated flight systems. Recent technical analyses from USAARL examining neuroadaptive automation frameworks demonstrate that real-time cognitive state monitoring could enable dynamic adjustment of automated support systems.[12] This approach suggests that implementing intelligent systems capable of responding to variations in pilot cognitive states could optimize workload distribution and enhance operational efficiency across diverse flight conditions. The systematic variations in BAT ratios with airspeed changes are one such physiological measure that could provide potential triggers for future adaptive systems.

From a training perspective, the individual differences observed in cognitive adaptation strategies suggest the need for personalized training approaches. The clear patterns of individual variation in our data support the development of training programs that account for different cognitive processing styles while maintaining standardized performance outcomes. The progressive changes in BAT ratios over flight segments indicate potential windows for optimal performance and risk periods that should be considered in route planning. Furthermore, our findings also have implications for the development of real-time monitoring systems. The clear relationship between route characteristics and EEG patterns suggests the possibility of developing predictive models for cognitive workload, similar to those proposed by Jiang et al. for cognitive competency. Such models could provide early warning of potential cognitive overload situations, allowing for proactive intervention.[13]

The relationship between route design and cognitive demands appears more nuanced than traditional difficulty metrics suggest. Our findings highlight the benefits of advanced assessment methods, particularly neurophysiological measurements, in FVL platforms. By quantifying cognitive engagement through EEG derived metrics, we gained valuable insights that can shape aviation system design, training protocols, and safety procedures. However, incorporating a more diverse array of physiological metrics is imperative to gain a comprehensive understanding of cognitive workload. This evidence-based approach to understanding pilot cognitive demands offers a more precise tool for optimizing route design and operational decision making.

Flight simulators, while valuable training tools, cannot fully replicate the actual experience and demands of operating a real aircraft, which may influence how pilots process information and make decisions. To gain a more comprehensive understanding of pilots' cognitive processes, researchers should consider expanding their measurement techniques beyond basic EEG metrics. Limitations of the EEG metrics that are captured during this experiment are highlighted in our previous publication.[2] Additional EEG measurements could reveal more nuanced aspects of cognitive demand patterns during different flight phases and decision-making scenarios. Furthermore, incorporating other physiological measurements such as heart rate variability and pupillometry could provide deeper insights into how pilots' workload and cognitive demands fluctuate throughout flight. These complementary measurement approaches could help identify subtle changes in mental workload that might not be captured by EEG alone. The limited scope of the three flight routes examined in this study, while providing valuable data, represent only a narrow segment of possible flight scenarios. To develop a more complete understanding of pilots' cognitive approaches and decision-making strategies, future research should examine a broader range of flight routes with varying complexities, environmental conditions, and operational challenges. This expanded scope would help identify how pilots adapt their cognitive strategies across different flight scenarios and conditions.

The data obtained from this study directly informs the design of experimental routes for upcoming FVL program evaluations. Building upon the observed relationships between airspeed, route characteristics, and cognitive workload, test matrices are being developed that systematically explore cognitive demands at airspeeds exceeding 240 kn. The findings of increased cognitive load above 200 kn suggest the need to carefully examine pilot performance at the speeds that FVL aircraft will achieve. Route segments are being designed that deliberately incorporate the elements found to induce consistent cognitive engagement patterns in the Deep River Valley route, while strategically integrating the variable navigation demands from the Narrow Corridor route that produced adaptive cognitive responses. These hybrid routes will help evaluate how pilots manage cognitive resources when transitioning between high-speed cruise segments and complex tactical maneuvers. The temporal patterns observed in the current study are informing the duration and sequencing of these test segments.

Additionally, the USAARL team is developing real-time EEG monitoring protocols specifically calibrated for high-speed flight conditions. These protocols will incorporate machine learning algorithms trained on the current dataset to predict potential cognitive overload situations during FVL flight testing. This neurophysiological monitoring system will be particularly crucial during initial envelope expansion flights, where pilots will be operating in complex and difficult flight scenarios.

The individual differences in cognitive adaptation strategies observed in this study are guiding the development of pilot selection and training protocols for FVL aircraft. Future experiments will evaluate whether these individual response patterns remain consistent at higher speeds and whether specific cognitive strategies correlate with enhanced performance in FVL-specific mission sets.

The analysis of EEG-based cognitive engagement measurements provides valuable insights for aviation route design and pilot performance optimization. The study reveals that different route characteristics elicit distinct patterns of cognitive engagement, with implications for safety, training, and operational efficiency. The systematic variations observed across routes, airspeeds, and time periods demonstrate the utility of EEG measurements in understanding and optimizing pilot workload.

The findings suggest that route design should consider not only traditional factors like distance and fuel efficiency, but also cognitive demands on pilots. The integration of EEG data in route planning could lead to more balanced flight paths that optimize pilot performance while maintaining safety margins. Future research should focus on developing standardized metrics for cognitive workload assessment in route design and investigating the relationship between EEG patterns and pilot performance outcomes.

The results also highlight the importance of individual differences in cognitive response patterns, suggesting that flexible route designs and personalized training approaches may be beneficial. The implementation of these findings could lead to improved route design methodologies that better account for human factors and cognitive limitations, ultimately enhancing aviation safety and efficiency.

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