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Use of Dry Electrode Electroencephalography (EEG) to Monitor Pilot Workload and Distraction Based on P300 Responses to an Auditory Oddball Task

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Abstract. This study aims to examine whether dry electrode EEG can detect and show changes in the P300, in a movement and noise polluted flight simulator environment with a view to using it for workload and distraction monitoring. Twenty participants completed take-off, cruise and landing flight phases in a flight simulator alongside an auditory oddball task. Dry EEG sensors monitored the participants' brain activity throughout the task and P300 responses were extracted from the resulting data. Results show that dry EEG can extract P300 responses as participants register oddball tone stimuli. The method can indicate workload for each condition based on the outputs from the EEG electrodes; landing (M= 287.5) and take-off (M= 484.6) procedures were more difficult than cruising (M= 636.6). With the differences between cruising and landing being statistically significant (p = .001). Outcomes correlate with participant NASA-TLX scores of workload that report landing to be the most difficult.

Keywords: P300 · flight simulation · workload · dry EEG · Human Factors · NASA-TLX

1 Introduction

1.1 The P300

Electroencephalography (EEG) is an electrophysiological monitoring method which is used to record electrical activity of the human brain from multiple electrodes/sensors placed on the scalp [1]. Event-related potentials (ERPs) are often extracted from the EEG signal. An ERP is a measured brain response that is generated by the brain as a result of and related to, a specific sensory, cognitive or motor event occurring internally or externally [2]. ERPs are particularly useful as they can be recorded noninvasively whilst also providing a range of useful information about cognitive processes such as stimulus detection and attention. When recorded by EEG, the P300 (sometimes referred to as P3 or P3b in literature) surfaces as a positive deflection in voltage with a latency of roughly 250 to 500 ms (**Fig.1**) [3].

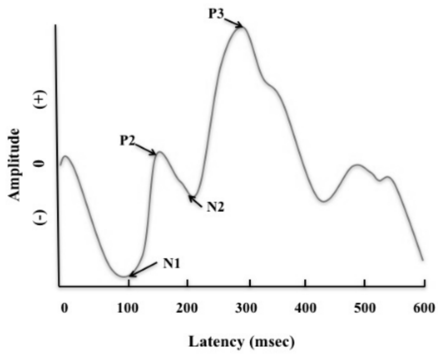

Fig.1 An image of a P300 response to an unexpected stimuli (image from Waryasz 2017 [4])

The P300 amplitude is sensitive to the amount of attentional resources engaged during dual-task performance. Normally a primary task varying in cognitive demand is completed whilst the participant is engaged in a secondary task of mentally counting visual or auditory oddball stimuli. As the primary task increases in difficulty the P300 amplitude decreases. This is due to the primary task taking up more mental resources, thereby less are available to devote to the secondary oddball task. Hence, the amplitude of the P300 decreases to reflect the decrease in attentional resources devoted to the task. This occurs regardless of the modality of the primary task [5].

1.2 EEG and Flight Simulation

Since EEG emerged in the 20th century, there has been little variation in how EEG is measured. Currently manufacturers and researchers are moving towards developing wireless, mobile-based EEG and this has driven the development of alternative electrodes for physiological monitoring. The conventional wet adhesive Ag/AgCl electrodes used almost universally in clinical applications today provide an excellent signal but are not compatible for mobile use [6]. Technological advances in the area, such as a new generation of dry electrodes and wireless EEG caps, have opened the way for EEG to now be used in a much wider range of instances and places even more of a priority on developing aspects such as usability and signal quality [7]. In their review of the dry sensor EEG development, Lopez-Gordo et al. (2014) [7] suggest that although a broad diversity of approaches have been evaluated without a consensus in procedures and methodology, performance is not far from that obtained with wet electrodes. Hence, dry electrodes can be considered a useful tool in a variety of novel applications. One area of interest for dry electrode EEG is flight simulation. A wireless and portable EEG headset allows for more accurate flight-testing as pilots can interact normally without concern for wiring. A concern of utilising dry EEG however is that the movement of these dry electrodes against the scalp can severely interfere with the EEG signal, hence, research has been trying to resolve the issue [6].

Callan, Durantin, & Terzibas (2015) [8] utilised dry EEG in a motion platform based flight simulator and compared this to an open cockpit biplane to determine if the technology can be used in such a noise-polluted environment. Their participant completed a passive task using random auditory presentations of a chirp sound (as this would not interfere with the flight task), to illicit ERPs. Their investigation suggested that dry EEG can be used in an environment with considerable vibrations, wind, acoustic noise and physiological artefacts and still achieve good single trial classification performance necessary for successful measurement.

However, Callan et al's [8] study only used one subject and used a 72 electrode cap (of which only a maximum of 46 were not rejected from each condition). The study proposed here aims to use a smaller dry EEG headset (with a smaller number of electrodes: 8) positioned based on prior research to locations showing the effectiveness of the parietal (P3, Pz and P4) sensors in recording the P300 and their neighbouring locations (C3, Cz and C4). Parietal locations have been established as areas more sensitive to the presentation of the P300 ERP and have been used in many P300 studies e.g. [9]. Additional measurement was taken at Oz and Fz as the P300 can be detected along the midline. This experiment will use more participants to gauge the effectiveness of the dry EEG across multiple individuals and will also utilise the oddball task (a task known for eliciting the P300 in neuroscientific research [10] and varying levels of flight complexity to manipulate workload). In other words this experiment is a development of Callan et al. (2015) [8] to evaluate the usefulness of portable dry EEG with multiple subjects in monitoring workload changes and attention allocation in a flight simulator setting.

2 Method

2.1 Equipment

Flight Simulator. The MP520 Engineering Flight Simulator configured to the default Cessna C172 was used in this experiment (**Fig. 2i**). The C172 is a single-engine, fixed wing aircraft. The model encapsulates a number of hardware systems within the main components, which include the cockpit housing, and the Instructor Operator Station (IOS). The simulator is equipped with flight and engine controls including; the control side-stick for pitch and roll control, rudder pedals for yaw and two throttle levers to control thrust. Switches operate flaps, spoilers, landing gear and brakes. As inexperienced participants were used, all flight performance data was displayed on a head-up display (HUD) overlaid on the visual scene. The communications system included a headset, which enables cockpit communication to the IOS intercom. Flight data, such as altitude, pitch and speed, were automatically recorded. The data logging rate was set to 1Hz. The data was recorded as an Action Script Communication file (.ASC) which was exported to Microsoft Excel for analysis.

EEG Enobio 8. Enobio (Neuroelectrics, Barcelona, Spain; **Fig.2ii**) is a wearable, wireless EEG sensor with 8 EEG channels and a triaxial accelerometer, for the recording and visualisation of 24 bit EEG data at 500 Hz. The Necbox is the core and the control unit of Enobio. The Necbox is a battery-operated device that connects through Bluetooth to the Neuroelectrics Instrument Controller (NIC) software running on a computer. The 10-electrode cable contains 8 channels, numbered from 1 to 8, for EEG monitoring, and two reference channels labelled with CMS and DRL. The Ear clip is an easy-to-use alternative to the sticktrode. It is a dual reference electrode because it is used to connect the two reference channels, CMS and DRL, to the same earlobe. A Neoprene Cap holds the sensors in place. In this study the locations Fz, Cz, C3, C4, Pz, P3, P4 and Oz were used (**Fig. 2iii**).

Fig. 2 Experimental design; i) Merlin Flight Sim , ii) ENOBIO set-up, iii) Sensor locations

Paradigm set-up. Audacity software was used to cut a 1000Hz soundtrack into a sound file 0.06 seconds long. A 0.01 second period of silence was played before 0.01 seconds of a fade in, 0.03 seconds of sound and 0.01 seconds of fade out (0.05s sounds have been used in literature e.g. [11]. This fade-in and fade-out effect smoothed the tones. The same was done for a 2000Hz soundtrack. PsychoPy software was used to create a two-tone oddball paradigm. A Psychopy database was set up to schedule the presentation sequencing and onsets of the normal and oddball stimuli. This way all participants will receive the same number of normal and oddball tones and at the same points of the trial. Three different sequences were created; one for each of the three trial types. In Psychopy a basic task was created with in introductory screen, an inter-stimulus interval (ISI), tone and end aspects. A loop was created around the ISI and tone to run for the length of the Excel file. Lastly, the Psychopy code was edited to incorporate a Lab-Streaming Layer which was linked to the Enobio recording software, NIC. This sent markers to the EEG recording to mark when a sound occurred and what type of sound occurred in the recording to isolate ERPs.

2.2 Procedure

Participants were pre-screened for the experiment by a self-exclusionary medical requirements sheet. Accepted participants were assigned a two hour slot in which to complete the experiment. On the day, participants were briefed on the experiment, the EEG cap function and reminded to move their heads as little as possible throughout. The participant signed a consent form and the EEG cap was fitted with the ear clip attached to the left ear as a reference. Lastly, an impedance reading was taken using a multi-meter (readings above 0 and below 20 kΩ were acceptable and all participants fulfilled this requirement prior to testing). Any issues, for instance signal problems or sensor-scalp contact, were identified and remedied at the beginning of the experiment.

Participants then completed a 3-trial learning session of their first procedure using the flight simulator. One trial with a verbal talk through of the procedure and one without, and an optional third trial if their performance could be improved. The participant then completed a recorded independent flight procedure. Next, participants were introduced to the oddball task and were given a 30-second practice session to aid familiarisation with the normal and oddball tones. The communications system operated via two headsets, one for the pilot and one for the instructor. When the oddball task was occurring, the instructor placed the headset at the speaker of the laptop to transfer the sound to the pilot's headset. There was no echoing of the sound due to the enclosure of the simulator. Participants then repeated the flight procedure with the listening task. This flight learning sequence was repeated for each of the three trials.

Trials were randomised between participants to help remove learning effects e.g. some started with take-off and others with cruising or landing. Furthermore, the first half of participants completed the control flight condition first and the second half completed the oddball flight condition first.

At the end of each trial a NASA-TLX questionnaire was given to participants i.e. after take-off, cruising and landing. The NASA-TLX is a useful self-report measure to gauge participants' own opinion of how difficult the task is [12]. Participants were instructed to rate each of the six dimensions a score from 0-20 and the raw scores were used for analysis purposes. Participants were also given additional questions asking how well they followed the instructions, how well they feel they performed and which of the three flight procedures was the most difficult in their opinion.

2.3 Data Analysis

EEG recordings were imported into the EEGLAB [13] add-on for Matlab (a software programme that enables analysis and design processes using Python coding) where they were pre-processed. Channel locations were then added and data was filtered using a 0.5Hz high pass filter and a 40Hz low pass filter. Using ERPLAB (a plug-in for the EEGLAB software [14]) the EEG file was epoched (the extraction of time windows) from 200 ms pre-stimulus (before the marker) to 800 ms post-stimulus (after the marker). The data was also baseline corrected to the period pre-stimulus.

Once data was epoched, artefact rejection techniques available in ERPLAB were utilised to identify 'bad' epochs. The techniques used were moving window peak-to-peak threshold, simple voltage threshold, blocking and flat lining, Sample-to-sample threshold and rate of change. If a bad channel was identified the channel would be removed from the artefact rejection phase as it would result in all epochs being flagged for rejection. Once 'bad' epochs were flagged, the data was viewed to manually identify any visual trials not picked up by the artefact rejections techniques. These epochs were then removed from the dataset. A median ERP was calculated for each sensor in each condition for each participant (8 x 3 x 20). Once this was done the mean across the sensors and conditions was found (8 x 3). From these mean waveforms the area under the curve was calculated using the Trapezium rule in Matlab to quantify the difference in P300 responses.

Flight performance was measured on the basis of how accurately participants followed the instructions e.g. percentage accuracy in the timing of meeting task requirements. For example, raising the landing gear at 250ft following take-off. A further measure was the monitoring of participants pitch and altitude over the course of the trial and comparing to the average to gauge any deviations in flight path. The final measure taken from participants was their self-reported workload and task difficulty in the NASA-TLX.

2.4 Hypotheses

Flight performance- performance will be consistent between the oddball and non-oddball flight conditions due to participants prioritising the manual flight task over the listening task.

Oddball performance- accuracy of the oddball task will be affected by the type and complexity of flight task; the cruising flight task will show the greatest accuracy. A greater margin of error is more likely for landing and take-off as these are more difficult and place a greater load on working memory, landing will show the biggest error as this is the most difficult and time pressured task.

ERP analysis- outputs will show that with increased workload the P300 amplitude and area will decrease. Tones may be missed due to prioritising the flight task over the oddball when in conditions of higher workload. In the cruising task the area will be the greatest as this is the least demanding task, followed by take-off and landing.

NASA-TLX- subjective workload measures will be higher for the landing and take-off tasks than for cruising. Landing will be perceived as the most workload inducing task, followed by take-off and cruising rated as being relatively easy compared to the other trials.

3 Results

3.1 Physiological Measures- Oddball Performance and ERP Outputs

Results for the oddball task showed that participants were the most accurate in the cruising condition (Mean estimate error = -0.96%) and least accurate in the landing condition (Mean estimate error = +4.48%). Performance in the take-off condition fell in between (Mean estimate error = +1.40%). This could imply that participants were not attending the oddball task as much in the landing scenario and were attending the task more in the cruising condition. **Fig. 3** below shows participant's percentage error in the task.

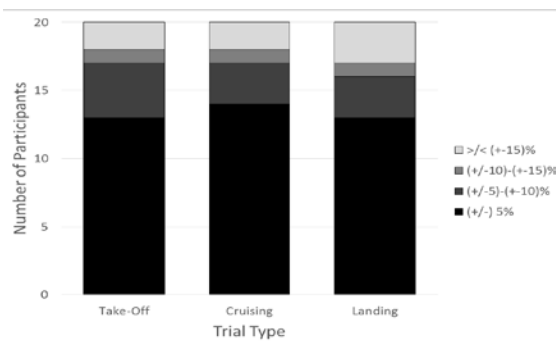

Fig. 3 Participant percentage error in the Oddball counting task

Some participants also appeared to struggle with the take-off task. Three participants performed perfectly in the oddball task across all three conditions. As stated previously, gaining a score of less than 75% in the oddball task would mean the participant has not fulfilled the task adequately; from the information above, two participants (P14 and P18) failed the task during take-off, two participants (P17 and P18) failed the cruising oddball and three participants, (P17, 18 and 19) failed the landing task. P18 failed all three listening tasks by over- or under-estimating the number of oddball tones in the task.

From individual ERP outputs, a grand average was calculated for each procedure and the graphical outputs below show the wave pattern for each sensor. Fz, Cz and Pz are the core areas for measurement of the P300 and these are the sensors displayed below. The C4 and P3 sensors were more difficult to get reliable readings from due to variability in participant head shape and suffered from offset interference in cases. As a result, they are excluded from the results; below in **Fig. 4** the average P300 measurements are displayed for each flight task.

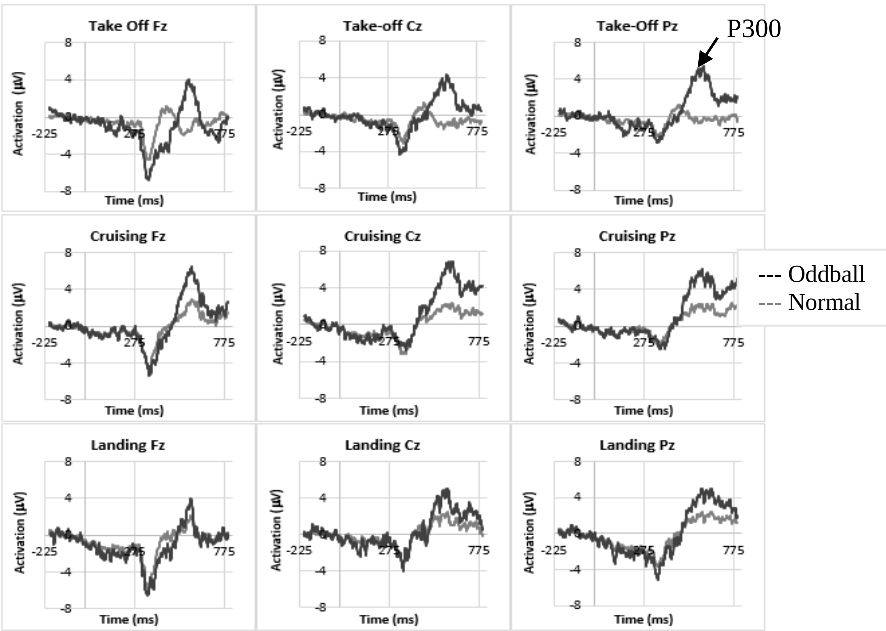

Fig. 4 ERP outputs for Fz, Cz and Pz sensor locations across the flight tasks

From **Fig. 4** it appears that the cruising and take-off conditions show more activation than the landing condition, indicating that more attention is devoted to the oddball task in these conditions. In order to analyse the relative activation differences between flight procedures a positive waveform analysis was carried out using the trapezoidal method on all positive inflections to quantify the area under the curve between 450ms and 798ms. The comparison between areas is shown in **Fig. 5.**

From **Fig. 5** is it apparent that cruising shows the most activation at for all channels but shows similar activation to take-off at Pz. From the proposed theory of activation representing attentional resource allocation. This shows that participants devoted more attention to the oddball task in the cruising condition. This is also reflected in their oddball performance, as the performance in the task was more accurate. The reverse pattern is found in landing in which less attentional resources are allocation to the oddball task according to the area under the curve for the ERPs and this coincides with this being the task in which oddball performance was the poorest.

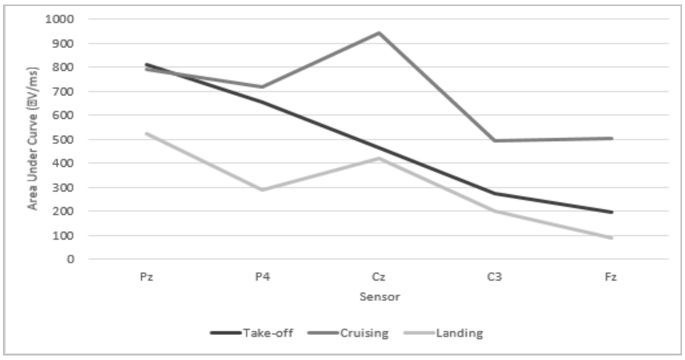

Fig. 5 Positive Waveform Analysis for each flight procedure with respect to the sensor location (parietal to frontal locations)

T-tests were used to measure any significant differences in area between conditions (Bonferroni correction, p = .0167) only the difference between cruising (M= 636.6, SD = 46489.5) and landing (M= 287.5, SD = 24997.7) was statistically significant (t (6) = 6.62, p = .001). There was no significant difference between take-off (M= 484.6, SD = 52212.5) and cruising (p = .160) or take-off and landing (p = .017).

3.2 Subjective Measures- NASA-TLX

The NASA-TLX measures individuals' subjective opinions on six factors. For the purposes of this experiment, these have been divided into two categories, demand and performance. For demand the higher the score the more difficult the task was and for performance the higher the score the worse people felt they performed and the more effort and frustration the task inferred on the participant. Results from the questionnaire show cruising to have the lowest demand and lowest performance of the three tasks (Demand= 16.30, Performance= 21.45). Take-off came in between (Demand= 23.10, Performance = 23.25) and landing had the highest demand and highest performance (Demand = 26.80, Performance= 27.50).

This coincides with the ERP outputs as less attention was devoted to the oddball task in the landing and take-off procedures than to the cruising. In terms of performance, participants felt they performed the best in the cruising task and least well in the landing task as a higher score reflects the performance, effort and frustration involved in the task. Two Freidman rank tests were carried out, one for demand and one for performance rankings. For demand, the Friedman test showed there was a significant variation in demand across the three conditions (χ^2 (2, N=20) = 12.342, p = .002). Wilcoxon signed rank tests (adjusted p = 0.0167) showed that only the difference between cruising (Mean Rank= 2.58) and landing (Mean Rank = 1.50) ranks were significant (W= 8.67, N=20, *p* = .005) with landing being significantly more demanding than the cruising condition. There was no significant difference between take-off (Mean Rank= 1.93) and cruising (*p* = .025) or between take-off and landing (*p* = .163). The Friedman test for performance showed there was a significant difference in performance between the three conditions (χ^2 (2, N=20) = 6.911, *p* = .032). Here the Wilcoxon signed rank test showed no significant interactions between take-off (Mean Rank = 1.98) and cruising (Mean Rank= 2.43, *p* = .205), cruising and landing (Mean Rank= 1.60, *p* = .024) and between take-off and landing (*p* = .115) when the adjusted *p*-value is used.

3.3 Performance/ Behavioral Measures- Flight Task Performance

Take-off. Participants' were instructed to pitch up to 15 degrees at a speed of 65 knots and maintain this until 1000 ft where they were to use pitch control to attempt to remain at 1000 ft for the remainder of the trial. Landing gear was to be retracted at 250 feet. Performance in the ascent was relatively consistent for participants. The range of maximum deviation from the average altitude was 76.23 feet to -64.85 feet from average for control conditions and 83.66 feet to -77.97 feet in the oddball condition (P9 data was excluded from the deviation analysis for the control as they veered off course halfway through the ascent under control conditions). The Regarding pitch control, the range of maximum deviation from the average was 7.55 to -11.07 for the control condition and 13.56 and -9.26 for the oddball condition. Lateral control of the plane can be an issue for some participants; one participant veered as far as 454m left of the straight course in the control condition and one participant veered over 1000m to the right in the oddball condition. For take-off, participants had to pitch upward at an indicated speed of 65 knots. Generally, participants followed this instruction very well. All participants took off very close to 65 knots, 75% were within 5% of the target speed for the control flight and 70% for the flight with the listening task, the remaining 15 and 20% respectively, fell within 10% of the target speed. Another instruction was to retract the landing gear of the aircraft at an altitude of 250ft. Participants were much less accurate at raising the landing gear at 250ft; two of the twenty participants completely forgot to perform the task in the dual-task condition. Two people fell outside 15% of the target altitude in the normal condition and one in the dual-task. One participant in each condition was between 10 and 15% of the target.

Cruising. For this procedure participants had simply to maintain their altitude at 1000ft by controlling the pitch of the aircraft. Regarding staying at 1000ft participants performed reasonably well, for the control condition participants flew with a deviation range of +9.61% and -11.2% of the target 1000 ft. For the oddball condition performance was more or less the same with a deviation range of +5.06% and -17.18% of the target 100ft range. Similar to take-off, lateral control was the most inaccurate part of the procedure. In the control condition deviation ranged from 410.53m to the left rom start point to 241m to the right, interestingly the oddball condition range was larger with one participant veering as far as 912.18m off course yet another participant held the straight trajectory perfectly for the entirety of the trial.

Landing. In this procedure participants had to descend from an altitude of 2000ft at a pitch of -3 degrees to land on the runway and deploy the landing gear and flaps at 500ft of altitude. Generally, participants performed consistently on their descent

(135.13ft above and 182.29ft below the average in the control flight and 239.22ft above and 239.47ft below in the oddball condition). Once participants reached the point of switching on the flaps and landing gear, however, the flight path deviation was the greatest (455.03ft above and 259.81ft below the average path in the control and 312.16ft above and 313.89ft below in the oddball condition). The average pitch for the trial was -3.58 in the control with a range of +26.73 to -11.91 and a -3.58 average in the oddball with a range of +27.73 to -11.03. This shows participants tried to maintain the -3 degree pitch throughout, the deviations in range are mainly when the flaps are deployed as this causes lift in the aircraft, which is more difficult to control. All except one participant successfully landed on the runway in both conditions, one participant over shot due to not deploying the flaps completely and losing control of the descent. Only one participant deployed the landing flaps outside of a 15% error rate, all the others were +/-15% in accuracy.

4 Discussion

As predicted in our hypotheses, the dry electrode EEG was sensitive enough to detect changes in the P300 in a movement and noise polluted environment. This agrees with the research carried out by Callan and colleagues in their 2015 study [8]. Further to this, the method used above allowed for further ERP analysis to determine positive waveform area. The results support the hypothesis in that largely cruising area was higher than take-off and landing had the smallest area overall.

The t-tests carried out on the positive waveform analysis showed that the difference between cruising and landing conditions was significant but not between take-off and cruising and take-off and landing. This makes sense when the task requirements are considered. Take-off was considered an intermediate workload as it has some of the pressure and workload involved in landing and then becomes more similar to cruising as the trial continues. It follows that take-off is not significantly different from either of those tasks. Whereas, cruising is a consistent monitoring and marginal adjustment task, landing is a focused procedure that requires manual interaction with the simulator, thresholds to meet and a target. Hence, the tasks differed from each other on level of difficulty with cruising being easiest, landing being the most difficult and take-off falling somewhere in-between. The results showed that landing is significantly more difficult than cruising but neither are significantly different from take-off.

The results of the subjective NASA-TLX measure of this experiment showed Cruising to be the easiest task according to the demand questions and participants felt marginally more content with their performance in cruising than the other tasks. When t-tests were performed, the only significant difference was between the demand of cruising and of landing. This corresponds to the effect we see in the ERP analysis. Interestingly there were no significant differences in performance scores and this also reflects the effects we see in the flight data. This could reflect a task-prioritisation coping mechanism that has been seen throughout research and specific instructions can lead to prioritisation [15]. Yogev-Seligmann, et al. (2010) [15] found that adults significantly increased gait speed compared to the control condition when told to prioritise gait. Gait speed was reduced when priority was given to the cognitive task. In this study, participants were given no particular instructions on which of the two tasks to prioritise (flight/listening task), it could be that the lack of prioritisation meant participants prioritised the ecologically valid flight task; the task that in reality could have serious consequences if not performed adequately. In future work it may be interesting to see how participants cope when told to prioritise one task over another.

As predicted, flight performance did not vary significantly between normal and oddball conditions. This could support the theory that individuals when faced with dual task conditions prioritise the primary task [15]. In terms of oddball performance, the average percentage error did change with task in that landing had a higher average percentage error but this was still within 5% of the actual answer. Take-off average was within 2% accuracy and cruising average was within 1% average accuracy. What is interesting in the study is the diversity with which participants adapted to aircraft control. P1 struggled in lateral control of the simulation in the normal condition but not as much in the oddball condition for take-off. A possible explanation could be practise effects (as they completed the normal condition first and completed the take-off procedure first). A recent study [16] showed that both implicit and explicit knowledge help in dual task performance i.e. knowledge gained from single task conditions can benefit performance in dual task conditions. Alternatively, it could be reasoned that divided attention made performance better. Interestingly dual task training can improve the automatisation of the primary task [17].

An interesting avenue for future research could be the effect of personality on novel task performance. The anxiety-performance relationship [18] relates to sporting achievement and the phenomenon of 'choking under pressure'. Anxiety can cause an impact on motor performance, mediated by the individual's confidence in the automaticity of performance under stress; this is termed skill establishment [18]. The more established and automatic the skill becomes, the less affected it will be by participant anxiety/ nerves. This could be a potential avenue for future investigation as well as the role of practice and how this interacts with personality.

Overall, cruising and landing show significant differences in workload with take-off workload somewhere between. This three-measurement approach to participant's workload (physiology, self-report and performance) has shown effectiveness in determining the level of workload certain conditions and procedures induce. Future work could apply the methodology to different scenarios and conditions using qualified pilots to gauge workload and the differences in how pilots cope with workload compared to inexperienced user used in this study. Whilst the procedure has shown a lot of promise, there are improvements to the methodology that could be made to investigate aspects in further detail. One improvement could be to use varied cap sizes to help with better electrode placement and participant comfort.

In conclusion, the dry electrode EEG cap has shown a great potential for deciphering ERP outputs to a small scale of analysis that are relatable to other workload measures. For instance the differences in NASA-TLX results due to phase of flight simulation were in the same direction as those of flight-phase differences in ERP positive waveform analysis. This opens up multiple avenues for future research in this, and other, disciplines.

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