

The evaluations of the impact of the pilot's visual behaviours on the landing performance by using eye tracking technology

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Abstract. Introduction. Eye tracking technology can be used to characterise a pilot's visual behaviour as well as to further analyse the workload and status of the pilot, which is crucial for tracking and predicting pilot performance and enhancing flight safety. **Research questions.** This research aims to investigate and identify the visual-related factors that could affect the pilot's landing operation performance (depending on whether the landing was successful or not). **Method.** There are 23 participants who performed the task of landing in the Future system simulator (FSS) while wearing eye trackers. Their eye tracking parameters including proportion of fixation count on primary flight display (PFC on PFD), proportion of fixation count on out the window (PFC on OTW), percentage change in pupil diameter (PCPD) and blink count were trained for classification using XGBoost according to whether they landed successfully or not. **Results & Discussion.** The results demonstrated that eye-movement features can be used to classify and predict a pilot's landing performance with an accuracy of 77.02%. PCPD and PFC on PFD are more crucial for performance classification out of the four features. **Conclusion.** It is practical to classify and predict pilot performance using eye-tracking technologies. The high importance of PCPD and PFC on PFD indicates that there is a correlation between pilots' workload and attention distribution and performance, which has important implications for future predictive and analytical research on performance. The prediction of performance using eye tracking suggests that pilot status monitoring has a useful application in flight deck design.

Keywords: Eye tracking, pilot monitoring, performance classification, future flight deck.

1 Introduction

Human factors have always been one of the most important factors that affect flight safety. According to [1], there is approximately 80% of accidents happened due to human factors. Therefore, to enhance flight safety, it is important to effectively evaluate the status and performance of pilots. Previous research demonstrated that pilots' operating performance could be affected by age, experience, physiological status, workload and how complex the system they were interacting with [2], [3]. Specifically, the complex human-computer interaction (HCI) design could pose a challenge for pilots to maintain good performance [4]. Since the modern flight deck is highly information integrated, complex aircraft systems make the pilot status monitoring and a full understanding of the pilot's information acquisition and management processes mandatory requirements for flight deck design. As the most important and common source for information acquisition, vision and visual behaviour analysis have been well-researched in the past few years [5], [6]. Visual behaviour could characterise the human's workload and situational awareness (SA), and further evaluate the working status and capacity [5], [6]. Benefiting from the development of remote and non-intrusive camera-based eye tracking techniques, the pilot's visual behaviour monitoring and analysis have become the main focus of the research recently, which plays an important role in the study of both HCI and pilot information management in flight decks [7]. Many studies have investigated visual patterns and pupil characteristics utilising eye tracking techniques in order to better understand human information processing in different areas, such as cognitive task evaluation [8], [9], scanning behaviours investigation [10], interface evaluation for vehicle [11], and HCI design in flight deck [5], [12]. In the aviation sector, the use of eye tracking could assist researchers to understand the impact of the new flight deck layout on the pilot's SA and performance, and further improve the flight deck design [7]; to understand the differences in monitoring strategies between novice pilots and experienced pilots to improve pilot training efficiency [13]; and even to use eye tracking data as an input so that pilots can manoeuvre the aircraft using their pupil behaviours like blink and gaze [14]. With the further introduction of touchscreen and augmented reality (AR) technologies into flight decks and the need for single-pilot operation, the application of eye tracking technology in flight decks is likely to play an even more important role. In detail, the existing eye tracking research focuses on the investigation of fixation, saccade, pupil diameter and blink. Among these, fixation and saccade are often used in SA-related research, which can effectively describe human attention allocation [15]. In contrast, pupil diameter and blink are considered as physiological parameters to analyse workload and arousal levels [16]. To sum up, these studies have contributed to the exploration of eye behaviour and human cognitive processes and workloads, but it is still a long way for real applying in the aviation industry.

The implementation of efficient pilot status monitoring is crucial for the future design of the flight deck in order to manage pilot workload and evaluate pilot performance to improve flight safety. Current research on pilot status monitoring has focused on understanding attention distribution and measuring pilot cognitive workload. The researcher found that the distribution of fixation can effectively reflect the distribution of human attention and suggested that this may influence the pilot's decision-making

process [12], [17]. Moreover, by examining whether the pilot has a reasonable attention distribution, researchers can evaluate the effectiveness of display designs [18]. The research on evaluating cognitive load by using eye features like pupil diameter and blink rate have been conducted in many application domains [9]. Depending on the tasks performed, the blink rate shows different trends with workload levels. Blink rate rises during high workload tasks such as computation and verbal communication [19], while blink rate is lower during low brain load tasks such as detection and search [20]. Similarly, pupil diameter has been suggested to correlate with workload levels [21]. To verify if subtitle would increase cognitive workload, Kruger et al. measured the pupil diameter of subjects before and halfway through the experiment and introduced the percentage change in pupil diameter (PCPD) as an indicator of cognitive load. They found that subtitle condition in fact created a lower cognitive workload [22]. Furthermore, some research employed the extracted eye features and estimated workload to evaluate the task performance. Coyne et al. claimed that there is an inverted U-shaped relationship between workload and performance [23]. Alhanbali et al. found that a larger pre-stimulus pupil diameter in the digits-in-noise task was associated with lower task performance [24]. Van et al. observed a strong linear relationship between the temporal derivative of pupil diameter and task performance measures [25]. Although the feasibility of using eye features to characterise the human workload and evaluate task performance has been proved in these studies, only a few task circumstances have been examined in studies on the operational performance of pilots based on their visual behaviour and eye features [23]. Moreover, the current analysis of performance using diameter or blink alone still suffers from poor accuracy and is severely limited by the type of task [26]. Eye tracking research that analyses pilot performance stays in the stage of workload evaluation, with fewer studies achieving performance classification and prediction [12]. Achieving accurate classification and prediction of performance is important for the application of eye tracking technology to assist pilot status monitoring in flight decks. Therefore, this study intends to investigate the relationship between eye tracking features and pilot performance in order to implement pilot monitoring in future flight decks. Specifically, this research focuses on the pilot's landing performance (depending on whether the landing was successful or not) and further investigates which pupil parameter has the most potential for evaluating performance during flight. The research questions are as followed.

RQ1: Is it appropriate to categorise pilot performance in landing tasks according to fixation distribution, diameter, and blink?

RQ2: How significant are fixation diameters, distributions, and blinks for performance analysis?

2 Method

2.1 Participant

There were 23 participants invited for this research, age from 22 to 58 years ($M = 31.6$, $SD = 10.3$). The participants' fixed-wing experience was from 0 to 300 total flight hours

($M = 64.7$, $SD = 91.0$). The data of this paper was gathered from human participants and only for the research purpose, approved by Cranfield University Research Ethics System (CURES/14853/2021). Each participant was presented with the contract before the trial, the experiment was only carried out if they signed the contract and they had the right to end the trial at any stage and delete all data.

2.2 Experiment design

The study's objective is to employ the Instrument landing system (ILS) landing scenario as a test to investigate the application of eye tracking data for performance classification. Participants were asked to perform a landing task with the Instrument landing system (ILS) scenario in this simulator with eye tracker glasses on (as shown in Fig.1). The flight dynamics model of the aircraft is based on a Gulfstream G550 general business aircraft. The aircraft starts in a straight line on Runway 15R at Incheon International Airport (ICAO: RKSI), Seoul, Korea, a distance of 5 miles. The initial speed was 150 knots and the altitude was 1400 feet. Weather conditions were clear and there was no wind influence. The throttle lever, landing gear and autopilot controls are all automatic. All the flight data would be recorded in the simulator automatically. The environment was kept properly illuminated and stable during the experiment to improve the accuracy of the eye tracking data collected. There were two areas of interest (AOI) being discussed in this research, primary flight display (PFD) and out the window (OTW) view.

Before the trial, all participants were provided with the consent form consisted of the experiment and research design. All participants took the following procedures: (1) complete the demographical data including age, gender and flight hours (5 minutes); (2) briefed the experiment process, simulator and eye tracker used (5 minutes); (3) seat in the FSS to familiarise the simulator layout (5 minutes); (4) wearing and setting the eye tracker (10 minutes); (5) perform the ILS landing scenario (5 minutes); (6) debriefing and answering questions (5-10 minutes). It took around 40 minutes to complete the experiments for each participant.



Fig. 1. Participant performed the ILS landing scenario in FSS



Fig. 2. Landing scenario on navigation display

2.3 Apparatus and data pre-processing

This research was conducted using Rolls-Royce Future System Simulator (FSS) at Cranfield university. This simulator was granted the iF DESIGN AWARD in 2021 [27], the FSS is a highly integrated future flight deck simulator with four large reconfigurable touchscreens and two small side screens. This simulator allows pilots and researchers to explore the best practice for future single-pilot operation flight deck with highly autonomous engine system and new technologies [28], [29].

The Pupil-Labs eye tracker was used in this research for eye tracking data collection. This eye tracker consists of a world camera (for synchronisation of user perspectives) and an eye camera (for monitoring eye characteristics and movement) fixed in a plastic frame. The resolution was 1280*720 pixels with a sample rate of 60 frames per second. The right eye of participants would be tracked by the eye camera to collect the pupil parameters and movements including pupil diameter and blink. In this research, eye fixation was defined as consecutive gaze points that fall into a circle within a radius of 1.5° and duration between 150ms and 800ms in line with the previous research [30]. For analysis, the visual parameters including fixation count, pupil diameter and blink were collected while participants performed the landing scenario.

There were four eye tracking parameters selected for this research: proportion of fixation count on PFD (PFC on PFD), proportion of fixation count on OTW (PFC on OTW), percentage change in pupil diameter (PCPD) and blink count. Eye tracking data were recorded throughout the experiment, where PFC on PFD and PFC on OTW were the fixation counts on PFD and OTW divided by the total fixation counts. The PCPD was calculated as the amount of change in participants' pupil diameter in the experimental situation compared to the off-task situation. The off-task state diameter was the average diameter of participants in the steady state for 15 seconds prior to the experiment.

2.4 Classification method

As one of the most commonly used algorithms in applied machine learning, XGBoost [31] is employed in this study for performance classification. It is a tree-based ensemble machine learning method, which grows multiple decision trees (weak learner) and combines them together into a prediction model (strong learner). As a kind of gradient-boosted tree method, it grows a new tree in a greedy manner to reduce the residuals of the previous model in each iteration.

The employed dataset $\mathcal{D}$ has n instances and m features. In this study $n = 23$ and $m = 4$. The prediction result $\hat{y}_i$ for an input instance x_i can be written as:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (1)$$

where f_k is a function of an independent tree with the specific tree structure and leaf weight. K is the number of the additive functions. F represents the space of the classification and regression trees (CART). The objective function $\mathcal{L}^{(t)}$, at the t -th iteration, that needs to be optimised can be expressed as:

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (2)$$

where l is the loss function that measures the truth y_i and the prediction $\hat{y}_i$, and $\Omega(f_t)$ is the regularisation term that penalizes the complexity of the model to avoid overfitting.

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|\omega\|^2 \quad (3)$$

3 Results and discussion

K-fold cross-validation method was used to evaluate the generalizability performance of the model. In this study, the K was set as 3. Approximately, 66% of data has been used in the train set and 34% of data has been used in the test set. The cross-validation was repeated 5 times for the model performance evaluation. The results are presented in Table I. It can be seen that the average prediction accuracy and standard deviation of the used method are 77.02% and 4.31%, respectively.

Table 1. 3-fold cross-validation results for model performance evaluation

Accuracy	Repeats					Average
	1	2	3	4	5	
Mean	73.81%	82.74%	74.40%	79.16%	75.00%	77.02%
standard deviation	1.68%	5.52%	8.49%	3.14%	2.70%	4.31%

Fig. 3 presents the importance of the evaluated features in the trained classification model. It includes 3 subfigures for a set of 3-fold cross-validation. The F score refers to the number of times that a feature is used to split the data across all trees. From this figure, it is clear that PCPD (feature 2) and PFC on PFD (feature 0) are used most frequently for growing trees, which are more important for the classification.

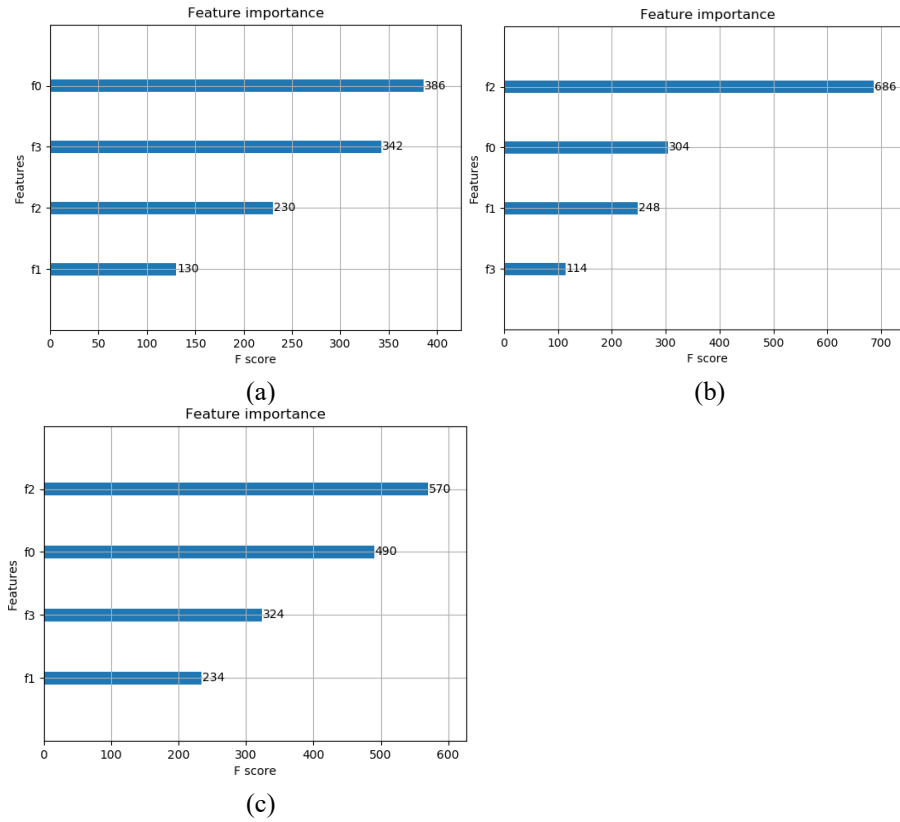


Fig. 3. Feature importance for the classification model. Subfigures (a), (b) and (c) represent the results for each fold in a 3-fold validation set

The PCPD (feature 2) had the highest importance as shown in Fig. 3(b) and Fig. 3(c) ($F\ score_2 = 686$, $F\ score_3 = 570$). It emphasises the diameter variation, which can effectively reflect variations in landing success rate because of its strong association with the workload. Different methods for evaluating diameter have been employed in workload and performance studies using diameter, including baseline diameter, pre-stimulus diameter, PCPD, and derivatives of diameter [24]. Some significant results have been obtained from these studies, for example, baseline diameter and pre-stimulus diameter are both considered to have a correlation with mission completion rate, while the derivative of diameter has a linear relationship with behavioural performance [25]. However, previous studies have commonly used correlation analysis, and the results are

influenced by the type of task and load level, yielding different or even contradictory patterns [23]. This study directly employs a machine learning approach to verify the potential of PCPD for landing task classification, which has important implications for further implementation of the classification and evaluation of pilot performance. At the same time, these multiple diameter-related parameters may vary in their validity for performance studies and make practical application inconvenient due to a lack of standardisation. Therefore, comparing and filtering these parameters to find out which is more efficient for analysing performance and workload is also necessary to introduce eye tracking technology into practical applications in the future.

As shown in Fig. 3(a), PFC on PFD (feature 0) was the highest important factor ($F_{score_1} = 386$), while in Fig. 3(b) and Fig. 3(c), PFC on PFD was the second factor ($F_{score_2} = 304$, $F_{score_3} = 490$). This demonstrates that the fixation distribution also has a great impact on the pilot's performance. The PFD provides important altitude and speed information during the ILS landing, making the PFC on PFD important for attention distribution and decision-making [15]. Reasonable distribution of attention has an important impact on maintaining good performance [5]. Additionally, previous research had found significant differences in the fixation distribution between experienced pilots and novice pilots, which could result in a performance gap [32]. However, although PFC on PFD had a significant impact on the performance results, the weighting of PFC on OTW was lower in the case of all three models. This may be because, in the ILS landing scenario, the fixation distribution of participants was highly concentrated in PFD and OTW, which resulted in a high correlation between PFC on PFD and PFC on OTW, thus affecting the importance of PFC on OTW. More rigorous data downscaling may be required in subsequent studies to rule out this possibility.

Unexpectedly, Blink had the lowest importance in both Fig. 3(a) and Fig. 3(b) ($F_{score_1} = 130$, $F_{score_2} = 234$), which indicates that blink count had a poor effect on performance. Blink was considered to have a significant correlation with the workload while under a high workload, the blink rate would increase [33]. However, in our study blink was less important for performance classification. This may be due to individual differences, as we found that blink frequency varied considerably between participants, with some participants averaging less than 10 blinks per minute and others perhaps as high as 30-40 blinks per minute. In this study, the blink count over the length of the experiment was used directly, which did not eliminate individual differences. Further research can try to use blink rate of change instead of blink count to obtain better classification results.

As a pilot study, there are some limitations to this study regarding the sample size, the scenarios designed, and the chosen parameters. The sample size selected was relatively small and may not include all levels of pilot experience. However, this research is a proof of concept study and focuses on verifying the feasibility of using eye tracking technology to achieve the pilot's performance classification. Also, the scenario evaluated is limited, which is ILS landing and the complexities of the flight have not been simulated. However, landing, as the task most prone to safety issues during commercial flights, is somewhat generalised as a simulation task and in future research, we will further introduce landing tasks affected by turbulence in order to better simulate complex flight situations. Finally, there were only two parameters related to attention

distribution (PFC on PFD and PFC on OTW) and two parameters related to physiological changes and cognitive workload (PCPD and blink count) selected from all eye tracking parameters for performance classification. Parameters such as fixation duration and saccade, which have a correlation with pilot attention allocation, were not selected for this model. In our further research, these parameters will be processed and applied to the model in an appropriate way.

4 Conclusion

This paper investigated the impact of the pilots' visual behaviours on their landing performance. Specifically, the pilots' visual movement has been tracked and characterised by four features, PFC on PFD, PFC on OTW, PCPD and blink count in this study, and the XGboost algorithm has been further employed to achieve the performance classification. The results showed that the pilots' landing performance can be classified and predicted based on eye movement features. The employed method achieves 77.02% accuracy. Moreover, among the four selected features, PCPD and PFC on PFD are more important for performance classification, which suggests there is a significant effect of pilot workload and attention allocation on performance. For future work, the sample size and the number of scenarios used can be further expanded, as well as the different features of eye-tracking data. Such research could provide a further understanding of how pilots' performance is affected by their visual behaviour under different circumstances. In conclusion, the use of eye-tracking technology is feasible to achieve pilots' performance classification and prediction. The prediction of performance through eye tracking indicates that pilot status monitoring has a practical application in flight deck design. Eye tracking will be of greater importance for pilot monitoring in the future flight deck design, which could further promote the efficiency of information acquisition and management, and enhance flight safety.

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