# A Cognitive Load Based Multi-Modal Driver Performance Ranking Model

### Overview

Professional driving is a discipline which requires an individual to possess exceptional cognitive abilities and skills for them to maintain situational awareness, react quickly to changing driving conditions, avoid accidents and make swift decisions under immense pressure during racing conditions. It is anticipated that a professionals driving performance can suffer when the demands of cognitive workload exceed their usable threshold.

The notion of cognitive workload influencing individual performance is further motivated in a study done by Hart [2] where researchers were able to develop a model for predicting an individual's cognitive workload based on various factors. This modelled idea can be further extended and applied to professional drivers under racing conditions to minimise erroneous driving through driving style improvements during sections of high cognitive workload.

Electroencephalography (EEG) has emerged as a powerful method for better understanding cognitive workload [3, 4, 5] and the factors that contribute thereto. This method provides a high temporal resolution that is sensitive to cognitive changes enabling improved resolution when combined with other physiological data such as heart rate, respiration, and eye movements, to provide a more comprehensive understanding of the cognitive workloads of an individual.

An efficient machine learning ranking model, capable of extracting latent driver patterns across similar drivers can aid them in improving their ability to process information better during high demands of cognitive workload, which will lead to more consistent and better driving performance.

## Description

The human factor is a critical aspect of a competitive motorsport team that is challenging for teams to measure by virtue the unique traits that each person possess. By considering an individual's cognitive load during simulated driving sessions, observations can be identified that indicate high and low driving performance which are then able to be addressed and improved upon.

The outcome of this research study is to create a propitious machine learning artefact capable of extracting and ranking a race car drivers performance, against other drivers, based on their cognitive load during training simulations. The artefact will assist motorsport teams by understanding driver patterns better so that the entire open-loop driver system can be optimised, not only the closed-loop car system.





Participants are provided a Direct Drive wheel capable of 5.5N.m torque along with load cell pedals to provide optimal realism during simulation. This will provide detailed feedback to the participant during driving to be able to distinguish what is happening with the car. Ideally, virtual reality will also be included for more immersion and eye tracking during data acquisition.

The simulator used will provide real-time telemetry data of the car during driving which will be utilised for the performance of the driver. Below shows the telemetry data captured through the Motec software utilised by professional race engineers during simulation. Telemetry data offers precise information on braking, accelerating, steering, engine performance, and tire slip, capturing detailed vehicle movements. This data allows direct comparisons between laps, ensuring driver consistency and enabling the development of effective racing strategies.



Transformer models are utilised to extract detailed context-aware representations of driving behaviours such as aggressive acceleration and hard cornering, which reflect a driver's performance. Coupled with the machine learning model for EEG, these models produce dense vector embeddings that encapsulate key features defining driving skills. In the proposed framework, these embeddings are collated and serve as input to a listwise ranking algorithm, like LambdaRank or ListMLE. This combined data is used to determine a final ranking for each individual, based on their driving performance and cognitive load, in comparison to others.

#### References

The figure above serves as an indicator to the EEG cap which participants will be wearing to measure the most commonly studied waveforms - delta (0.5 to 4Hz); theta (4 to 7Hz); alpha (8 to 12Hz); sigma (12 to 16Hz) and beta (13 to 30Hz). an adaptive filter based on the accelerometer signal as a reference is applied across the 16 recorded channels to remove distortion (noise) from the recorded signals. The resultant signals are then analysed in both the frequency domain and time domain to extract features residing in the theta and alpha frequencies, since the frontal and parietal cortex are the main identifiers of a person's cognitive workload.

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