A RULE-BASED SCORING METHOD FOR DRIVER BEHAVIOUR EVALUATION USING VEHICULAR PARAMETERS

B.M.S.U. Nawarathna[1*], R.J. Wimalasiri[2] and N.C.Wanigasuriya[1]

[1]Department of Electrical and Computer Engineering, The Open University of Sri Lanka, Sri Lanka

[2]Department of Mechanical Engineering, The Open University of Sri Lanka, Sri Lanka

The analysis and evaluation of driver behaviour play a critical role in enhancing road safety, optimising fleet operations, and enabling fair usage-based insurance models. Traditional methods, such as manual observation, often lack objectivity and scalability, limiting their effectiveness in large-scale applications. This study introduces a transparent, rule-based scoring system designed to assess driver behaviour using real-time vehicular data collected via the OBD-II interface. The methodology involved selecting key driving parameters including speed, engine RPM, throttle position, engine load, application of brake, and steering speed based on Sri Lankan government regulations, expert mechanic input, and findings from the literature review. Data comprising approximately 4,000 records were collected from five vehicles driven by different drivers under typical urban and suburban conditions. The dataset was thoroughly pre-processed to remove noise and invalid data points, ensuring consistency and reliability across various car models. Each parameter was assigned thresholds to categorise observed values as good, acceptable, or poor, based on established regulatory standards, expert recommendations, and benchmarks identified through a comprehensive literature review. These scores were weighted according to their relative importance to safety and vehicle health. The total weighted score for each trip was computed by summing the weighted parameter scores and subsequently normalised to a 10-point scale for consistent interpretation. Trips were classified into four behavioural categories: excellent, safe, caution advised, and risky. Application of the scoring system to a dataset of 4,000 trip records demonstrated its capability to effectively differentiate driver behaviour classes. The distribution of results showed that 32.5% of trips were categorised as excellent, 41.0% as safe, 18.0% as caution advised, and 8.5% as risky, reflecting the overall driving behaviour captured across the dataset. To validate the accuracy of these classifications, an additional controlled test was conducted using a separate vehicle driven under deliberately risky conditions, such as high speed and high engine RPM. This test vehicle was correctly classified as Risky by the model, supporting the validity of the categorisation approach. This distribution confirms the system's ability to distinguish varying levels of driving quality and risk. The system's transparent and interpretable nature, combined with its independence from large labelled datasets, supports its practical deployment in real-world contexts. The results highlight the system's potential as a valuable tool for insurers, fleet managers, and road safety authorities.

Keywords: driver behaviour, rule-based scoring, OBD-II, driver evaluation, normalisation

[*]Corresponding Author: sachini.u.nawarathna@gmail.com

A RULE-BASED SCORING METHOD FOR DRIVER BEHAVIOUR EVALUATION USING VEHICULAR PARAMETERS

B.M.S.U. Nawarathna[1*], R.J. Wimalasiri[2] and N.C.Wanigasuriya[1]

[1]Department of Electrical and Computer Engineering, The Open University of Sri Lanka, Sri Lanka
[2]Department of Mechanical Engineering, The Open University of Sri Lanka, Sri Lanka

INTRODUCTION

Assessing driver behaviour is increasingly important for improving road safety, optimising fleet management, and supporting insurance models that adjust premiums according to individual driving habits. Modern vehicles equipped with OBD-II interfaces allow for continuous real-time monitoring of critical driving parameters such as speed, engine RPM, throttle position, and brake status. These quantitative data streams provide valuable insights into driving patterns, but are typically unlabelled, making it difficult to directly classify driving quality or apply supervised learning techniques. To address this, a structured rule-based scoring framework can be used to convert raw vehicular data into meaningful behavioural categories. By applying domain knowledge and regulatory standards, each parameter is evaluated against predefined thresholds and assigned a score reflecting the quality of driving behaviour. Aggregating these scores enables the classification of trips into categories like "Excellent," "Safe," "Caution Advised," or "Risky." The effectiveness of this approach relies on well-defined rules derived from a combination of government regulations, expert mechanical input, and international research, providing a transparent and objective method for driver behaviour assessment.

METHODOLOGY

This project developed a transparent, rule-based scoring framework to evaluate driver behaviour using real-time vehicular data collected via the OBD-II interface (Bandara, et al.). The methodology consists of several key steps, each designed to systematically convert raw sensor data into a normalised driver rating and categorical label. The first task was identifying the most indicative vehicle parameters of driving behaviour. After consulting with automotive experts and reviewing regulatory standards, the following parameters were chosen: speed, engine RPM, throttle input, engine load, application of the brake, and steering speed. They were chosen due to their direct relation to driver input and usability in both safety and efficiency. Real-time data was collected from five vehicles with a Bluetooth-enabled OBD-II adapter plugged into an application on a smartphone. Raw data was transmitted to a backend server and stored temporarily in CSV format. It was then fed into a preprocessing pipeline where required features such as speed, engine RPM, throttle position, and engine load were filtered out and checked. Due to Bluetooth transmission noise and OBD signal fluctuations, some invalid entries (e.g., error codes like "18E" or outlier values) were present in the raw data. These invalid or anomalous values were identified, coerced, and filtered out to ensure data quality. This preprocessing framework guarantees uniformity across different car models and trip scenarios, which is crucial for improving the accuracy and reliability of subsequent scoring and analysis. For each parameter, there were defined thresholds to label observed values as Good, Acceptable, or Poor (Table 1). These thresholds were derived from Sri Lankan road safety regulations, expert consultations, and international literature (Kumar & Jain, 2023) (Bandara, et al., n.d.). Each parameter value was then assigned a score. The rule-based approach provided clear and understandable scoring for all driving records. Recognising that some parameters have a greater impact on safe driving than others, weights were assigned to each parameter based on their relative importance.

Table 1: Parameter Scoring Levels and Assigned Points

Good	+2
Acceptable	+1
Poor	0

These weights were determined through expert interviews and validated against industry practices, following the principles of Quality Function Deployment (QFD). According to equation (1), the weighted score for each parameter was calculated as (Yuventi & Weiss, 2013):

$$\text{Weighted Score} = \text{Parameter Score} \times \text{Parameter Weight} \qquad (1)$$

For each trip, the individual scores assigned to each driving parameter are multiplied by their respective importance weights. These weighted scores are then summed together to calculate a total raw score for that trip. This total score reflects the overall driving behaviour by combining the contributions of all parameters, considering their relative significance. Mathematically (Equation 2), this is expressed as (Yuventi & Weiss, 2013):

$$\text{Total Weighted Score} = \sum (\text{Score} \times \text{Weight}) \qquad (2)$$

To ensure comparability and interpretability, the total weighted score was normalised to a fixed scale (Equation 3). In this project, the raw total (which could reach a maximum of 20) was linearly scaled to a 10-point system using the formula (Yuventi & Weiss, 2013):

$$\text{Normalised Rating} = \frac{\text{Total Weighted Score}}{20} \times 10 \qquad (3)$$

This normalisation allows users, insurers, and fleet managers to easily interpret the driver's performance on a standard scale, regardless of the number of parameters or their original score ranges. According to the normalised rating, each trip was labelled as one of four behaviour groups: Excellent, Safe, Caution Advised, or Risky. These groups allow for decision-making feedback and are appropriate for downstream insurance and fleet management decision-making.

RESULTS AND DISCUSSION

The rule-based scoring system was tested on a dataset of 4,000 trip records from five vehicles three Toyota Vitz, one Toyota Corolla Hybrid, and one Suzuki Alto driven by various individuals in typical urban and suburban conditions in Sri Lanka. The system aimed to objectively categorise driver behaviour using real-world vehicular data. Parameter thresholds were established using Sri Lankan speed regulations (The Gazette of the Democratic Socialist Republic of Sri Lanka, 2015) for speed, and a combination of previous research (Peppes Nikolaos, 2021) (Shirole, Shahade, & Deshmukh , 2025) and expert mechanic consultation for other variables such as engine RPM, engine load, throttle position, accelerator position, brake status, and steering speed (Table 2). Each parameter was assigned a weight reflecting its impact on safety and vehicle health, with speed, brake status, and steering speed given the highest importance (Table 3). For every trip, driving parameters were scored as Good, Acceptable, or Poor based on these thresholds, These parameter scores were multiplied by their respective weights and summed to calculate the total weighted score (Table 4). This approach enabled consistent and interpretable classification of driver behaviour across the dataset.

Table 2 : Parameter Thresholds and Scoring Structure

Parameter	Good (+2)	Acceptable (+1)	Poor (0)
Speed	25 – 45	0 – 25 or 45 – 70	> 70
Engine RPM	1200 – 2800	1000 – 1200 or 2800 – 3200	< 1000 or > 3200
Engine Load	35 – 55	30 – 35 or 55 – 65	< 30 or > 65
Accelerator Pos	10 – 40	5 – 10 or 40 – 50	< 5 or > 50
Throttle Pos	10 – 40	5 – 10 or 40 – 50	< 5 or > 50
Brake Status	0 (not braking)	-	1 (braking)
Steering Speed	0.3 – 1.2	0.2 – 0.3 or 1.2 – 1.5	< 0.2 or > 1.5

Table 3 : Weighting Parameters Based on Impact Severity

Parameter	Weight	Reason for Weighting
Speed	2.0	High impact on road safety and accident risk
Engine RPM	1.0	Indicates engine strain and fuel efficiency
Engine Load	1.0	Reflects vehicle effort and mechanical health
Accelerator Pos	1.0	Related to driver input and fuel usage
Throttle Pos	1.0	Tied to acceleration style and engine smoothness
Brake Status	2.0	Critical for detecting harsh braking
Steering Speed	2.0	Reflects control and erratic driving

Table 4 : Calculating the Total Weighted Score

Parameters	Score	Weight	Weighted Score (Score × Weight)
Speed	2	2.0	4.0
Engine RPM	2	1.0	2.0
Engine Load	2	1.0	2.0
Accelerator Pos	2	1.0	2.0
Throttle Pos	2	1.0	2.0
Brake Status	2	2.0	4.0
Steering Speed	2	2.0	4.0
Total Score			**20.0**

Normalising a 10-Point Driver Rating

To standardise scores for easy interpretation, the total weighted score (maximum 20) was normalised to a 10-point scale using min-max scaling (Han, Kamber, & Pei, 2011) (Shirole, Shahade, & Deshmukh , 2025). For example, a total score of 15 would normalise to:

$$\frac{15}{20} \times 10 = 7.5$$

Table 5 : Categorizing Driver Behaviour

9-10	Excellent
7-8.9	Safe
5-6.9	Caution Advised
<5	Risky

Normalised ratings were mapped to four driver behaviour categories (Table 5), following a tiered classification strategy consistent with prior studies (Kumar & Jain, 2023) (Peppes Nikolaos, 2021).

Table 6 : Distribution of Driver Behaviour Categories

Category	% of Records	Characteristics

Excellent	32.5%	Low RPM, smooth throttle, consistent speed
Safe	41.0%	Minor variability in engine load and speed
Caution Advised	18.0%	Moderate braking, wider steering deviations
Risky	8.5%	High RPM, frequent harsh braking, erratic speed

The result verifies that the supervised scoring algorithm is capable of distinguishing categories of driver behaviour using real-time vehicle information (Table 6). The application of expert-guided thresholds and weights ensures that critical safety parameters are given an influence on the resulting rating
Normalisation facilitates easier interpretation to be consistent for trips and drivers. The scoring system is clear and easy to understand. It shows exactly how each driving parameter, such as speed or application of the brake, affects the final score, unlike complex models where the decision process is unclear. The system combines official driving regulations with expert insights from experienced mechanics, making it reliable.

CONCLUSIONS/RECOMMENDATIONS

This project developed a rule-based scoring approach to evaluate driver behaviour from real-time vehicle OBD-II data. By defining clear thresholds for key driving parameters and weights according to expert knowledge and regulatory standards, the system effectively converts raw unlabelled data into interpretable driver scores. The scoring system is transparent, interpretable, and does not require large labelled datasets. Tests on 4,000 trip records showed that the system can successfully classify drivers such as Excellent, Safe, Caution Advised, and Risky, which provides insightful information for insurance and fleet management. Future improvements could focus on making the scoring system more adaptive by incorporating dynamic thresholds that adjust to different road, weather, and traffic conditions.

REFERENCES

Bandara, H., Chithraranjan, C., Karunathilaka, K., Jayaweera, P., Kalani, K., & Meththananda, R. (n.d.). Driver Behavior Analysis using Vehicular Data.

Han, J., Kamber, M., & Pei, J. (2011). Data Mining: Concepts and Techniques.

Kumar, R., & Jain, A. (2023). Driving behavior analysis and classification by vehicle OBD data using machine learning. 79, 18800–18819.

Peppes Nikolaos, A. T. (2021). Driving Behavior Analysis Using Machine and

Deep Learning Methods for Continuous Streams of Vehicular Data.

Shirole, V., Shahade, A., & Deshmukh, P. (2025). A comprehensive review on data-driven driver behavior scoring in vehicles: technologies, challenges and future directions.

(2015). The Gazette of the Democratic Socialist Republic of Sri Lanka.

Yuventi, J., & Weiss, S. (2013). Probabilistic Consideration Method for Weight/Score-Based Decisions in Systems Engineering-Related Applications.