

It Matters Who Is Behind the Wheel: Driver Monitoring Feature Analysis Using Explainable AI

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Abstract

This work-in-progress examines how gaze-based features and individual driver characteristics influence takeover performance prediction in partially automated vehicles. We present preliminary findings from a driving simulator study (N=33) that used a decision-tree (XGBoost) machine learning model and explainable AI techniques (permutation feature importance and SHAP analysis). Results show that driver profile features—particularly professional training, experience, and age—emerged as highly predictive of takeover readiness alongside traditional gaze metrics like fatigue indicators. While current Driver Monitoring Systems (DMS) approaches and regulatory recommendations focus on universal gaze thresholds, our preliminary analysis reveals that individual driver characteristics may be more important for predicting takeover performance. These findings suggest potential for developing adaptive automotive interfaces that adjust based on driver profiles rather than one-size-fits-all approaches. The preliminary results highlight the need for careful consideration when designing driver monitoring systems and automotive interfaces for partially automated vehicles.

CCS Concepts: • **Human-centred computing** → **User studies; Laboratory experiments; HCI theory, concepts and models.**

Additional Key Words and Phrases: Driver Monitoring Systems, Takeover Performance, Explainable AI, Gaze Behaviour, Partial Automated Driving

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1 Background

As partially automated vehicles become increasingly available, safety concerns arise about how such technology might affect drivers' capabilities to prevent crashes in safety-critical situations. According to SAE [26], despite being partially/totally relieved of the motor control requirements of the driving task, drivers of a partially automated vehicle are still required to monitor the environment and resume control in case the system reaches a

limitation or leaves its predefined operational design domain.

Previous research has reported that lack of active engagement with driving, induced by automation, may have detrimental effects on drivers' capabilities to monitor the road environment effectively, especially for long periods of time [see 11, 22]. Survey [24] and driving simulator studies [3] have also reported that drivers of partially automated vehicles have a higher likelihood of engaging in non-driving-related activities when compared to manual driving. Hence, compromising their ability to respond to a potential safety-critical situation.

Current European regulations are enforcing Driver Monitoring Systems (DMS) for driver distraction and drowsiness in modern vehicles [see 8]. DMS can assess the driver's capability to resume control in a timely manner during safety-critical situations. Following global regulations [8, 31], most DMS development recommendations [7, 15] focus on detecting visual distraction away from the forward roadway (Advanced Driver Distraction Warnings - ADDW), or fatigue/low driver arousal (Driver Drowsiness and Attention Warning - DDAW) using fixed safety thresholds. For instance, Euro NCAP recommends that driver glances away from the road for longer than 2 seconds should trigger an ADDW [6].

However, this approach has limitations. Research has shown DMS gaze metrics' efficacy for estimating cognitive distraction and load is highly variable across individuals [10, 32], with high heterogeneity in the predicted effects of cognitive load/distraction on drivers' gaze. These results suggest different drivers might require different safety thresholds to achieve equivalent performance during resumption of control.

There is an opportunity to enhance our understanding of relationships between different camera-based driver metrics, driver state, and their performance during resumptions of control from partial automation. However, this relationship is significantly complex and analytically challenging. Traditional statistical methods struggle to effectively capture these multifaceted relationships, particularly because individual driver characteristics (e.g., driving experience, personality, and age) may influence performance outcomes. Therefore, we leverage machine learning (ML) to capture relationships between DMS features and drivers' takeover performance [27], then apply eXplainable Artificial Intelligence (XAI) techniques [14] to enhance ML models' interpretability.

In this work in progress, we present preliminary results from applying the XGBoost algorithm to a driving simulator dataset where safety-critical transitions of control were required [12]. The predictive value of different DMS features was assessed, and feature selection was made through a permutation feature importance analysis [1], with the features' predictive values measured using SHapley Additive exPlanations (SHAP) values [20].

2 Methodology

We used an existing driving simulator study [see 12] to showcase the application of ML and XAI techniques in understanding drivers' takeover performance in partially automated vehicles. Our approach leverages ML models as an analysis tool rather than a predictive and generalisable model. Hence, this methodology prioritises the relevance of feature-based patterns and their interaction with individual variability over predictive accuracy and generalisability. We seek to provide insights into feature importance for predicting takeover readiness, examining both gaze-based metrics and individual driver characteristics. Below, we first describe the simulator study for context, followed by a description of the ML analysis.

2.1 Simulator Study

The simulator study assessed driver response following a takeover request (TOR) in partial automation under the effect of artificial manipulations of cognitive load (2-back task), and visual attention (ambient occlusion). The study received approval from the university's ethics board (approval number FREC 2023-0487-560).

2.1.1 Participants. 34 drivers (14 women), aged between 22 and 56 years old ($M = 38.02$ years, $SD = 12.03$ years), took part in this study. All drivers had at least 3 years' driving experience in the UK, drove at least twice a week and had no previous experience with vehicle automation. The sample included 15 night-shift workers and 12 participants with advanced driver training (e.g., police, ambulance drivers, and firefighters). The final dataset contained 105 individual takeover events extracted from 33 drivers (13 women).

2.1.2 Apparatus. Our research centre driving simulator, a 8-degree-of-freedom motion-based driving simulator housing a Jaguar S-type vehicle cabin with fully operational controls was used for this study. The simulator is surrounded by a 4m spherical projection dome with a projection angle of 300° (Figure 1A). The Seeing Machines PC-DMS 3 was used to extract drivers' head- and gaze-based metrics, at an average sampling rate of 48 Hz (Figure 1B).

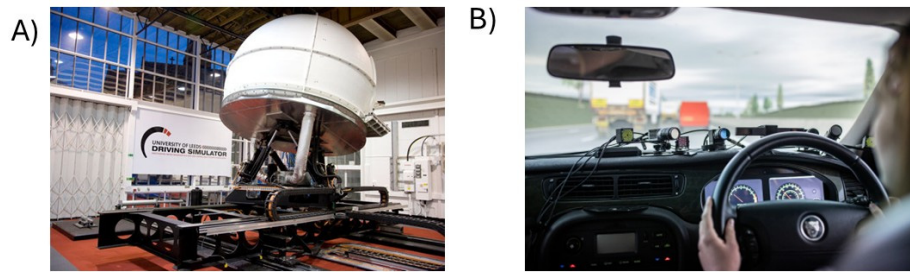


Fig. 1. Driving simulator setup. A) shows the external environment of the simulator and the motion system, and B) shows the internal environment of the projection dome containing the vehicle's cabin.

2.2 Experimental Design

The experiment followed a mixed design. Distraction manipulation (Occlusion, 2-Back, occlusion + 2-Back) and event criticality (non-critical takeover, 3s time-to-collision takeover, 4s time-to-collision takeover) were used as the within-subject independent variables. Fatigue manipulation (night-shift drivers, day-shift drivers) and driver training (non-expert drivers, expert drivers) were adopted as between-subject independent variables. Participants completed a single experimental drive, with ten driving automation events, in a fully counterbalanced order.

Participants drove in the middle lane of a 3-lane motorway with ambient surrounding traffic, assisted by an L2 automated system [26]. Automation controlled both the lateral and longitudinal movement of the vehicle, keeping it in the middle of the centre lane at a constant speed of 70 mph, maintaining a 3-second minimum distance from any lead vehicles. Each of the ten automation events lasted 2 minutes and 20 seconds, and drivers were instructed to monitor the environment at all times. Drivers were required to resume control of driving in response to a TOR, which was characterised by an auditory tone and a change in colour of a steering wheel icon from green to red, presented in the dashboard area.

2.2.1 Distraction Manipulation. The "Occlusion" manipulation was used to simulate intermittent visual distractions from the driver, such as glances towards smartphones or at the vehicle's infotainment system [9, 17, 25]. This is achieved by a three-second intermittent superimposition of an opaque grey screen on the simulated driving scene, occluding the forward roadway, dashboard, and mirrors. The occlusion happened in repeated cycles every 9 seconds.

The secondary "2-Back" task manipulation [21] was used to impose driver cognitive load. This involved a random presentation of the numbers 0 to 9, every 2.25 seconds, using the vehicle's speakers. Drivers were asked to verbally

repeat the second-to-last number they heard in the list. They were instructed to perform this task to the best of their ability but were also informed that they could pause and restart the task to maintain a safe drive. Lastly, the “occlusion plus 2-back task” manipulation involved the completion of the 2-back task throughout the intermittent occlusion periods.

2.3 Procedure

Upon arrival, drivers received a safety briefing about the safety procedures and were instructed about the experimental task. Upon signing a consent form and providing their demographic information (age, gender, annual mileage, driving experience and driver training details), they performed a practice drive, accompanied by the researcher, to familiarise themselves with the simulator environment and the experimental task. The researcher then left the simulator dome, and participants completed the experimental drive. By the end of the drive, participants provided a short feedback about their experience and were compensated £30 for their participation. The experiment lasted about 50 minutes in total.

2.4 Machine Learning and Explainable AI Analysis

Our analysis used XGBoost [4] due to its ability to handle mixed categorical and continuous features in our dataset. XGBoost is a gradient-boosting algorithm designed to handle categorical features efficiently with reduced over-fitting. The target variable was drivers’ reaction time from takeover request to first collision-avoidance manoeuvre. Drivers’ reaction time was recorded as the time gap between the trigger of the TOR and drivers’ first relevant manoeuvre towards collision avoidance [i.e., steering wheel input above 2° to any direction or brake pedal input force bigger than 1N/m, in line with 18].

Three categories of predictor features were included in the dataset: 1) gaze-related metrics captured by the PC-DMS. These included the average amplitude-velocity ratio of drivers’ blinks (AVR), as an indicator of drivers’ arousal/fatigue state [for an explanation of the metric’s calculation, see 16], stationary gaze entropy [29] as a proxy of drivers’ cognitive load [see 10, 13], gaze proportion to different areas, and yaw/pitch gaze dispersion. The “AttenD” attention buffer [30] was also used as a validated metric to account for drivers’ accumulated visual distraction over time (the AttenD algorithm considered the occlusion periods as “eyes off road”). 2) Individual driver characteristics (i.e., profile features); and 3) contextual features of the driving scenario during takeovers (such as event order and time to collision).

We employed Permutation Feature Importance (PFI) and SHAP values as our XAI techniques to identify feature attribution—a process that determines the importance of each input variable relative to the target variable when applied to data subsets [2]. PFI [1] assessed feature importance by measuring performance reduction when feature values were randomly shuffled, while SHAP [20] provided insights into how individual features contributed to model predictions. Features with zero or negative permutation importance were identified for potential exclusion in subsequent model iterations. This process was repeated iteratively until the model yielded no features with negative values. The features were extracted from a 5-second window preceding the takeover request, consistent with previous research (Yang et al., in press). Model performance was evaluated using 5-fold cross-validation (creating an 80%-20% split for each fold) with metrics including RMSE, MAE, R2, and explained variance score. The source code used to develop the prediction models generated in this work in progress—and the dataset used—can be found in our GitHub repository:

https://github.com/jorgpg5/PDRA_XAI.

3 Results

3.1 Model Performance

The XGBoost model achieved reasonable performance for this complex prediction task (RMSE: 0.343s, MAE: 0.275s, R2=

0.4439, explaining 35% of variance in takeover reaction times). Given the criticality of the experimental scenario with 3-second or 4-second time-to-collision events, the model’s mean absolute error of approximately 0.3 seconds represents meaningful predictive capability for this safety-critical domain.

3.1.1 Model Ranking. The PFI analysis (see Figure 2 for the final PFI feature scores) led us to exclude six features of the final iteration of the model: AttenD; Gaze entropy; Total glance time to rear mirror; Total glance time to passenger wing mirror; Total glance time to driver wing mirror; and Gender.

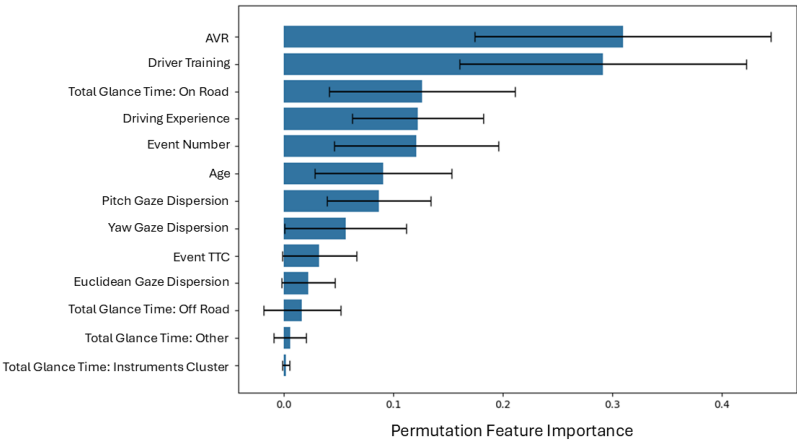


Fig. 2. Feature ranking provided by the PFI analysis. The chart displays the relative importance of features ranked from most to least influential, with error bars indicating variability.

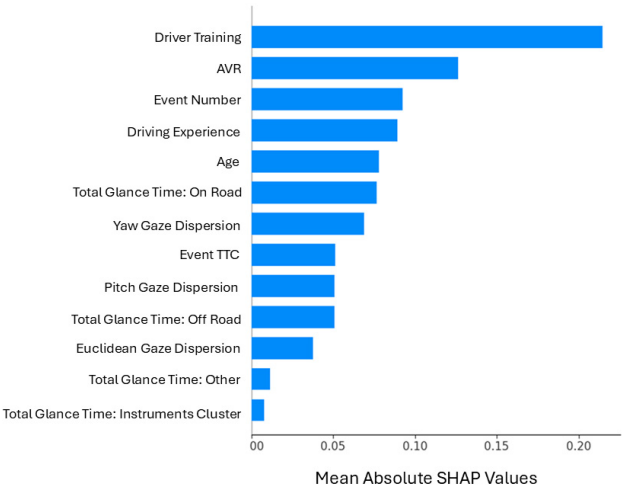


Fig. 3. Feature ranking provided by SHAP. The chart displays the average impact magnitude of each feature on model predictions, sorted from most to least influential.

Based on the preliminary best-ranked features of the selected model’s SHAP values (Figure 3), it seems that profile-related features, such as driver training (0.215), driving experience (0.0893), and age (0.0781), are the most relevant

predictor features. For gaze, features related to fatigue prediction ($AVR=0.1262$) or visual distraction from the road environment (e.g., total glance time on road = 0.0768 and yaw gaze dispersion = 0.0689) seem to be the best-performing predictors of drivers' takeover performance. The high importance of event order (0.0926) may suggest learning effects for the experimental scenario.

4 Discussion

This work in progress aimed to provide an initial evaluation of the predictive value of gaze and profile-related features of a DMS on drivers' takeover performance. To do so, XGBoost models were optimised (through hyperparameter tuning) and fitted to a driving simulator dataset where safety-critical transitions of control were required, and the predictive value of features was assessed using XAI techniques. Considering the criticality of the experimental scenario, the models' MAE comprises less than a 10% error margin from the max time to collision.

The study preliminary results suggest that the majority of the best-performing predictor features were profile-related, responsible for minimising the model's information loss. The two best-performing gaze features were related to drivers' fatigue/arousal state [AVR, 16] or drivers' visual attention to the road environment (glance time on the road). This finding is in line with current DMS implementation recommendations [6, 15] and regulations [8, 31], which state that the assessment of drivers' state in a DMS system should focus on the prevention of visual distraction and extreme fatigue states.

The irrelevance of features relating to drivers' visual attention to peripheral regions conflicts with findings from Schnebelen et al. [28], who suggest that drivers' situation awareness [5] is correlated with their attendance sources of information, away from the road centre. Our results also suggest the exclusion of gaze-based features thought to be predictive of cognitive load (i.e., gaze entropy). Therefore, although driver readiness has been previously linked to drivers' cognitive state [see 10, 23], it seems that these constructs may not be directly related to drivers' takeover performance.

On the other hand, the high relevance of driver profile in this work in progress may suggest that, based on their higher experience or advanced training, some drivers may be more capable of detecting situation criticality, reacting promptly to an imminent hazard. Although XAI techniques can provide a level of interpretability, it is still not clear how these features are correlated with other predictor variables in the real world. Nonetheless, these preliminary findings may highlight that people with distinct experience and training levels may have different strategies for monitoring the environment and detecting safety-critical situations. Thus, our preliminary results may suggest that DMS systems should aim to understand individual driver behaviour characteristics and adapt warnings to their performance to improve acceptance and adoption of these safety features.

5 Futurework

Future research should investigate the comparative performance of different ML approaches for this prediction task. While our preliminary analysis used XGBoost due to its ability to handle mixed categorical and continuous features, additional studies should examine other ensemble methods such as XGBoost and LightGBM. Comparing different architectures in parallel can ensure consistency in a feature importance analysis, avoiding potential biases from one specific model. Importantly, comparison against a linear regression baseline would help establish whether the non-linear relationships captured by ML techniques provide meaningful improvements over traditional statistical approaches for predicting takeover performance.

Longitudinal studies could also help us understand how driver-specific features evolve with their increasing familiarity with the automated systems. Such studies may reveal whether the importance ranking of profile features diminishes as

drivers gain experience with automation or whether these remain significant predictors over time. Additionally, further investigation into potential interactions between gaze features and driver profiles could identify synergistic relationships that might enhance prediction accuracy beyond what either feature could provide independently. Finally, examining a wider range of gaze features, beyond those included in current DMS guidelines, could identify new metrics that provide a higher predictive value for takeover performance.

6 Conclusions

This work in progress examines the predictive value of camera-based gaze features and individual driver profile data on takeover performance in SAE Level 2 AVs. Our preliminary findings may have revealed several important insights for the development of DMS and its regulation.

First, our analysis demonstrated that relying solely on gaze features may lead to less reliable predictions of drivers' takeover performance. While some gaze features showed predictive value—particularly AVR and total glance time on the road—the most influential predictors were individual profile characteristics. Driver training, driving experience, and age consistently demonstrated higher SHAP values, indicating their greater importance in explaining takeover performance. As AVs become increasingly prevalent, understanding these individual differences in takeover readiness will be crucial for ensuring safe transitions of control and supporting drivers in their evolving role within automated driving systems.

Our preliminary results and findings point to the need for DMS developers, regulatory bodies, and UI designers to adopt more human-centred design approaches [19] that can learn about and adapt to individual drivers. In practical terms, our results suggest that current DMS approaches that focus primarily on standard gaze-based metrics like visual distraction and fatigue detection [as recommended by 7, 15] may be complemented by systems that can adapt to individual driver characteristics.

The preliminary results of this work contribute to the automotive user interfaces community by suggesting that individual driver characteristics may be more important than traditional gaze metrics for predicting takeover performance, challenging current one-size-fits-all DMS approaches. The implications extend beyond DMS development to the broader automotive UI design space, where designers could leverage driver profiles to create adaptive experiences that balance engagement with readiness for takeover. For example, interfaces could modulate information density, interaction modalities, or interruption strategies based on driver characteristics such as experience level or training. This approach represents a shift toward more personalised human-vehicle interfaces that acknowledge driver heterogeneity rather than treating all drivers as a homogeneous group. Such adaptive systems could inform next-generation design standards that balance universal safety requirements with adaptive capabilities tailored to individual driver behaviours and preferences.

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