Measurement of pilots' fatigue, attention and vigilance using EEG, ECG and EYE tracking in the simulated environment

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Abstract: *The concept of the Human Performance Envelope (HPE) brought the idea of interdependence between multiple ergonomic factors together with their influence on pilots' performance. After the analysis of the aviation incidents, Eurocontrol experts had selected nine ergonomic factors (stress, fatigue, mental workload, situation awareness – (SA), attention, vigilance, communication, teamwork and trust) which affect the pilots' performance. In the previous article [1], was proposed a hybrid model (mathematical - heuristic), which is suitable for the study of HPE, because the mathematical part could be applied to study the physiological ergonomic factors (workload, stress, mental fatigue, situation awareness, attention and vigilance), based on physiological measurements, while the heuristic part could be used to analyze the psychosocial ergonomic factors (trust, teamwork and communication) determined by direct observations, questionnaires studies and incident report analysis. The aim of this paper is to validate the proposed mathematical model, through physiological measurements (ECG, EEG, RR and eye tracking) for ergonomic less studied factors (according to the literature analysis): Fatigue, Attention and Vigilance. Using a single pilot, the measurements were conducted in three distinct scenarios on the King Air C90 simulator at INCAS - Strejnicu. The findings demonstrated that the physiological parameters were impacted by the difficulty of the flights.*

Key Words: *Human Performance Envelope (HPE), pilots, simulator, ECG, EEG, eye tracking*

1. INTRODUCTION

Nowadays, due to progress in technology and an increase in the number of flights, aviation has become increasingly difficult. However, humans are the primary actors in this complex system because they are legally in charge of all choices, including technological ones. For this reason, human error is the primary cause of most accidents. According to ICAO (International Civil Aviation Organization), in 2024, incidents involving loss of control-in-flight (LOC-I) and bird strikes (BIRD) accounted for more over 80% of the fatalities. The other types of incidents that resulted in fatalities were: controlled flight into or towards terrain (CFIT), turbulence encounter (TURB), security related (SEC), runway incursion (RI), system/component failure or malfunction (powerplant) (SCF-PP), ground handling (RAMP) and airprox/TCAS alert/loss of separation/near midair collisions/midair collisions (MAC) [2].

Captain David Moriarty supports the idea that the failures which cause accidents are not the result of hazards. For instance, when an airplane's engine fails, it's due to the improper upkeep, due to mistakes in design, or perhaps it was done incorrectly. Therefore, technical failure involves human mistake in some way [3].

International organizations develop and carry out various safety initiatives, such as Future Sky Safety (started by EREA and financed by the European Union's Horizon Program 2020) or the European Plan for Aviation Safety (EPAS), to lower the frequency of aircraft accidents and increase safety. The objective of these two programs is the same: to increase aviation safety by using ergonomics.

Furthermore, Future Sky Safety project extended the concept of Human Performance Envelope (HPE) on pilots [4], as initially the concept was applied on Air Traffic Controllers, by Edward Tamsyn in her PhD Thesis "Human performance in Air Traffic Control". The HPE concept brought the idea of dependency between various ergonomic aspects and their influence on air traffic controllers' performance, since all prior studies viewed one human factor as an independent variable and another as a dependent one. Nine ergonomic factors - stress, fatigue, mental workload, situation awareness (SA), attention, vigilance, communication, teamwork, and trust — that impact pilot and ATC performance were chosen by Eurocontrol specialists after they analyzed the aviation incidents and accidents [5].

Afterwards, a literature analysis was done in order to define HPE boundaries, which conclude that mental workload, stress and situation awareness have been examined more than the others (fatigue, attention, vigilance, communication, teamwork and trust). One possible explanation is that the less well-studied human components are more challenging to evaluate, necessitating more time for testing, physiological measures, and sociological techniques [6].

2. PREVIOUS RESEARCH

Furthermore, a subsequent study extended the application of complex systems theory to the Human Performance Envelope (HPE) framework. As an outcome, was developed a mathematical model describing physiological ergonomic parameters, integrated within a hybrid mathematical–heuristic structure [1]. The proposed methodology demonstrates the adaptation of Stănciulescu's hybrid macroeconomic model to the context of the HPE concept, thereby providing a quantitative foundation for analyzing human performance dynamics [7].

Such hybrid model is suitable for the HPE study, because six ergonomic factors (mental workload, stress, fatigue, situation awareness, attention and vigilance) can be analyzed through physiological variables (heart rate, heart rate variability, respiration rate, alpha, beta, theta brain waves, blink rate, pupil diameter), which can be measured using different tools like ECG, EEG and eye tracking. On the other side, the heuristic component is appropriate for the psychosocial ergonomic factors like communication, teamwork and trust which can be investigated through the use of questionnaires, observations, interviews or incident report analysis. Thus were determined variables for the state equations for the mathematical part, as follows (table 1): six ergonomic factors represent output variables and the physiological parameters are the state variables. Various researchers have measured a range of physiological parameters; however, the most pertinent ones were consolidated by Future Sky Safety into a set of Cards [4], which served as the basis for defining the state variables and their corresponding signs.

For each ergonomic factor, specific physiological variables were identified based on their measurable influence on that factor (table 2). As an example, under stressful conditions, physiological responses typically include an increase in Respiratory Rate (RR), Heart Rate (HR), and Systolic Blood Pressure (SBP), accompanied by a decrease in Heart Rate Variability (HRV). Consequently, the stress (S) ergonomic factor was represented by the following set of physiological parameters: HbO_2, RR, HR, SBP, MT, EDA, AD, NAD and HRV. In alignment with the data provided by the HPE Factor Cards [4], each physiological variable was further characterized by a directional sign - positive (+) or negative (−) - to denote whether the parameter increases or decreases in response to changes in the corresponding ergonomic factor.

Table 1 – State variables and output variables for mathematical model

Variables of state (at a specific moment t)		Output variables	
$HbO_2(t)$	Oxygenated Hemoglobin	MW	Mental Workload
HR(t)	Heart rate	S	Stress
HRV(t)	Heart rate variability	F	Fatigue
SBP(t)	Systolic Blood pressure	SA	Situation Awareness
RR(t)	Respiratory rate	A	Attention
BR(t)	Eye blink rate	V	Vigilance
BD(t)	Eye blink duration		
PD(t)	Pupil diameter		
ABP(t)	Alpha band power		
BBP(t)	Beta band power		
TBP(t)	Theta band power		
DBP(t)	Delta band power		
MT(t)	Muscle tension		
EDA(t)	Electrodermal activity		
AD(t)	Adrenaline		
NAD(t)	Noradrenaline		
SEM(t)	Saccadic eye movement		
MA(t)	Mental activity		
CABFV(t)	Right cerebral arterial blood flow velocities		

Table 2 – State equations and conditions for mathematical model

$$\frac{d}{dt}MW(t) = \alpha_1 HR(t) + \beta_1 SBP(t) + \gamma_1 RR(t) + \delta_1 PD(t) + \omega_1 BBP(t) + \\ +\varphi_1 TBP(t) + \eta_1 MT(t) + \theta_1 EDA(t) - \kappa_1 HRV(t) - \lambda_1 BR(t) - \mu_1 BD(t) - \tau_1 ABP(t) \tag{1}$$

$$\frac{d}{dt}S(t) = \nu_2 HbO2(t) + \gamma_2 RR(t) + \alpha_2 HR(t) + \beta_2 SBP(t) + \eta_2 MT(t) + \theta_2 EDA(t) + \\ + \xi_2 AD(t) + \rho_2 NAD(t) - \kappa_2 HRV(t) \tag{2}$$

$$\frac{d}{dt}F(t) = \mu_3 BD(t) + \sigma_3 DBP(t) + \varphi_3 TBP(t) + \tau_3 ABP(t) + \kappa_3 HRV(t) - \delta_3 PD(t) - \\ - \chi_3 SEM(t) - \omega_3 BBP(t) - \alpha_3 HR(t) - \eta_3 MT(t) - \gamma_3 RR(t) - \theta_3 EDA(t) \tag{3}$$

$$\frac{d}{dt}SA(t) = \upsilon_4 MA(t) + \alpha_4 HR(t) - \kappa_4 HRV(t) - \lambda_4 BR(t) - \mu_4 BD(t) \tag{4}$$

$$\frac{d}{dt}A(t) = \alpha_5 HR(t) - \kappa_5 HRV(t) - \lambda_5 BR(t) - \mu_5 BD(t) - \tau_5 ABP(t) - \rho_5 CABFV(t) \quad (5)$$

$$\frac{d}{dt}V(t) = \alpha_6 HR(t) - \kappa_6 HRV(t) - \lambda_6 BR(t) - \mu_6 BD(t) - \tau_6 ABP(t) - \rho_6 CABFV(t) \quad (6)$$

$$MW_0 < MW(t)\ ,\ S_0 < S(t)\ ,\ \ F_0 < F(t) \quad (7)$$

$$SA_0 > SA(t)\ ,\ A_0 > A(t)\ ,\ \ V_0 > V(t) \quad (8)$$

To comprehensively assess human performance, additional conditions (7) and (8) were formulated to represent the effects of complex scenarios. Researchers commonly simulate stressful environments — such as through technical failures, multitasking activities, turbulence or bad weather conditions — in controlled settings like flight simulators or workplace simulations [8]-[10]. These induced conditions result in measurable physiological and cognitive changes, including an increase in *Mental Workload* ($MW_0 < MW(t)$), *Stress* ($S_0 < S(t)$), and *Fatigue* ($F_0 < F(t)$). Conversely, key performance - related variables such as *Situation Awareness* ($SA_0 > SA(t)$), *Attention* ($A_0 > A(t)$), and *Vigilance* ($V_0 > V(t)$) decrease over time. This formulation enables the mathematical representation of dynamic human state variations under stressful situations, thereby enhancing the accuracy of models used to predict and evaluate performance in demanding operational contexts.

3. METHOD

The objective of this study is to validate the proposed mathematical model using physiological measurements - including electrocardiography (ECG), electroencephalography (EEG), respiratory rate (RR), and eye-tracking data - focusing on ergonomic factors that have been comparatively underexplored in the literature, namely fatigue, attention, and vigilance.

Fatigue is recognized as a critical factor that can adversely affect pilot's performance and has been identified as a contributing cause in several aviation accidents. Notable examples include the DC-8 crash in Guatemala Bay (1993), Korean Air Flight 801 (1999, resulting in 228 fatalities), and American Airlines Flight 1420 (1999, resulting in 11 fatalities) [11].

Despite extensive research, the concept of fatigue remains insufficiently defined within the scientific community. The distinction between mental fatigue and drowsiness is particularly challenging, as their overlapping neurophysiological features suggest they exist along a continuum of mental states, with drowsiness representing a transitional phase between wakefulness and sleep [12].

According to the state equation (table 2) and evidence from existing literature, fatigue can be assessed through electroencephalography (EEG), electrocardiography (ECG), eye-tracking techniques. As fatigue level increases, specific physiological indicators tend to rise—such as eye blink duration (BD), delta band power (DBP), theta band power (TBP), alpha band power (ABP) and heart rate variability (HRV). Conversely, other parameters, including pupil diameter (PD), saccadic eye movement (SEM), beta band power (BBP), heart rate (HR), muscle tension (MT), respiration rate (RR), and electrodermal activity (EDA), typically exhibit a decrease.

Attention and vigilance significantly impact pilot's performance; however, certain aspects of these ergonomic constructs remain insufficiently clarified within the scientific community. In the literature, the terms vigilance, sustained attention, and passive monitoring are often used interchangeably to describe the same phenomenon, contributing to conceptual ambiguity and challenges in its measurement [3]. Attention and vigilance tends to decline under conditions of fatigue and boredom, posing challenges for tasks that require continuous monitoring, such as piloting. Pilots must maintain attention to multiple sources of information—including environmental factors, aircraft systems, and communications—despite the difficulty of sustaining a high level of alertness over extended periods [13].

Consequently, the physiological indicators associated with attention and vigilance exhibit similar patterns. Specifically, heart rate (HR) tends to increase, whereas heart rate variability (HRV), eye blink rate (BR), eye blink duration (BD), alpha band power (ABP), and right cerebral arterial blood flow velocity (CABFV) generally decrease (table 2).

3.1 Full flight simulator

The experimental trials were performed using the Beechcraft King Air C90GTx Full Flight Simulator (FFS). The simulator incorporates the state-of-the-art XT6 visual system created by RSi and is specifically designed for specialized and turboprop aircraft applications, allowing for a very realistic and immersive training environment. Furthermore, the simulator is equipped with a VanHalteren motion platform that enhances the fidelity of flight dynamics representation. [14] High-fidelity aerodynamic models, precisely responsive control systems, and finely detailed cockpit surroundings are all used in the whole flight simulator's design to faithfully replicate the real flight experience [15].

Fig. 1 - Beechcraft King Air C90GTx Full Flight Simulator (FFS)

3.2 Experimental environment

The participant at the experiment is a pilot with an average flying experience of 330 hours and with experience in using the Beechcraft King Air C90GTx Full Flight Simulator (FFS). Prior to data collection, the participant completed a questionnaire addressing general health status, major medical conditions, sleep duration, and other factors that could potentially influence physiological condition. Furthermore, written informed consent was obtained from the participant in accordance with ethical research standards.

All three simulation trials employed a closed-pattern flight scenario originating and terminating at Salzburg Airport (LOWS). Atmospheric conditions were configured with a lower-level wind layer characterized by a steady easterly flow—wind direction 90°—at an intensity of 15 knots. Throughout the simulated flights, the autopilot system was deactivated, necessitating manual operation of the aircraft for the entire duration of the mission. The landing was performed utilizing the Instrument Landing System (ILS). The flight adhered rigorously to instrument flight rules (IFR), relying solely on onboard instruments and excluding any external visual cues.

The initial simulated flight served as a baseline scenario, conducted under standard conditions without any notable events or adverse weather phenomena. The second scenario introduced moderate turbulence between altitudes of 1,000 and 5,000 feet and CAT I visibility, simulating a more dynamically unstable atmospheric environment.

The third scenario combined light turbulence, lateral wind components, CAT I visibility, heavy precipitation, and airframe icing, with particular emphasis on the accumulation of ice on the aircraft's wing surfaces. Each simulation session was conducted over an approximate duration of 15 minutes, whereas the complete experimental protocol extended over a total period of approximately 4 hours.

3.3 Instruments of measurement

During the simulation sessions, the pilot's physiological parameters were continuously recorded using the BIOPAC MP160, which is a high-precision, modular platform for physiological data acquisition and analysis, specifically engineered for advanced research in the life sciences. The central MP160 unit offers up to 16 analog input channels, Ethernet connectivity, an aggregate sampling rate of up to 400 kHz, and 16-bit analog-to-digital resolution [16].

In the present study, specialized acquisition modules were employed, including the ECG100C/D amplifier for cardiac electrophysiological recording, the EEG100C/D amplifier for cerebral activity measurement, and respiratory transducer units such as the RSP100C/D for monitoring respiratory dynamics. These modules were concurrently integrated with the MP160 data acquisition system, and the recorded signals were subsequently processed using the AcqKnowledge software, which provides automated analytical routines for electrocardiography (ECG), heart rate variability (HRV), electroencephalography (EEG), respiration, and other physiological parameters.

Additionally, eye movement and gaze behavior were recorded using Tobii eye-tracking technology, providing detailed insights into visual attention and cognitive workload during flight tasks.

The Tobii Pro Glasses 2 is a wearable eye-tracking device with 4 eye tracking cameras developed for behavioral research in real-world contexts. It combines a head-mounted unit, a high-definition scene camera, binocular eye-tracking sensors, and infrared illumination to deliver accurate measurements of visual fixation, viewing behavior and gaze direction. The system facilitates real-time monitoring as well as post-session analysis of eye movement data and synchronized video, allowing for objective assessment of visual attention in naturalistic settings [17].

Fig. 2 – Pilot wearing BN-EEGCAP-SYS, BN-BIOSHIRT and Tobii Pro Glasses 2

The integration of these measurement instruments within the simulated flight environment facilitated a comprehensive analysis of the interactions among pilot physiology, visual attention, and task performance. This methodology allowed the synchronized acquisition of multimodal data under conditions that were both realistic and controlled, thereby ensuring participant safety and experimental rigor.

4. DATA ANALYZING

Following the acquisition of physiological data using the BIOPAC system and Tobii Pro Glasses 2, all recorded signals were subjected to comprehensive analysis. Studying parameters including heart rate, heart rate variability, respiration, and electroencephalographic (EEG) activity were processed and evaluated using AcqKnowledge - the proprietary software developed by BIOPAC for the visualization, processing, and quantitative analysis of physiological data. The electrocardiographic (ECG) signals acquired via the BIOPAC MP160 system were recorded in the AcqKnowledge software as voltage variations representing cardiac electrical activity, expressed in microvolts (µV). However, in accordance with conventional practices in scientific research, cardiac activity is typically quantified in terms of heart rate, measured in beats per minute (BPM). Therefore, the Find Rate automatically function available in the Analysis menu of AcqKnowledge was applied to the electrocardiogram (ECG) signal, in order to detect consecutive cardiac cycles and to calculate the heart rate in beats per minute (BPM) throughout the recording. As a result was generated a separate graph representing cardiac frequency in BPM units.

The Find Rate function within the AcqKnowledge software is designed to identify cyclic patterns or peaks in physiological waveforms and to calculate associated rate-related parameters. The underlying algorithm can utilize a basic threshold detection approach or incorporate more sophisticated techniques, such as noise rejection filters and temporal windowing, to improve peak detection accuracy. Beyond BPM, the Find Rate function is capable of extracting various quantitative metrics from periodic data, including frequency (Hz), maximum and minimum peak amplitudes, peak-to-peak intervals (P–P), signal area, and mean values. The Find Rate function was similarly utilized for the analysis of respiratory and electroencephalographic (EEG) signals. Prior to EEG data acquisition, all relevant frequency bands - alpha, beta, delta, theta, and gamma—were selected within the channel configuration settings. As a result, each cerebral frequency band was treated as a separate channel within the AcqKnowledge software. Subsequently, the Find Rate function was applied to each EEG channel using the output parameter set to frequency (Hz) and the signal type specified as EEG, thereby generating distinct graphical representations for each cerebral wave band.

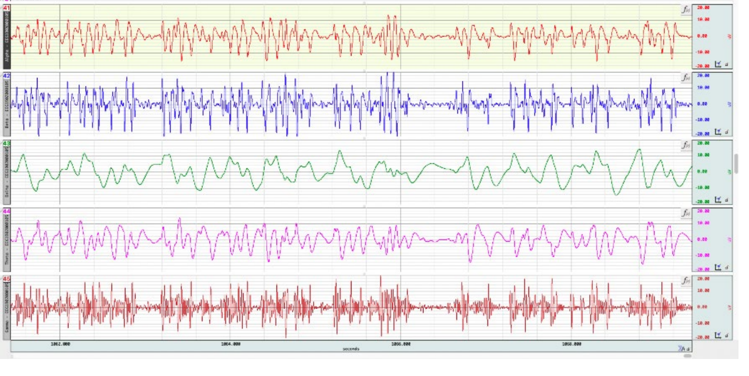


Fig. 3 – Acqknowledge representation of cerebral waves (alpha, beta, delta, theta, gamma)

Heart rate variability (HRV) was assessed using the Multi-Epoch HRV Statistical function within the Analysis menu of the AcqKnowledge software. This function processed the ECG data and generated an output Excel file containing parameters such as left edge, right edge, RMSSD, SDSD, and pNN50. For the purposes of this study, only the RMSSD values were employed, given that this metric is the most commonly reported and broadly recognized indicator of HRV in the scientific literature.

The RMSSD index, derived from inter-beat interval differences, represents the square root of the mean of the squared differences between consecutive NN intervals. The NN50 index denotes the number of successive NN interval differences greater than 50 milliseconds, while the pNN50 index is computed as the ratio of NN50 to the total number of NN intervals. Collectively, these short-term variability metrics capture high-frequency components of heart rate fluctuations and, as a result, demonstrate a strong mutual correlation [18].

The data acquired from the Tobii Pro Glasses 2 eye-tracking system were processed using the Tobii Pro Lab software. Each recording, saved as an individual project on the device's SD card, was imported into Tobii Pro Lab, where key flight events - such as the take-off initiation, turbulence zone, and landing commencement - were identified and annotated. Subsequently, gaze position, pupil diameter, and fixation metrics were exported into a separate Excel file via the Metrics and Data Export function located in the Analyze menu. For the purposes of this study, the primary variable extracted from the eye-tracking dataset was pupil diameter. Eye blink frequency and blink duration were further derived using an algorithm developed by research engineer Marcus Nystrom [19]. The algorithm offers two distinct methods for determining blink rate: one based on eye openness and another derived from pupil diameter. In the present study, the latter approach was selected, as the Tobii Pro Glasses 2 eye-tracking system does not record any eye openness data. The algorithm was implemented within the Python programming environment, where variations in pupil diameter were analyzed to extract blink-related parameters. Additionally, within the Python programming environment, the dataset was segmented into distinct categories corresponding to the different phases of flight. Then data was exported in Excell file for further analysis. Additionally, to generate the gaze plot for all three flight scenarios, the assisted mapping feature in Tobii Pro Lab was utilized. This functionality employs a computer-based algorithm that identifies correspondences between the video recordings obtained during the experiment and a reference image of the cockpit by analyzing visual parameters such as contrast and color distribution.

5. RESULTS

5.1 Physiological measurements - Heart rate (HR), Heart Rate Variability (HRV), Respiration Rate (RR)

By analyzing the heartbeats across the three different flight scenarios, it can be observed that the heart rate increases from approximately 90 BPM to 120 BPM toward the end of the recording, particularly during the landing phase. In addition, the cardiac rhythm exhibits noticeable fluctuations during the turbulence phase (flight 2, around minute 20). According to the mathematical model, an increase in fatigue is generally associated with a reduction in heart rate; however, the results of this study reveal the opposite pattern. Specifically, the heart rate recorded during the third flight was higher than that observed in the first flight, when the pilot was in a more rested state. Several factors may account for this finding. On one hand, the activation of the Glide Slope alert toward the end of the third flight may have elicited a stress response, momentarily elevating heart rate. On the other hand, the overall level of fatigue may not have been substantial, given that each simulated flight lasted no longer than 20 minutes and the entire experimental session spanned approximately three hours, conducted during midday.

To evaluate attention and vigilance, the second flight serves as a pertinent example, as the occurrence of turbulence necessitated heightened pilot concentration on aircraft control. Accordingly, the heart rate remained consistently elevated (above 90 BPM) during this phase, indicating an increased level of cognitive effort and physiological activation.

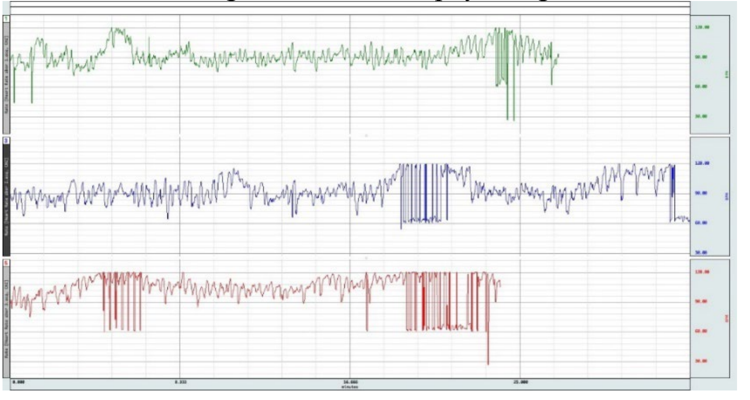


Fig. 4 – Heart rate (BPM) during three simulated flights

An analysis of the resulting graph reveals that heart rate variability (HRV) values ranged between 500 and 1000 during the first and third flight scenarios, while in the second flight, HRV values exceeded 1000. According to established state equations, HRV typically declines under stressful conditions; however, the recorded data suggest that the pilot did not experience substantial stress during the second flight, despite it being the most demanding scenario. Moreover, although fatigue is generally expected to be accompanied by an increase in HRV, the findings of this study indicate the opposite trend, as HRV values during the third flight were lower than those observed in the second. This outcome may be attributed to the same factors influencing heart rate—specifically, the activation of the Glide Slope alert and the relatively low level of fatigue, given the experimental conditions.

In terms of attention and vigilance - parameters that are expected to decline as fatigue increases - the observed rise in HRV contradicts the theoretical premise of the mathematical model (state equation). This discrepancy may be explained by the pilot's sustained concentration and heightened engagement in aircraft maneuvering tasks during the simulation.

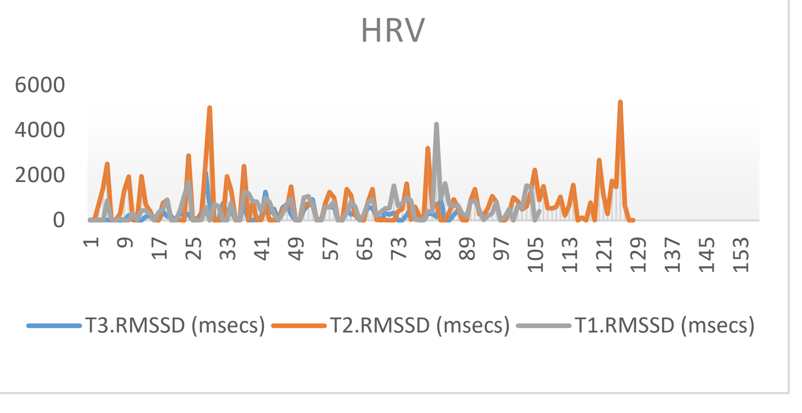


Fig. 5 – Heart rate variability (msecs) during three simulated flights

The analysis of respiration rate data reveals that during the second flight, the rate was markedly higher, most likely due to the increased complexity of this scenario, which was the longest and involved moderate turbulence. In contrast, no significant differences were observed between the first and third flights; however, the respiration rate tended to be slightly lower during the final flight, possibly reflecting the effects of accumulated fatigue, according to mathematical model. For the assessment of attention and vigilance, the second flight serves as a relevant case, as it demanded greater concentration compared to the other two scenarios. The respiration rate during this flight exhibited considerable variability, characterized by noticeable fluctuations, remaining relatively stable during the cruise phase but increasing during periods of turbulence and the landing phase. Therefore, it can be concluded that respiration rate increases proportionally with rising levels of attention and vigilance.

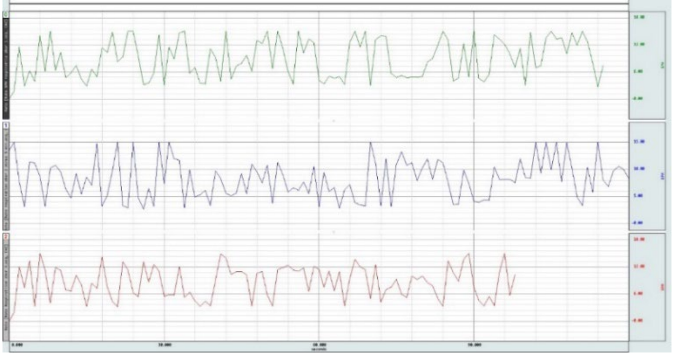


Fig. 6 – Respiration rate (BPM) during three simulated flights

5.2 Cerebral waves - Alpha Band Power (ABP), Beta Band Power (BBP), Delta Band Power (DBP), Theta Band Power (TBP), Gamma Band Power (GBP)

Alpha waves, generally oscillating within the frequency range of 8 to 13 Hz, are linked to states of relaxed wakefulness, diminished sensory input, and minimal cognitive activity. When a person performs tasks that call for prolonged focus or sophisticated cognitive processing, their amplitude usually decreases [20].

Alpha band activity analysis in the current study showed different patterns in each of the three flying scenarios that were simulated. Alpha activity exceeded 20 Hz and showed noticeable rhythmic fluctuation during the first flight, suggesting a calm but attentive state compatible with a low task difficulty. Alpha power was more consistent and stayed below 10 Hz throughout the second simulated flight, which took more mental effort because of the turbulence, indicating increased focus and attentional involvement. Alpha activity increased during the third flight in comparison to the second flight, although it did not surpass 20 Hz, indicating a partial return of relaxation that may be connected to emerging fatigue. So it confirms the state equation from mathematical model.

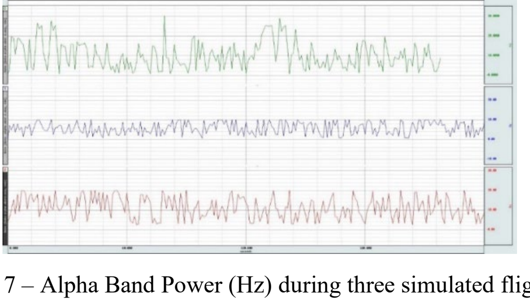


Fig. 7 – Alpha Band Power (Hz) during three simulated flights

Wakefulness, focused attention, and active cognitive processing are all linked to beta waves, which typically oscillate between 13 and 30 Hz. In all of the simulated flight situations in the current investigation, beta activity showed a maximum frequency of about 3 Hz, with a noticeable increase during the landing phase.

The increased cognitive load, motor coordination, and sustained focus needed for the exact control of the airplane during this demanding period of flight are probably reflected in this increase in beta power.

On the other hand, compared to the previous trials, beta wave activity significantly decreased during the last flight, with a higher percentage of frequencies falling below 1 Hz. This attenuation of beta activity, which suggests decreased cortical activation and attentional engagement, can be interpreted as an electrophysiological marker of fatigue. These results are consistent with neurophysiological data and mathematical model that shows reduced beta power is frequently linked to lower arousal and less mental effort when doing lengthy or repetitive tasks.

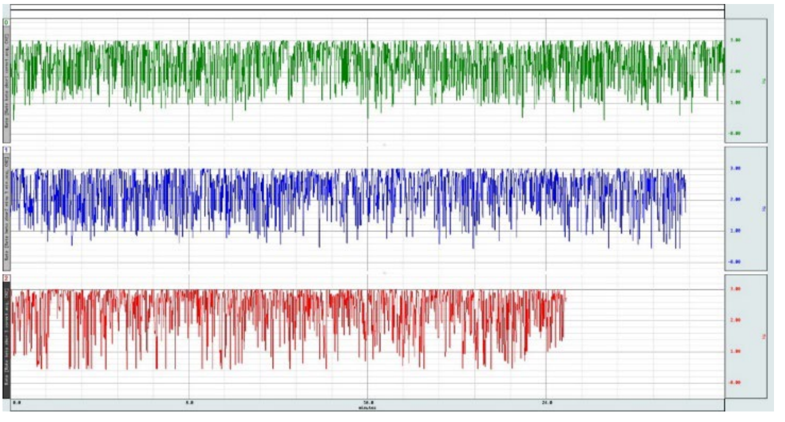


Fig. 8 – Beta Band Power (Hz) during three simulated flights

Delta waves are low-frequency brain oscillations, typically ranging between 0.5 and 4 Hz, and are predominantly associated with deep, restorative stages of sleep (slow-wave sleep). In awake individuals, elevated delta activity is often interpreted as an indicator of extreme fatigue, drowsiness, or reduced alertness, reflecting a shift toward lower cortical arousal and diminished cognitive processing [21].

In the context of the current experiment, the analysis of delta wave activity across the three simulated flight scenarios revealed no substantial differences between the first and the second flights, suggesting that the pilot maintained a consistent level of wakefulness and cognitive engagement throughout these trials. However, a decrease in delta wave amplitude was observed during the third flight.

This reduction indicates that, despite the cumulative workload and exposure to multiple flight simulations, the pilot did not reach a level of physiological fatigue severe enough to induce drowsiness or impaired alertness.

From a neurophysiological standpoint, this outcome implies that the pilot's cortical activation remained relatively high, supported by continued sensory and cognitive engagement with flight tasks.

In typical fatigue or pre-sleep conditions, (according to state equation) delta power would increase as a compensatory mechanism reflecting reduced neural responsiveness and attentional decline. The observed decrease, therefore, reinforces the interpretation that the pilot remained attentive and responsive, even during the final stage of the experimental session.

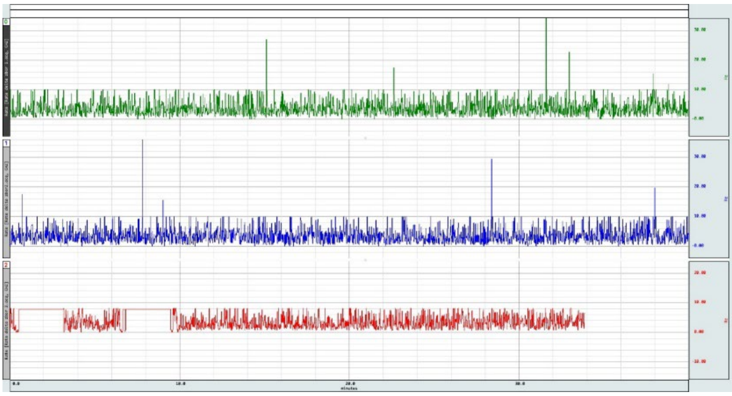


Fig. 9 – Delta Band Power (Hz) during three simulated flights

Theta waves, which typically oscillate between 4 and 8 Hz, are frequently linked to transitory states of consciousness including light sleep, contemplative calm, or the initial stages of drowsiness. Reduced cortical arousal and a shift toward introspective or low-attention mental states are commonly associated with elevated theta activity [22].

Analysis of the theta wave patterns in the three simulated flight scenarios in the current study showed similar activity in the first two flights, both of which had frequencies above 9 Hz and rather high amplitudes. This pattern indicates that during these flight sessions, sufficient attention and alertness were maintained, indicating a balanced cognitive state. During the third simulated flight, however, there was a decrease in the frequency and amplitude of theta waves, with peak activity occurring at about 8 Hz. Rather than a shift into drowsy or meditative states, this decline shows prolonged awake and active participation in task execution.

Consequently, the observed decrease in theta activity during the final flight supports the interpretation that, despite accumulated workload, the pilot maintained effective cognitive control and vigilance throughout the experimental session.

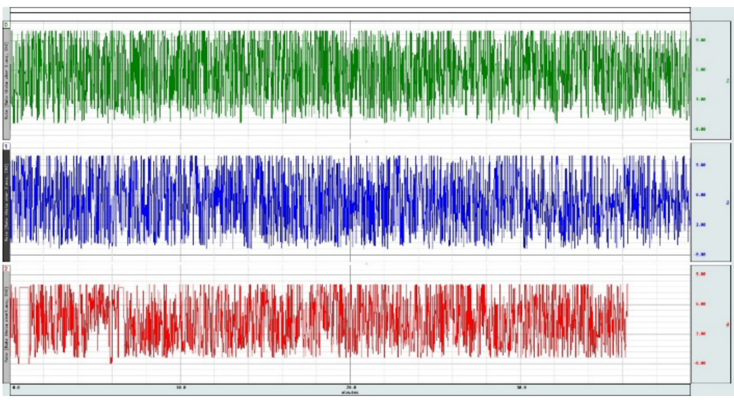


Fig. 10 – Theta Band Power (Hz) during three simulated flights

The highest-frequency band of cerebral oscillations is represented by gamma waves, which typically range from 30 to over 100 Hz. These waves are linked to intense cognitive processing, focused attention, and information integration across brain networks. They are frequently seen as indicators of increased working memory activity, prolonged focus, and perceptual awareness [23].

Analysis of the gamma frequency band in the current investigation showed consistently high activity levels with frequencies higher than 100 Hz in all simulated flying scenarios. This suggests that there was constant cognitive activity during the trial. Interestingly, the pilot showed the highest level of concentration and mental alertness at the start of the experiment, as evidenced by the fact that gamma wave amplitudes were highest on the first flight. The gradual onset of mental exhaustion or decreased cognitive intensity as task repetition and duration increased may be the cause of the subsequent decline in gamma activity during future flights.

These results are consistent with well-established neurophysiological research showing that gamma activity tends to diminish under tiredness or lower engagement and increases during tasks requiring sophisticated cognitive operations or sustained attention. Therefore, significant insights into changes in the pilot's cognitive state and mental stress during simulated flight performance can be gained from the observed variations in gamma power throughout the flight scenarios.

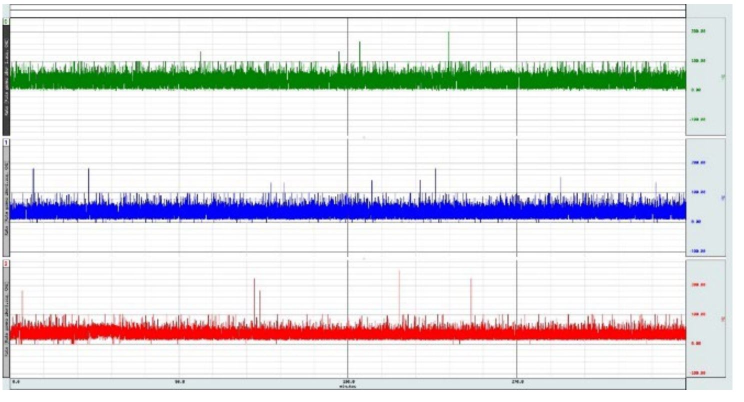


Fig. 11 – Gamma Band Power (Hz) during three simulated flights

5.3 Eye Tracker data – Pupil diameter (PD) and eye blink rate (BR)

According to established scientific literature and proposed mathematical model, as fatigue intensifies pupil diameter typically decreases, reflecting reduced physiological arousal and diminished sympathetic activation.

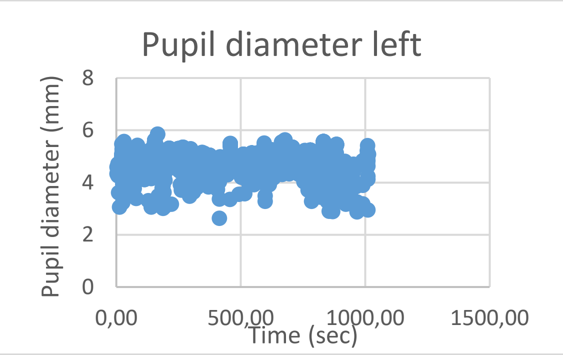
The right-eye pupil diameter did not, however, differ significantly between the three simulated flying scenarios, according to the analysis of the current data. With a minor rise observed on the second and third flights, the recorded readings stayed mostly constant, ranging from 3 mm to 6 mm.

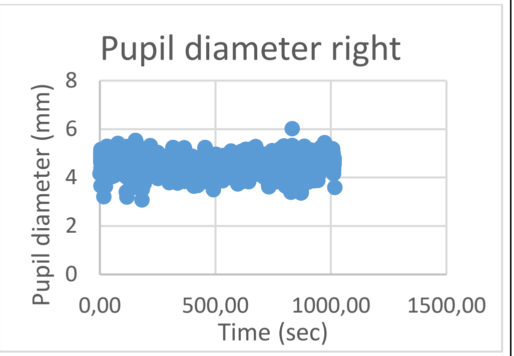
Examining the left-eye pupil diameter, on the other hand, revealed a distinct pattern, with values rising from the first to the second flight and then falling during the last scenario, reaching a maximum of approximately 5.5 mm. This asymmetry between the two eyes may be attributed to external factors rather than physiological differences. Specifically, the lighting conditions within the simulator could have influenced the measurements, as the pilot was seated on the left side of the cockpit, where onboard instruments and display panels are predominantly positioned on the right side, thereby exposing the right eye to greater illumination and potentially affecting pupil constriction.

Overall, these results imply that the little differences in pupil diameter between the two eyes were probably caused by environmental lighting circumstances rather than physiological fatigue effects.

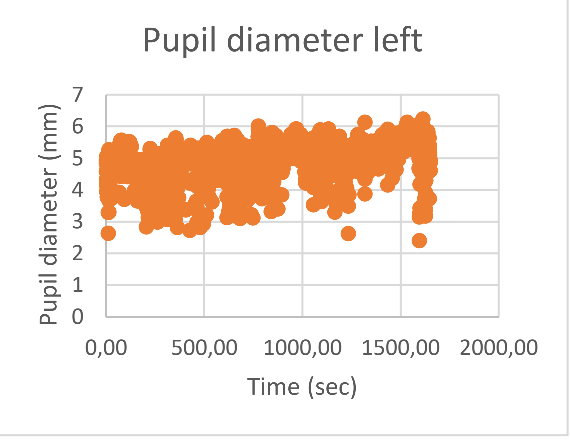
Table 3 – Pupil diameter for left eye and right eye during three simulated flights

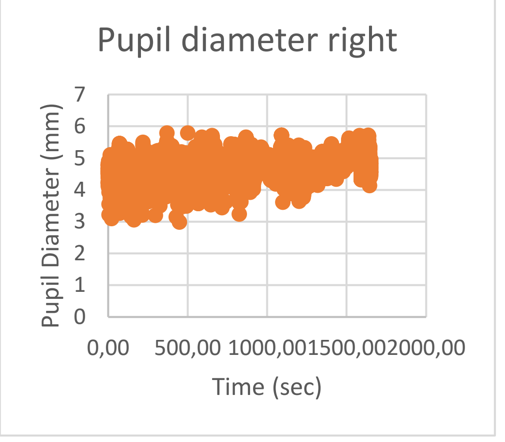
First flight



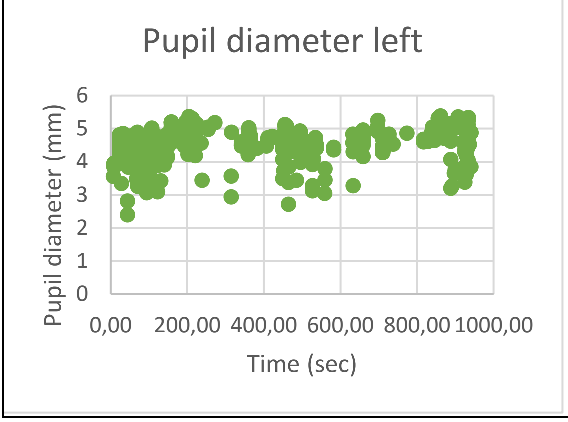


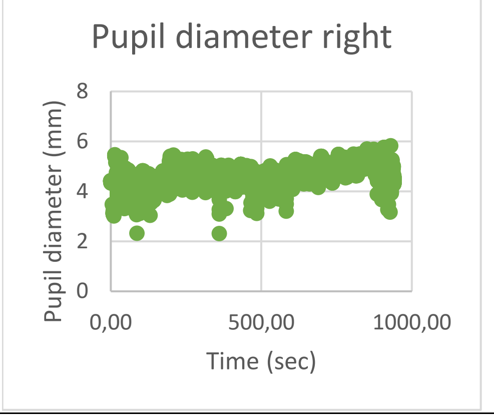
Second flight





Third flight





A reliable physiological measure that is frequently used in studies on attention and alertness is blink rate. According to scientific literature and mathematical model, a reduction in blink frequency corresponds to increased attentional demand or sustained vigilance, as individuals tend to suppress blinking during tasks requiring continuous visual or cognitive engagement.

Analysis of the data in Table 4, however, shows that the blink rate did not decrease but rather exhibited an overall increase across the experimental conditions. This trend may be interpreted as evidence that the pilot maintained a high level of concentration throughout the entire simulation, reflecting active engagement rather than diminished vigilance.

It's also noteworthy that the eye-tracking equipment collected a greater volume of data from the right eye, which may be attributed to variations in lighting conditions within the simulator. Similar to the findings regarding pupil diameter, the uneven illumination likely affected the accuracy and amount of data collected, resulting in discrepancies between the two eyes.

Table 4 – Blink Rate (BR) for left eye and right eye during three simulated flights

Flight phases Flight 1	Blink Rate left eye (Hz)	Registered data	Blink Rate right eye (Hz)	Registered data
Pre-flight	0,061	335	0,262	2078
Take-off	0,131	665	0,350	4906
Cruise	0,771	4611	0,993	22153
Turbulence	no turbulence	no turbulence	no turbulence	no turbulence
Landing	*5,61E+10*	25	0,077	444

Flight phases Flight 2	Blink Rate left eye (Hz)	Registered data	Blink Rate right eye (Hz)	Registered data
Pre-flight	*5,61E+10*	3	*5,61E+10*	21
Take-off	0,141	799	0,138	4582
Cruise	2,552	1339	5,216	11688
Turbulence	0,330	2029	0,162	5797
Landing	0,108	692	0,104	2683

Flight phases Flight 3	Blink Rate left eye (Hz)	Registered data	Blink Rate right eye (Hz)	Registered data
Pre-flight	0,692	203	6,145	2538
Take-off	0,333	94	7,402	6080
Cruise	0,566	177	6,386	9071
Turbulence	0,161	50	10,432	5209
Landing	0,235	8	10,329	784

Another tool of assessing attention and vigilance is the gaze plot (fig. 12), where numerical labels indicate the sequential order of visual fixations, while the size of each circle indicates the length of fixation, with larger circles denoting longer fixation times.

The Primary Flight Display (PFD), which offers critical flight parameters like airspeed, altitude, aircraft attitude, and navigational data, and the Multi-Function Display (MFD), which displays supplementary information like radar imagery, engine performance indicators, meteorological conditions, and external temperature readings, were the primary sites of the longest fixations, according to the analysis of the gaze plots for all three simulated flight scenarios.

It is also noteworthy that during the take-off and landing phases, the pilot directed visual attention outside the cockpit more frequently than during the cruise phase.

Fig. 12 – Gaze plot illustrating visual attention distribution across the three simulated flight scenarios: Flight 1 (grey), Flight 2 (green), Flight 3 (blue) – alongside the flight deck layout for Beechcraft King Air C90 Flight simulator

6. CONCLUSIONS

Although the main goal of the current investigation was to validate the suggested mathematical model, the results of the experiment showed that the subject was not sufficiently fatigued to show the shift from wakefulness to drowsiness. As a result, a number of physiological indicators, including heart rate, heart rate variability, and respiration rate, did not significantly change and, in certain cases, showed an unexpected increase instead of the expected drop. On the other hand, cerebral frequency bands—alpha, beta, delta, theta, and gamma—show notable changes when cognitive activity declines as a result of weariness, making electroencephalography (EEG) a more useful technique for evaluating fatigue than electrocardiography (ECG). Furthermore, although though theta and gamma band power were not originally included in the suggested mathematical model, they were also examined.

Furthermore, eye-tracking technology constitutes an appropriate tool for the analysis and monitoring of attention and vigilance. Pupil diameter and blink rate are markers of attentional level, and the assisted mapping function used for eye fixation analysis makes it possible to identify focal areas within the cockpit. However, it should be noted that the accuracy of eye-tracking data may be slightly impacted by experimental settings, especially lighting fluctuations.

This experiment serves as a preliminary investigation for more extensive future studies, as the equipment was tested within a full-motion flight simulator, where factors such as vibration and ambient noise may introduce potential sources of interference. Moreover, the participant's familiarization with the experimental setup is expected to reduce emotional reactivity in subsequent trials, thereby minimizing the influence of adaptation or stress-related effects on the physiological measurements.

The results of this investigation show that while certain variables behave in a way that is consistent with the suggested mathematical model, others do not follow the expected pattern. As a result, more measurements are needed to guarantee the robustness and validation of the model. Additionally, it is anticipated that the accuracy and dependability of the variable estimations would gradually improve as the number of observations rises.

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