Student Drowsiness During Simulated Solo Flight

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INTRODUCTION: Pilot fatigue is a significant concern in aviation, where efforts are directed at improving rosters, developing models, and improving countermeasures. Little attention has been given to in-flight detection of fatigue/drowsiness. The aims of this research were to determine whether drowsiness is an issue and explore whether infrared reflectance oculography could prove useful for continuous inflight monitoring.

METHODS: Nine university-based pilot trainees wore activity monitors and completed diaries, prior to a simulated navigational exercise of approximately 4 h, during the secondary window of circadian low. During the flight they wore a head-mounted device. Oculographic data were collected and converted into a single number, using the Johns Drowsiness Scale (JDS), with increasing values indicating greater drowsiness (range 0.0 to 10.0).

RESULTS: Peak JDS values reached 6.5. Values declined from shortly before top of descent, continuing until landing. Two of the nine participants (22.2%), reached drowsiness levels at or above a cautionary warning level, below which is considered safe for driving a motor vehicle.

DISCUSSION: The results of this study revealed the timeline and levels of fatigue that might be experienced by student pilots; showing that drowsiness is a potential issue for student pilots operating in flying conditions similar to those in the simulation. Analysis indicated that pilots are likely to experience levels of drowsiness above a cautionary warning level when modeling predicted effectiveness below 90%, indicating a potential drowsiness issue for pilots. It was concluded that oculography is worthy of further investigation for use as an objective fatigue detection tool in aviation.

KEYWORDS: pilot, fatigue, drowsiness, objective measure.

Corbett MA, Newman DG. *Student drowsiness during simulated solo flight*. Aerosp Med Hum Perform. 2022; 93(4):354–361.

Pilot fatigue is widely held as being a significant problem in modern aviation operations.[3,9] From a risk management perspective, it follows that anything that can be done to minimize this threat to safety is a positive step. However, before setting about managing or mitigating a threat, one must first determine the existence and extent of the threat. Research efforts have focused on improving work schedules, developing predictive fatigue models, and the development of countermeasures and mitigation strategies. Little effort has focused on routine continuous in-flight monitoring and detection of fatigue or drowsiness. The persisting challenge has been to find an objective tool which can be utilized to measure the fatigue state of an operator in the aviation domain, while being minimally invasive in terms of the pilot's functional operation of the aircraft. The research being reported on here is one part of an investigation of objective tools for the monitoring of drowsiness or fatigue.

Utilizing the defenses-in-depth model[7] as a basis enables the layering of fatigue defenses from the simplest through to the most complex. Within this model there are three levels of proactive action and two levels of reactive action. Level 1 involves sleep opportunity and average sleep obtained. Classically, aviation has used Level 1 defenses, such as prescriptive duty and rest rules, or fatigue modeling. Level 2 involves the actual sleep obtained, which some organizations have employed by considering prior sleep and wake information. Level 3 involves behavioral symptoms such as symptom checklists, self-reporting scales, or physiological monitoring. Once minimization through Levels 1 and 2 have done all that they can, it is still possible for fatigue to have an adverse impact on safe and

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This manuscript was received for review in October 2018. It was accepted for publication in January 2022.

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DOI: https://doi.org/10.3357/AMHP.5275.2022

efficient flight. Therefore, the ultimate aim is to detect it early and then mitigate the threat that it poses before safety is adversely impacted. This paper begins the investigation of a Level 3 tool which utilizes continuous physiological monitoring of drowsiness through infrared reflectance oculography.

In an earlier paper,[4] the author concluded that infrared reflectance oculography showed potential as a tool for monitoring the drowsiness of pilots, but noted three aspects. The author recommended validating the system as a research tool by a comparison with polysomnography, that compliance with various regulations regarding electro-magnetic interference for use in the aviation environment was needed, and that further investigation into the useability of the equipment in aircraft was warranted. Validation against standardized measures has subsequently been performed.[1,2] Electro-magnetic compliance issues, relevant to equipment use in the aviation domain, was addressed by the Royal Australian Air Force Institute of Aviation Medicine (RAAF IAM). This paper is concerned with addressing the third concluded recommendation: to evaluate the use of oculography in-flight as a drowsiness detection tool.

This study was undertaken as the first in a series to investigate whether the potential drowsiness of student pilots in a University-based pilot training program could be monitored using infrared reflectance oculography. As part of a wider investigation into in-flight drowsiness detection in pilots, this study used a simulator scenario to address the aim of determining whether drowsiness was an issue for student pilots. This would involve investigating the timeline and levels of drowsiness that might be experienced by student pilots. Secondary aims included investigation of correlations involving sleep onset latency, standardized scales, and bio-mathematical modeling.

METHODS

Subjects

The study protocol was approved by the Swinburne University Human Research Ethics Committee (Approval Number 2012/056). Each subject provided voluntary and informed written consent prior to entry into the study. Screening was performed to exclude individuals who regularly consumed large doses of caffeine (>240 mg $\cdot$ d^{-1}) or alcohol (>2 standard measures/day, where one standard measure contains 10 grams of alcohol), had any health or sleep-related issues, or had recently undertaken shift-work or transmeridian travel.

Potential subjects were recruited from a cohort of student pilots in a university-based aviation program. All subjects held Class 1 medical certificates and were licensed to fly the aircraft type being simulated in this study. Subjects all held a Private Pilot License issued by the Civil Aviation Safety Authority of Australia and were in the navigation phase of their Commercial Pilot License training. No remuneration was given for participation.

Equipment

A head-mounted infrared reflectance oculography device (Optalert®, IAM research configuration, Optalert Pty Ltd, Victoria, Australia) was utilized. The equipment was comprised of a pair of glasses that are adjusted to fit the individual's facial structure. Short pulses of infra-red (IR) light from a light emitting diode (LED), positioned below and in front of the left eye, are repeated 500 times per second. Because of the manner in which the LED and phototransistors are mounted, they do not obstruct the eyelids, nor do they impinge on the primary field of vision. The total amount of IR light reflected back from the eye and eyelid is detected by a phototransistor mounted beside the LED. The glasses are connected by a USB cable to a processor and data storage device for later download to a computer using original equipment manufacturer proprietary software (ODMS, version 1.8.1; Optalert Pty Ltd). The processor, data storage device, and battery were housed in a Faraday Box, which was contained within a padded bag for this study. The version of the equipment used in this study is capable of collecting up to 24 h of continuous data. The Optalert equipment has been utilized in the commercial road transport and mining industries to detect operator drowsiness.

Subjects wore a clinical-grade activity monitor and data logger (Actiwatch version AW-64, Philips Respironics, USA) on the wrist of the nondominant hand. In accordance with other fatigue studies in the aviation domain, a sensitivity setting of medium (wake threshold of 40 activity counts) was chosen to provide the most accurate relationship with polysomnography assessed sleep periods.[16] Data were analyzed using a dedicated software analysis program (Actiware® version 6.0.9; Respironics, Inc).

A Redbird FMX (Redbird Flight Simulations, TX, USA) aircraft simulator was configured to emulate a Cessna 172 with a Garmin G1000 glass cockpit display system and autopilot. The Garmin G1000 with autopilot configuration greatly reduced the workload of the student, thus increasing the likelihood of drowsiness. This aircraft configuration was one the subjects were already familiar with, since they were conducting their flight training in similarly-equipped Cessna 172 aircraft.

A Work-Sleep Diary was developed for use in this study. The Work Diary contained details of the work start and finish times, and a description of the work undertaken. The Sleep Diary contained details of the sleep location, timings of sleep periods, and a subjective sleep quality scale. Both diaries contained the Samn-Perelli Fatigue Scale (SPFS), as developed by the United States Air Force School of Aerospace Medicine (USAFSAM), to reduce the time required of aircrew in a field research setting to report subjective fatigue data.[15] The SPFS was recorded at the beginning and end of each work period, together with immediately before and after each sleep period.

The Epworth Sleepiness Scale (ESS) is a standardized measure of daytime sleepiness.[10] As a subjective measure of sleepiness prior to the simulator session, all subjects were administered an ESS survey.

The Fatigue Avoidance Scheduling Tool (FAST) (Fatigue Science, Vancouver, Canada) is a bio-mathematical model used to assist analyzing the fatigue state of subjects at the beginning of the simulation. Data from an AW-64 was uploaded into FAST to model particular individuals. The diary data were used to enhance the integrity of the modeling. FAST is a software decision aid designed to assess and forecast performance changes induced by sleep restriction and time of day effects, with the primary output being a population mean curve of predicted effectiveness. Subjective contextual data were collected from subjects through the use of discussions and interviews held by the researchers.

Procedure

Work/Sleep diary and actigraphy data were collected from each subject for 7 d prior to the day of the simulator flight. During those 7 d, subjects went about their regular activities. On the 8th d the subjects were instructed to awaken by no later than 07:00. Subjects were allowed to go about their normal routine prior to arrival at the simulation center at 11:00. On arrival, subjects were fitted with the oculography equipment. An ESS survey was administered at this time. No caffeine intake, nor napping, nor any other fatigue management strategy was permitted on this day, with confirmation of compliance checked prior to commencing the simulation. After oculography fitment, subjects received a route and weather briefing for their simulated flight. Between arrival at the center and the start of the simulator exercise, discussions and interviews were held with the subjects by the researchers.

A navigational exercise of approximately 4 h was flown during the secondary window of circadian low, with the subject randomly assigned one of two navigational routes. The two routes were chosen from the library of routes used by the training service provider to remove any predictability which might afford the subject any fatigue-related advantage. Routes were over featureless terrain with a small-town airport as the turning point at the midpoint of the exercise. With a planned take-off time of 12:00 (local) and a duration of approximately 4.8 h, the route and timing mirrored the practices followed by the flying school used by the university and subjects for the navigation phase of their training. Flights were performed in accordance with the standard training procedures for the institution, where procedures are designed to align with and train for commercial airline styled operations. The aircraft was manually flown for the departure and arrival sequences. The G1000 autopilot was employed for the majority of the en-route sequence flown. The simulator was configured with light and variable wind, nil significant cloud, nil significant weather, good visibility, freezing level above the planned cruising altitude, no icing, and no turbulence. Oculography data were collected continuously from immediately prior to engine start until immediately following engine shutdown.

Statistical Analysis

Data were downloaded to a commercially available spreadsheet program (Excel, Microsoft, USA). Statistical analysis of the data was performed using a statistical software package (SPSS ver. 23.0, IBM, USA). Analysis focused predominantly on the drowsiness data. Drowsiness data are described with the Johns Drowsiness Scale (JDS) using a proprietary algorithm to generate values in the range 0.0 to 10.0. Increasing numbers in the JDS indicate a higher state of drowsiness. JDS is a composite index based on weightings from different characteristics of blinks and saccadic eye movements in alert and sleep deprived subjects derived by multiple regression analysis. JDS has been validated against objective measures such as reaction times in alert and drowsy subjects, and driving simulator performance in alert and drowsy subjects.

Data were analyzed both from an individual and from a population mean perspective. Analysis occurred with significant points in the simulation, means against time, and rolling periodic averages. Pearson's Correlations (r) were investigated between ESS and SOL data. Correlations were also investigated between SOL and FAST data.

RESULTS

Complete sets of data were collected from nine male subjects, with a mean age of 23.0 (± 4.6) years (range 19–33). The study was open to both male and female students; however, no female potential participants volunteered to take part in this study. The outcome was judged to be an artifact of the research applicant pool which contained more male than female students.

The ESS survey yielded the data displayed in **Table I**. Sleep onset latency (SOL) provides another indication as to whether a person may be suffering from the effects of excessive fatigue.[8] SOL was automatically calculated by the Actiware for each sleep period for which actigraphic data had been collected. Average SOL for the data collection period of each subject is provided in Table I as a measure of pre-existing fatigue levels. Analysis showed a weak negative correlation between ESS and SOL ($r = -0.359$).

The average FAST predicted effectiveness of subjects at the beginning of the simulator session was 93.7% (± 3.8). FAST predicted effectiveness of 100–90 is indicative of a person with normal daytime duty with an 8-h period of excellent sleep at night. It represents acceptable levels of performance for workers in safety sensitive work environments and represents a low level of fatigue-related risk.[6] **Fig. 1** presents the bio-mathematical modeling of subject S02 for the study period as being representative of the average member of the studied population. Details of performance metrics and fatigue factors are provided for the

Table I. SOL and Subjective Daytime Sleepiness Prior to Simulation.

SUBJECT	ESS SCORE	SOL (min.)
S01	9	3.00
S02	2	6.11
S03	2	10.69
S04	3	18.13
S05	3	10.67
S06	2	5.43
S07	8	6.86
S08	2	15.75
S09	3	0.29
Mean	3.8 ± 2.7	8.55 ± 5.81

$r = -0.359$

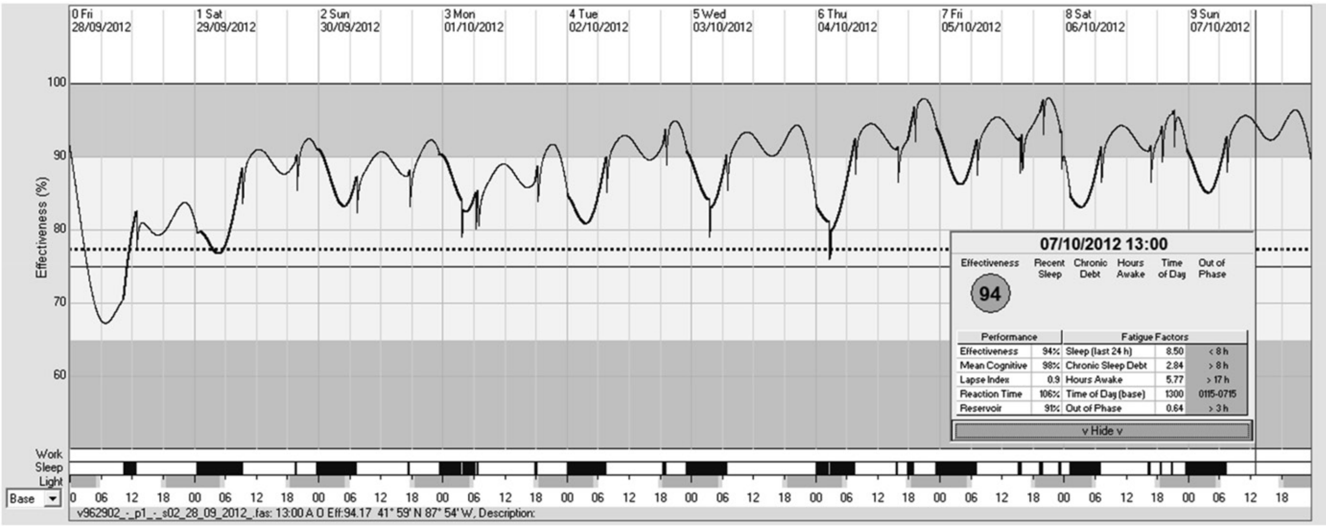

Fig. 1. Bio-mathematical modeling of subject S02 for the study period.

start of the simulation. It shows that the individual was receiving at least 8 h of excellent sleep per day, predominantly at night. Instances involving the use of supplemental napping can also be seen. The correlation between FAST and SOL data was weak ($r = 0.14$).

Fig. 2 shows the values of JDS against time in the simulation, of subject S02. It shows a pattern of cyclical increases and reductions in the level of drowsiness. This sort of pattern was typical of all participants. JDS values from the entire data collection pool varied from 0.0 to 6.5. Peak JDS values of subjects varied 2.0 to 6.5 (mean 3.73 ± 1.4).

Fig. 3 displays the population mean of JDS values against time in the simulation in minutes with the common point of origin being the start of the simulator session. A linear trend line ($y = 0.002x + 1.1667$) yielded a low r^2 value (0.2238). Generally, the higher the r^2, the better the model fits the data.[12]

It was hypothesized that a curvilinear model might better fit the population data which resulted in a four-order polynomial curve being investigated. In return, this yielded a better fit with the data ($r^2 = 0.314$). However, this was still not to a degree that could be considered as optimal. The issue appeared to be the minute-by-minute variance in JDS values caused by factors within the algorithm that calculates the JDS. This resulted in frequent short duration fluctuations, as seen in Fig. 2. A 20-min rolling periodic average provided the optimum smoothing for the data. Using a polynomial curve of best fit ($y = -2E\text{-}09x^4 + 7E\text{-}07x^3 - 4E\text{-}05x^2 - 0.0012x + 1.3254$), provided an acceptable r^2 value (0.6743). The data and curve are presented in **Fig. 4**.

Table II details the amount of time that each subject spent with a JDS value of 4.5 or higher, expressed as a percentage of the total data collected for that subject. It also contains details on the amount of time with a JDS value of 5.0 or higher, expressed as a percentage of the total data collected for that subject. Peak JDS values are also provided for each subject. Of the nine subjects tested, two (22.2%) reached levels of drowsiness at or above the motor transport cautionary warning level. Those subjects spent a mean of 11.0% of their time at this elevated level. Of the subjects tested, 22.2% reached a drowsiness level at or above the motor

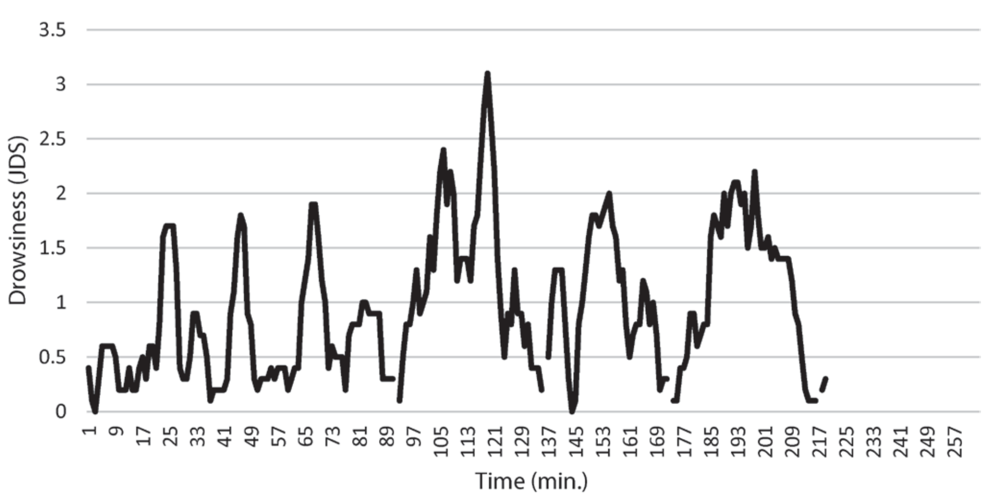

Fig. 2. JDS values against time in simulation of S02.

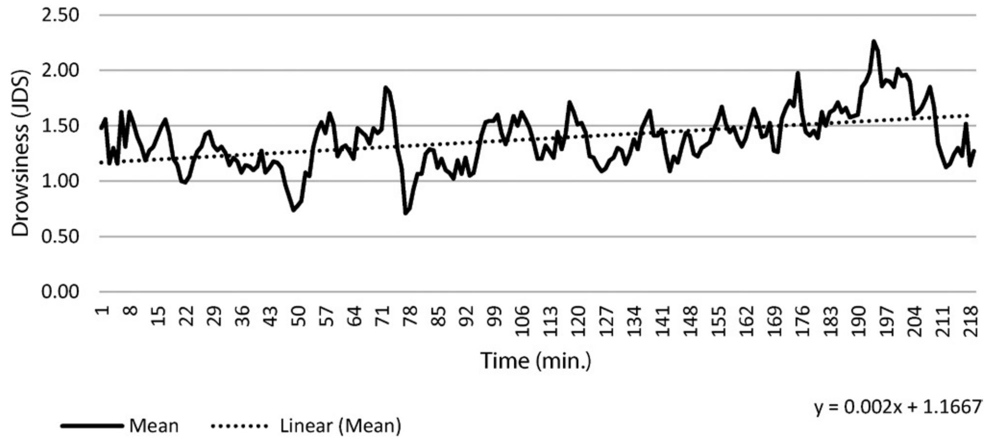

Fig. 3. Mean JDS values against time in the simulation.

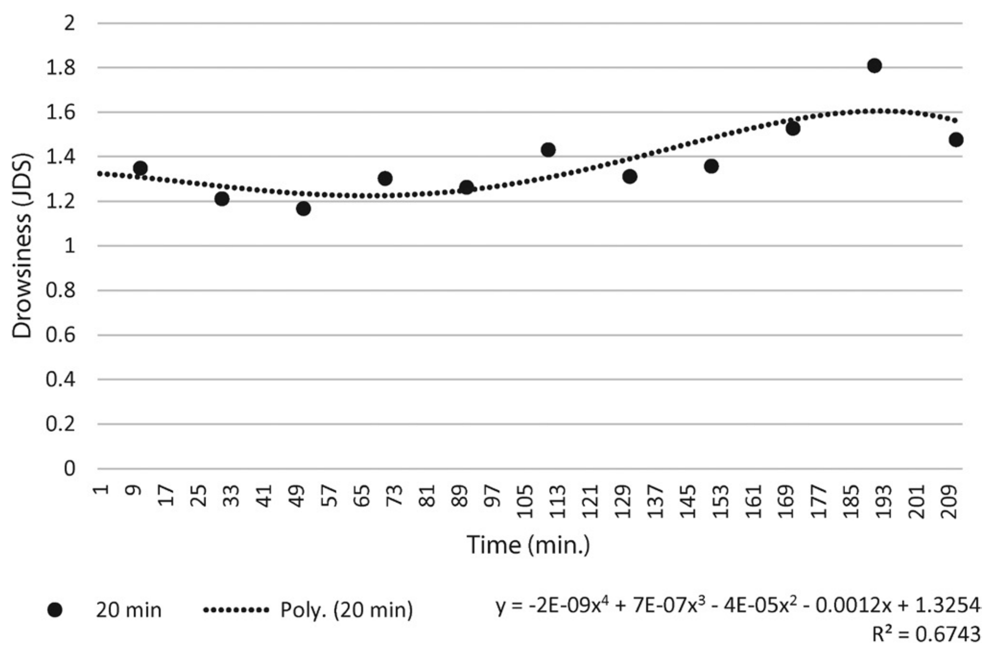

Fig. 4. 20 min mean JDS values during simulation.

transport critical warning level. Those subjects spent an average of 6.85% of their time in this elevated condition.

The simulation was directly observed by one of the researchers throughout the data collection period. At no time did any flight deviate from its intended flight path by more than 200 ft vertically nor 5 mi laterally. No emergency situations were observed to have developed during the simulation. All landings occurred in a safe manner.

Table II. Percentage of Time Spent at or Above Cautionary and Critical Warning Levels, With Peak JDS.

SUBJECT	CAUTIONARY % (JDS ≥ 4.5)	CRITICAL % (JDS ≥ 5.0)	PEAK VALUE JDS
S01	14.2	11.0	6.5
S02	0.0	0.0	3.1
S03	0.0	0.0	2.6
S04	7.8	2.7	5.3
S05	0.0	0.0	4.0
S06	0.0	0.0	3.1
S07	0.0	0.0	2.0
S08	0.0	0.0	4.3
S09	0.0	0.0	2.7

DISCUSSION

The results of this study demonstrated that during a simulator serial the drowsiness of student pilots in a University-based pilot training program could be monitored, using infrared reflectance oculography.

The data analysis revealed the timeline and levels of fatigue that might be experienced by student pilots; showing that drowsiness is a potential issue for student pilots when operating in flying conditions similar to those experienced in the simulation. To ensure that the findings were not an artifact of the simulated environment, a verification activity was planned for an in-flight study of student pilots flying the same routes, in the same aircraft type and configuration, later in the research series.

Lower ESS scores are normally considered preferable, with respect to fatigue related risk. As the Australian normative mean ESS score is 4.6[10] and Australian driving simulator data is 5.5,[17] the subject pool mean score (3.8 ± 2.7) was healthier than the broader population. The two highest scores were determined to have an average amount of daytime sleepiness, as defined by the scale developers.[10] The remaining seven scores were assessed as being unlikely to be abnormally sleepy.[10] Based on this analysis, it was determined that daytime sleepiness was not likely to be a confounder in this study.

Modeling showed that the average subject was in a well-rested state, leading up to the day of testing. The subjects generally started the simulation in a fatigue-related state considered acceptable for workers in a safety sensitive role. Modeling of the actigraphy and diary data with FAST showed consistency in the predicted effectiveness states of the subjects at the beginning of the simulator session (93.7% ± 3.8). The majority (77.8%) were in the 90–100% predicted effectiveness zone of the modeling, representing a low level of fatigue-related risk to performance.

The two notable exceptions to the above were S01 and S04, who both had periods of predicted effectiveness of less than 90% occurring during the planned simulator sessions. Their respective FAST models predicted that the subjects would spend the greater proportion of their simulator session in the 65–90% predicted effectiveness zone. Working in this zone comes with performance equivalent to having missed one night of sleep. Therefore, it is possible that drowsiness might be an issue for those pilots in this study.

However, the two subjects noted above (S01 and S04) differed from the two who had elevated ESS scores (S01 and S07), which in turn differed from the two who had the lowest SOL (S01 and S09). With S01 being common in all three, the combination of the factors led to belief that subject S01 was the most likely individual to have elevated JDS values, and/or extended periods of elevated JDS values. Analysis of the JDS data confirmed the prediction, in both peak and period dimensions; highlighting that S01 was at the highest fatigue-related risk, in this cohort.

The SOL data in Table I does not correlate well with the bio-mathematical modeling. There was a weak correlation ($r = 0.14$) between SOL and FAST data in this study. A mixture of SOLs is not necessarily surprising, given that the subjects were university students. The challenges involved in recruiting subjects from a university-based aviation program include the competing demands of their academic and flying training programs, combined with their social and any work pressures.

The discussions and interviews between the researchers and subjects revealed that it is plausible that the weakness of the correlation could be due to their work demands. Some were working more hours than others in order to financially support their studies. While this was reported by some to be adding to their fatigue state, others made comment about having a more vibrant social life. The findings discussed above support the seven-factors model, which showed demonstrated contributions to flight-related fatigue in the ab-initio pilot community.[11] The type of flight (cross country), training schedule (academic and flying), crew composition (single pilot), environment of the aircraft (noise levels and temperature), types of accommodation (varied between individuals), flight training-related issues (recent flight history, progress frustrations, part-time work), and biological issues were all seen at differing times to impact the fatigue state of the subjects.[11]

There was notable variation between the JDS traces of the subjects, with the variation being more pronounced than in the FAST modeling. It is possible that a degree of inter- and intraindividual variation was present, making modeling more difficult to analyze.

All of the simulator sessions finished with a landing at the end of the flight. The right side of Fig. 4 shows a change in the trajectory of drowsiness during this segment of the data collection, as illustrated by the polynomial curve. Lengthy periods of rising JDS values may have been curtailed by approaching critical points in the flight. A lowering of JDS values toward the end may be due to an increased arousal level, triggered by the arrival and landing sequence. The improvement in performance starts in the short period prior to top of descent (approx. 10 min.). This observation is consistent with other research that noted a performance rallying effect in the psychomotor vigilance test (PVT) data of aviators operating long duration duty periods.[5] In that work, there were statistically significantly better reaction times after landing than there were prior to top of descent, consistent with investigations into high workload demands of aviators.[14]

As noted, subjects experienced periods of elevated JDS values. The degree to which such elevated scores might be critical to flight safety cannot be highlighted, as at this point the industry has no clear guidance on what is considered to be an acceptable level of drowsiness for a pilot. Using oculography findings from the Monash University Accident Research Centre (MUARC) enables a frame of reference to be placed regarding the JDS data. MUARC concluded that a JDS value of 4.5 represents the road transport level 1 cautionary warning that a vehicle driver was becoming drowsy.[17] The MUARC team also concluded that a JDS of 5.0 represents the road transport level 2 critical warning that a driver was too drowsy to safely drive a vehicle.[17] Although the MUARC values were appropriate to the motor vehicle domain, further research is required to determine appropriate JDS values for cautionary and critical warnings in the aviation industry. It is believed that alerting levels for drowsiness in the cockpit are likely to be contextually dependent requiring that cautionary and critical values be determined for a variety of operational conditions. For example, from a risk-based perspective, the values suitable for high-level extended cruise might not be appropriate for use during an instrument approach to landing.

The data showed that there is a strong correlation ($r = 1.0$) between JDS values of 4.5 and above, with periods when predicted effectiveness is below 90%. The data indicate that pilots are likely to experience levels of drowsiness above the motor transport cautionary warning level when FAST modeling predicts effectiveness below 90%.

The peak JDS experienced during this study was 6.5. Given that the drowsiness scale is from 0.0 to 10.0, this may not initially appear particularly high. During the simulator sessions a researcher observed and monitored the subject throughout the session. At no time during data collection did a subject appear to fall asleep, however, their drowsiness state could not be directly observed. At no time did the handling skills of the subject pilot lead to excessive excursions from the intended flight paths, indicating that they were still considered safe and acceptable. This was seen as conformal with the design intent of the study. However, it does reinforce the question as to what is considered an acceptable level of drowsiness or fatigue for the safe and efficient operation of an aircraft.

It has been noted elsewhere that technology providing real-time on-line detection of drowsiness could provide the pilot with immediate information and feedback on their current state, enabling them to engage in the use of appropriate fatigue countermeasures.[13] Further research needs to be done in evaluating the use of bio-feedback, as this has potential for utilization in fatigue risk management.

The oculography configuration tested can collect up to 24 h of continuous data. This provides opportunity for their use in data collection and analysis of duty periods that are of concern to the pilot and/or the operator of the service. It is, therefore, worthy of consideration for embedding into a fatigue risk management system (FRMS). Having objective data on the fatigue levels of pilots may enable managers to make better-informed decisions regarding the fatigue dimension of aviation risk management. When utilized in a manner similar to other industries, oculography has the potential to reduce the manpower burden of gathering the drowsiness and fatigue data in field settings. In those industries the data are securely downloaded and analyzed. Such a system could enable objective fatigue-related data to become an integral component of a FRMS in the aviation domain. Subjects in this study reported that it did not interfere with their ability to fly the aircraft. Formal investigation of user acceptability is an area planned for investigation and reporting on later in this series of studies.

This study was undertaken to investigate whether the potential drowsiness of student pilots in a University-based pilot training program could be monitored using the technology of infra-red reflectance oculography, to determine the drowsiness level of the wearer. The data showed that drowsiness was present among the tested population. The data revealed high levels of drowsiness among some of the student pilot population and that those pilots were likely to experience levels of drowsiness above the cautionary warning level when FAST modeling predicted effectiveness below 90%. It is not believed that a direct comparison of these data to the road transport industry is possible, as confounders may include the possibility that driving requires more ocular and cognitive engagement than flying over featureless terrain.

The current global climate is posing two primary fatigue related challenges to the pilot workforce. Firstly, major aircraft manufacturers are investigating alternatives to the extant two pilot model for airline operations. Changes and challenges to this model would benefit from unobtrusive real-time monitoring and data collection to help inform a risk-based decision about appropriate crewing. The second challenge is posed by the global pandemic, as pilots return to the cockpit following extended periods of absence. During such periods the rest and recovery habits of pilots are likely to have altered, leading to unexpected levels of fatigue and drowsiness in the cockpit. Real-time monitoring and data collection could help to inform managers of the fatigue risks posed to operations during the return to operations.

As a result of the data collected and analyzed it was concluded that infrared reflectance oculography is worthy of further investigation for use as an objective fatigue detection tool in the aviation domain for continuous in-flight monitoring of drowsiness.

ACKNOWLEDGMENTS

The authors would like to express their sincere thanks to the students enrolled in the Swinburne University of Technology aviation program, who freely gave of their time and effort to be subjects in this research.

Financial Disclosure Statement: The authors have no conflicts to declare.

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