Driving heterogeneity identification using machine learning
A review and framework for analysis

Yao, Xue; Calvert, Simeon C.; Hoogendoorn, Serge P.

DOI
10.1016/j.trip.2025.101511

Publication date
2025

Document Version
Final published version

Published in
Transportation Research Interdisciplinary Perspectives

Transportation Research Interdisciplinary Perspectives 32 (2025) 101511

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.elsevier.com/locate/trip

Driving heterogeneity identification using machine learning: A review and framework for analysis

Xue Yao *, Simeon C. Calvert, Serge P. Hoogendoorn

Department of Transport & Planning, Delft University of Technology, Stevinweg 1, 2628 CN, Delft, The Netherlands

ARTICLE INFO

Keywords:
Driving heterogeneity
Identification
Machine Learning (ML)
Traffic flow
Traffic data analysis

ABSTRACT

Driving heterogeneity significantly influences traffic performance, contributing to traffic disturbances, increased crash risks, and inefficient fuel use and emissions. With the growing availability of driving behaviour data, Machine Learning (ML) techniques have become widely used for analysing driving behaviour and identifying heterogeneity. This paper presents a systematic review of current ML-based methods for driving heterogeneity identification. The review organises key concepts and categorisations of driving heterogeneity, highlights strengths and drawbacks of various methods, and outlines applications of identification analysis. Based on the literature review, we propose a structured framework that guides the ML-based identification process. The framework starts with an extensive data collection and rigorous pre-processing process, followed by feature selection techniques that identify features most indicative of driving behaviours. Sophisticated models including supervised, unsupervised, semi-supervised, and reinforcement learning techniques are discussed with multi-perspective performance evaluation. This paper provides a comprehensive reference for researchers and practitioners to understand driving heterogeneity, supporting the development of data-driven solutions for improving traffic management and road safety.

1. Introduction

Driving behaviour plays a crucial role in shaping traffic flow, influencing road safety, and the overall sustainability of transportation systems (Khan and Das, 2024). The way a vehicle responds to driver inputs, along with environmental factors and propulsion dynamics, forms the basis of the vehicle-driver interaction. Importantly, drivers exhibit varying behaviours even under identical traffic conditions, a phenomenon known as driving heterogeneity. This variability has been shown to impact traffic performance by increasing crash risk, disrupting traffic flow, and contributing to higher fuel consumption and emissions (Ossen et al., 2006; Yao et al., 2024b). For example, delayed reaction times and reduced stimulus sensitivity have been linked to an elevated risk of rear-end collisions (Zhang et al., 2019). In mixed traffic environments where autonomous vehicles (AVs) and human-driven vehicles (HDVs) coexist, overlooking HDV heterogeneity can result in oversimplified AV behavioural models, thus increasing safety issues (Calvert and van Arem, 2020). These issues underscore the need for accurate identification and modelling of human driving variability for both simulation and real-world applications.

Identifying driving heterogeneity requires rich data capturing a wide range of driver actions, such as speed, acceleration, and braking, as well as contextual factors like road conditions, traffic density, and weather. These data can come from various sources, including floating car data (FCD) via smartphones and GPS, in-vehicle sensors, or high-resolution imagery from roadside cameras and drones (Lee and Jang, 2024). Based on driving behaviour data, heterogeneity analysis methods generally fall into two categories: subjective approaches (e.g., surveys and questionnaires) and objective approaches, which include rule-based logic, fuzzy systems, and increasingly, machine learning (ML) techniques (Priyadharshini and Josephin, 2020). With the rise of naturalistic driving datasets, ML techniques have become especially effective in capturing complex behavioural patterns due to their flexibility, high accuracy, and adaptability (Fernandes et al., 2024). Models such as Support Vector Machines (SVM), k-Nearest Neighbours (KNN), and Feedforward Neural Networks (FFNN) have been widely used to classify driving styles, often achieving accuracy rates above 90% (Sun et al., 2021; Zhang et al., 2010). Beyond traditional ML, deep learning models, including Long Short-Term Memory (LSTM) networks, have proven effective in modelling time-dependent behaviours, such as driver responses to external incentives or changes in driving workload (Hoogendoorn and Van Arem, 2013).

Several previous reviews have explored driving heterogeneity from different angles, such as distinguishing driving styles and manoeuvres (Bouhsissin et al., 2023; Abou Elassad et al., 2020), improving

* Corresponding author.
E-mail address: x.yao-3@tudelft.nl (X. Yao).

https://doi.org/10.1016/j.trip.2025.101511
Received 21 October 2024; Received in revised form 28 March 2025; Accepted 25 June 2025
Available online 8 July 2025

ADAS and safety systems (Lin et al., 2014; Martinez et al., 2017; Kaplan et al., 2015; Tselentis and Papadimitriou, 2023), and evaluating vehicle–cloud collaboration (Mei et al., 2025). However, these studies often focus on specific subdomains and vary in how they define and categorise driving heterogeneity. There remains a lack of a unified conceptual framework that systematically organises key definitions, methodologies, and application pathways. In particular, ML-based approaches differ substantially in terms of data processing, feature selection, and model design (Zhang et al., 2010; Wang et al., 2018; Silva and Eugenio Naranjo, 2020), making it difficult to determine which techniques are most suitable for a given traffic context.

To address these gaps, this paper presents a comprehensive review of ML-based driving heterogeneity identification and proposes a structured framework to support its practical implementation. Our review focuses on longitudinal driving behaviours, especially in highway settings, and covers various traffic and environmental conditions. The goal is to advance data-driven strategies for understanding, classifying, and modelling driving heterogeneity, ultimately enabling personalised driver support, better traffic management, and safer vehicle automation systems. The main contributions of this study are twofold:

(i) Comprehensive literature review: We consolidate existing knowledge on driving heterogeneity, organising key concepts, behavioural categories, and ML-based identification methods. This provides a foundation for researchers to navigate and build upon existing work.

(ii) A framework for analysis: We propose a structural framework that supports heterogeneity identification through data collection and pre-processing, feature selection, model training, and performance evaluation. The framework incorporates supervised, unsupervised, semi-supervised, and reinforcement learning techniques, with a focus on their strengths, limitations, and suitability for different data types and use cases.

The remainder of this paper is organised as follows: Section 2 outlines concepts of driving heterogeneity and discusses categorisation, applications, and identification tasks. Section 3 introduces the proposed ML-based framework for identifying driving heterogeneity. Section 4 presents key findings, implementation challenges, and directions for future research. Finally, Section 5 concludes the paper with implications for a safer, more efficient, and sustainable intelligent transportation system.

2. An overview of driving heterogeneity & identification

This section presents an overview of the review, as illustrated in Fig. 1. The need for driving heterogeneity identification (WHY) stems from its relevance to real-world applications including traffic management, personalised ADAS, and human-like AV design. The review then organises key concepts of driving heterogeneity (WHAT) in multiple dimensions. Finally, we introduce the methodological process (HOW) for ML-based driving heterogeneity identification. This visual guide provides a structured foundation for the rest of the paper and sets the stage for the proposed analytical framework.

2.1. Applications of driving heterogeneity identification

Identifying driving heterogeneity has practical values in improving traffic management, enhancing road safety, and enabling personalised driver support systems. In traffic operations, understanding variations in driver behaviour allows for better predictions of congestion and more effective control strategies, such as adaptive signal timings or alternative route recommendations. It also helps in detecting unusual or high-risk behaviours, which can support real-time interventions such as issuing warnings to nearby vehicles or alerting authorities (Ma et al., 2019; Abbas et al., 2011). In vehicle technology, heterogeneity identification enhances the customisation of Advanced Driver Assistance Systems (ADAS). For example, systems can adapt their feedback based on an individual's driving tendencies, providing earlier alerts to those prone to hard braking or enhanced lane assistance for frequent lane-changers (Feng et al., 2019; Zhang et al., 2021). Similarly, for automated vehicles (AVs), recognising and responding to diverse human driving styles enables AVs to behave more naturally and safely in mixed traffic environments (Martinez et al., 2017). These applications influence how we define and study driving heterogeneity by directing attention to specific behavioural differences and shaping the design of identification methods.

2.2. Concepts and categorisation of driving heterogeneity

Driving heterogeneity refers to the variability in driver traits, decision-making, and control actions. This variability manifests in both space and time (Zou et al., 2022), and can be categorised along three main dimensions: (i) **inter-driver** vs. **intra-driver** heterogeneity, (ii) **long-term** vs. **short-term** heterogeneity, and (iii) **global** vs. **special** behavioural patterns.

Inter-driver heterogeneity describes differences among drivers in similar conditions. For instance, some may accelerate more aggressively or maintain smaller headways than others (Ossen et al., 2006; Sun et al., 2021). In contrast, intra-driver heterogeneity refers to how the same driver may behave differently over time or across situations (Ossen and Hoogendoorn, 2011; Taylor et al., 2015). From a temporal perspective, long-term heterogeneity relates to persistent behavioural tendencies or driving skills developed over months or years, while short-term heterogeneity reflects temporary states like distraction or fatigue during a specific trip (Azadani and Boukerche, 2021). Lastly, global heterogeneity captures overall behaviour over a trip or time period, such as consistent car-following strategies (Sun et al., 2021), whereas special heterogeneity focuses on specific manoeuvres or behaviours, such as harsh braking or sharp turns (Sagberg et al., 2015).

Delineating these concepts provides a fundamental insight into understanding driving heterogeneity, which helps to describe heterogeneity in a human-comprehend manner. To operationalise these ideas, researchers identify driving heterogeneity using categories including: *Driving style* (e.g., aggressive, normal, mild), *Risk level* (e.g., safe, risky), *Driving skill* (e.g., novice, expert), *Irregular behaviours* (e.g., harsh braking), and *Driving patterns* (e.g., acceleration phases, lane changes). Table 1 summarises these categories, their descriptors, and the type of driving heterogeneity they address. Each plays a distinct role in capturing variability across time, context, and individual differences. For example, driving styles are often associated with inter-driver and long-term global heterogeneity, while risk level and irregular behaviour focus on short-term, situational variability. Additionally, driving pattern recognition provides a flexible tool for capturing both intra-driver variation and broader behavioural tendencies.

Together, these concepts and descriptors for identifying driving heterogeneity not only enhance our understanding of the multifaceted nature of driver behaviour but also facilitate the interpretation and development of ML-based interventions aimed at improving road safety and traffic management.

2.3. Methodologies for driving heterogeneity identification

Identifying driving heterogeneity is typically formulated as a classification problem, using behavioural data to distinguish among different drivers or driving patterns. Based on the literature review, three main methodological approaches can be distinguished:

1. Classifying driving behaviours into distinct groups to specific driving profiles.
2. Creating an extensive set for driving states without interpretation.

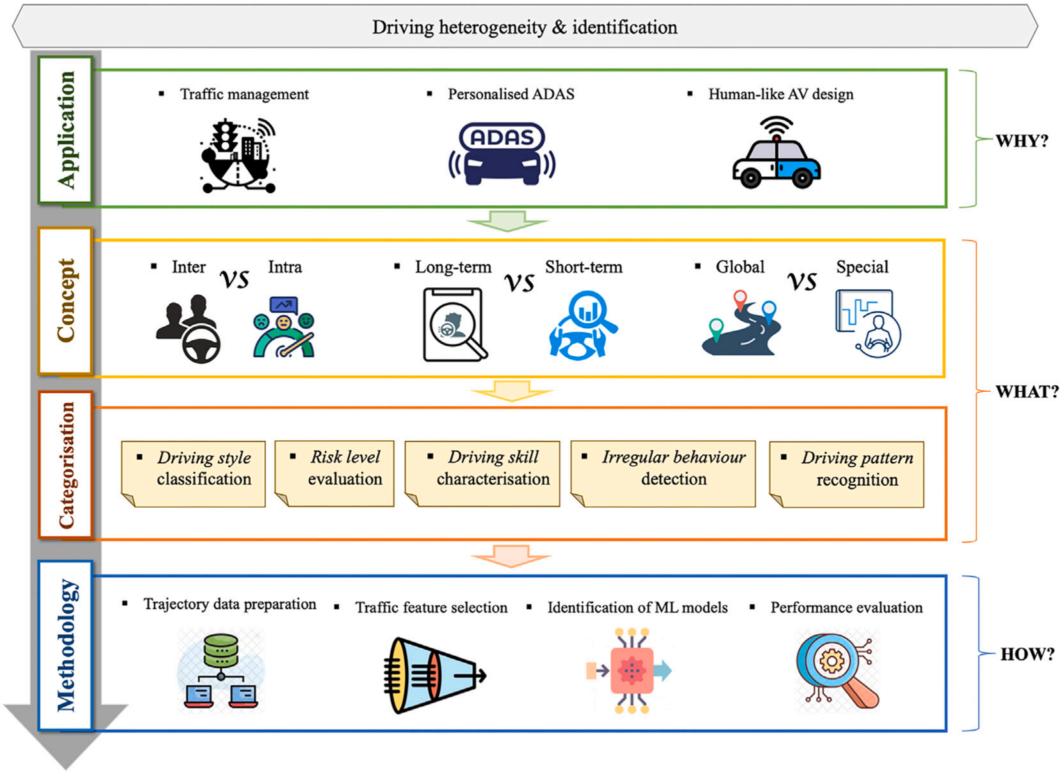


Fig. 1. An overview of the literature review paper.

Table 1
Categorisation of driving heterogeneity identification.

Categorisation	Descriptors	Inter	Intra	Long-term	Short-term	Global	Special
Driving style classification	Aggressive, radical, normal, cautious, etc.	✓	✓	✓	✓	✓	✓
Risk level evaluation	High-moderate-low risk, etc.	✓	✓		✓	✓	✓
Driving skill characterisation	Expert, typical, etc.	✓		✓		✓	
Irregular behaviour detection	Aggressive braking, aggressive acceleration, etc.	✓			✓		✓
Driving pattern recognition	Closing in, closing in, keeping, falling behind, etc.	✓	✓		✓	✓	✓

3. Decomposing complex driving behaviour into simpler, more fundamental patterns with interpretation.

The first approach assigns drivers to predefined categories or clusters, often based on discrete scales (e.g., 2 to 5 groups) or numerical indices (e.g., a score from 0 to 10). For example, drivers may be classified into aggressive (also termed radical), normal (moderate, conventional), or mild (timid, conservative) styles (Sun et al., 2021; Bejani and Ghatee, 2019; Liu et al., 2020; Feng et al., 2019; Liang et al., 2022). Similarly, driver skill levels have been grouped as novice, typical, or expert (Chandrasiri et al., 2016; Zhang et al., 2010; Zhu et al., 2018). While these classifications offer clear and interpretable outputs, they are limited in capturing the full range of behavioural diversity due to their coarse granularity. Furthermore, the thresholds used to define these categories are often subjective, potentially introducing bias into the identification process.

Instead of directly classifying or clustering, the second approach creates a broad space of behavioural profiles to represent driving heterogeneity more flexibly. For instance, Qi et al. (2019) proposed a high-dimensional style space containing over 20 behavioural types. Similarly, modelled individual behaviour using probabilistic distributions over different driving states rather than discrete groups (Ding et al., 2022). By acknowledging more characteristics, this approach can detect a wider range of variations in driving behaviour. However, this extensive categorisation approach might compromise the interpretation of driving profiles, thus limiting its implementation. This highlights the need for methods that can balance complexity and interpretability in behaviour modelling.

The third approach decomposes driving behaviour into simpler, fundamental components, commonly referred to as “primitives”, to analyse heterogeneity at a finer resolution. These primitives represent short, distinct behavioural segments with identifiable characteristics. For example, Wang et al. (2018) extracted primitives such as “following behind”, “closing”, “gentle acceleration”, and “aggressive deceleration” to model driving heterogeneity. Yao et al. (2023, 2025) introduced the concept of “action phases” as basic units to describe transitions in driving behaviour, enabling a clearer interpretation of behaviour dynamics. This approach allows for detailed analysis of intra- and inter-driver variability while maintaining semantic clarity, making it well-suited for both theoretical development and practical applications.

In summary, methodologies for identifying driving heterogeneity differ in their emphasis on interpretability, flexibility, and granularity. Category-based methods are simple and interpretable but limited in detail of behavioural characteristics; continuous profiling offers richer representation but lacks clarity; and pattern decomposition provides high interpretability with fine granularity. Machine learning (ML) techniques are commonly used across these approaches due to their capability to model complex behaviours and handle large datasets. In the

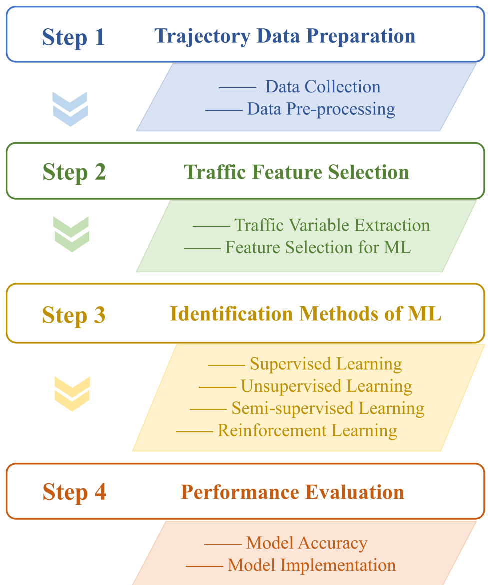


Fig. 2. A framework for ML-based driving heterogeneity identification.

next sections, we explore how ML is applied to support and enhance these methodologies.

3. A framework for driving heterogeneity analysis

In this section, we introduce the proposed framework for identifying driving heterogeneity using Machine Learning (ML) techniques. The framework is developed based on a comprehensive review of existing literature and consists of four main steps: *Trajectory Data Preparation*, *Traffic Feature Selection*, *Identification Models of ML*, and *Performance Evaluation*, as illustrated in Fig. 2. The initial step involves collecting, cleaning, and pre-processing raw driving data to ensure it accurately represents real-world driving behaviour. This step is essential for reducing errors and improving the quality of subsequent analysis. The second step, *Traffic Feature Selection*, focuses on identifying relevant variables from the pre-processed data that are most informative for modelling driving behaviour. Effective feature selection enhances model accuracy and reduces computational complexity. The third step, *Identification Models of ML*, applies the selected features to train ML models capable of detecting and classifying different driving behaviour patterns. This is the core step where heterogeneity is identified using various ML learning algorithms. Finally, *Performance Evaluation* assesses the effectiveness of the ML models. This includes not only traditional accuracy metrics but also interpretability, generalisation to new data, and real-time applicability in the real-world. The following sub-sections describe each step in detail, discussing the methods used in the literature along with their respective advantages and limitations.

3.1. Step 1: Traffic data preparation

Since ML models rely on data to learn and make predictions, the quality of input data is critical to successful driving heterogeneity identification. Therefore, the first step in the framework is preparing trajectory data, which includes data collection and pre-processing. This step ensures that the data used is clean, reliable, and representative of actual driving behaviours.

3.1.1. Data collection

Driving behaviour data is commonly collected using four methods: driving simulator, in-vehicle camera, sensor or hardware, traffic images, and floating car data (FCD, e.g., smartphone-based). These methods vary in controllability, data richness, quality, validity, and cost, as summarised in Table 2.

Controllability refers to how much researchers can influence the data collection environment. Driving simulators offer the highest control, allowing for designed experiments under specific conditions (Chandrasiri et al., 2016). In-vehicle equipment allows to collect driving data in certain traffic scenarios, such as curving sections or ramps (Liu et al., 2017), while unpredictable situations could happen in real-world data collection, thus with lower controllability than a driving simulator. Traffic images and FCD methods rely entirely on naturalistic driving, making them the least controllable. **Data richness** relates to the diversity and quantity of details available within a specific dataset. Driving simulators and in-vehicle equipment methods can provide driver information and manoeuvre-specific data and allow for repeatable data collection, but are limited in scale due to time and financial constraints. Conversely, traffic images and FCD methods capture large-scale driving behaviour but with less details about driver and manoeuvre information. **Quality** concerns the precision and objectivity of datasets. Data from driving simulators and in-vehicle equipment may suffer from observer effects. For example, drivers know they are observed and might exhibit different driving behaviours compared to driving in a real-world setting, thus reducing the objectivity of collected data (Higgs and Abbas, 2013). Traffic images and FCD capture real-world behaviours but face issues with sensor accuracy, video resolution, and post-processing errors. **Validity** measures how accurately the data reflects actual driving behaviour. Driving simulators have low validity due to artificial environments, whereas in-vehicle equipment, traffic images, and FCD provide higher validity by capturing real-world driving under diverse conditions. **Cost** refers to the expenses, time, and human effort needed for data collection. Driving simulators are expensive due to equipment and participant costs. In-vehicle systems range from affordable GPS devices to costly telematics. Traffic images require expensive infrastructure and high data-processing costs. FCD, utilising built-in smartphone sensors, is the most cost-effective but raises privacy concerns (Eren et al., 2012).

Each method offers trade-offs in terms of control, scale, and precision. Researchers can leverage these insights to tailor their data collection strategies effectively, aligning with their research goals and specific research questions. For instance, Studies focusing on detailed driver behaviour may prioritise driving simulators or in-vehicle equipment, while traffic management and policy research may favour traffic images or FCD for broader behavioural insights.

Fig. 3 shows the use of various data collection methods over the years in the reviewed papers. Thanks to the development of technologies such as telematics, GPS systems, and 5G, there is an increase in the availability and application of both FCD and in-vehicle equipment methods. The latter, in particular, has seen a trend towards more consistent and long-term usage in studies. As increasing numbers of publicly naturalistic driving datasets have become available since 2018, studies based on traffic image data have increased. Correspondingly, the use of driving simulator experiments and datasets has declined due to more available naturalistic data.

3.1.2. Data pre-processing

Collected driving trajectory data often contains noise and inaccuracies due to sensor errors, video quality limitations, and data extraction inconsistencies (Xie et al., 2020; Chen et al., 2020). These issues can distort analysis results and misrepresent driving behaviour. To enhance data reliability, various pre-processing techniques are applied to maintain data integrity and optimise input quality for ML-based driving behaviour analysis. Table 3 provides a summary of techniques

Table 2
Comparison analysis of driving trajectory data collection method.

Method	Controllability	Data richness	Quality	Validity	Cost
Driving simulator	High	• Scale: Small • Repeatability: Easy • Specific manoeuvres: Easy • Driver information: Easy	Affected by • Scenarios design • Observer effect	Low	High
In-vehicle equipment	Low	• Scale: Small • Repeatability: Easy • Specific manoeuvres: Easy • Driver information: Easy	Affected by • Observer effects	High	Moderate to high
Traffic images	No	• Scale: Large • Repeatability: Hard • Specific manoeuvres: Hard • Driver information: Hard	Affected by • Observation errors • Parsing errors	High	Moderate to high
FCD (Smartphone-based method)	No	• Scale: Large • Repeatability: Hard • Specific manoeuvres: Hard • Driver information: Hard	Affected by • Sensor accuracy	High	Low

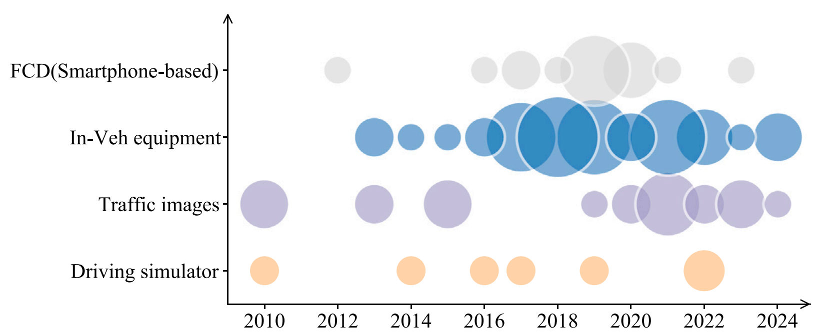


Fig. 3. Statistics of data collection methods over the year.

for outlier elimination, filtering, and data synchronisation. Regression-based methods and cubic interpolation are commonly used to detect and correct outliers by either adjusting values based on predictive modelling or estimating missing points from surrounding data (Sun et al., 2021; Ma et al., 2021). Additionally, filtering techniques, such as the Butterworth filter and Savitzky-Golay filter, are employed to smooth out noise while preserving critical data patterns (Guyonvarch et al., 2018; Lyu et al., 2022). To ensure temporal consistency, data synchronisation techniques adjust the sampling rates of datasets. Up-sampling is applied to sparse data to increase resolution and retain essential behavioural details, while down-sampling simplifies large-scale datasets, improving computational efficiency without significant information loss (Saleh et al., 2017; Ma et al., 2021).

Overall, each data pre-processing method has its specific purpose when dealing with noise and maintaining data integrity. To ensure that the data is accurately represented to derive meaningful driving characteristics, the selection of data pre-processing methods should be carefully chosen according to the nature of the dataset involved.

3.2. Step 2: Traffic feature selection

The second step in the proposed framework is traffic feature selection, which aims to reduce dimensionality by selecting relevant variables from the pre-processed dataset. While datasets often include many features, not all of them contribute meaningfully to identifying driving heterogeneity. Using irrelevant or redundant features can reduce model accuracy and increase computational cost. Therefore, feature selection is essential to improve model performance and interpretability.

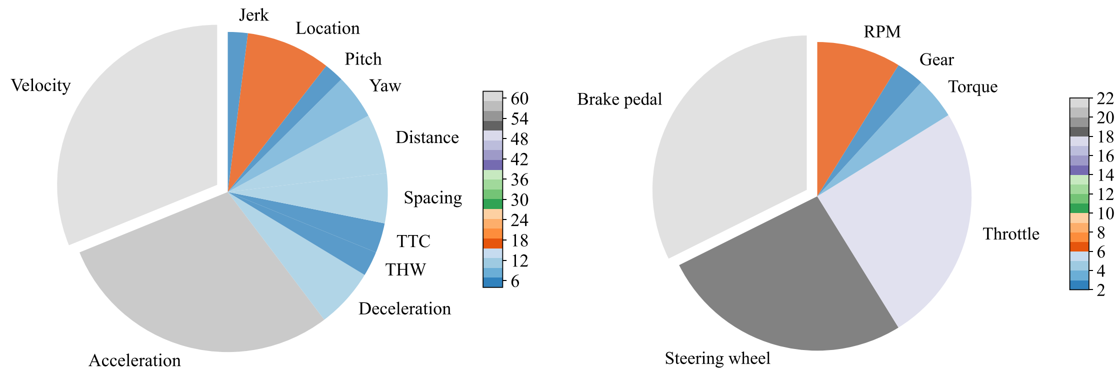
3.2.1. Traffic variable extraction

There is currently no universally agreed-upon sets of metrics for driving behaviour analysis in literature. According to Abou Elassad et al. (2020), metrics used in driving studies can be grouped into four categories: vehicle-based, behavioural, physiological, and subjective. Since this study focuses on trajectory-based analysis, we consider only vehicle-based variables, which include vehicle kinematic and dynamic features. Kinematic variables describe the vehicle's motion, such as speed and acceleration, while dynamic variables reflect the driver's control inputs, such as braking and throttle use. Both types of variables are widely used to characterise driving behaviour and detect heterogeneity (Taylor et al., 2015; Kim et al., 2013).

Fig. 4 summarises the use of these variables in existing studies. Kinematic variables are used more frequently than dynamic ones due to their strong correlation with driver responses to traffic situations. Velocity (used in 61 studies) and acceleration (57) are the most common variables for identifying driving heterogeneity. Among dynamic variables, braking (21), steering wheel angle (18), and throttle position (17) are frequently used because they provide direct information about driving behaviours. The importance of these variables depends on the specific type of heterogeneity being studied. For instance, throttle usage has been found to be a strong indicator of aggressive driving (Shi et al., 2015), while combining RPM, speed, and acceleration improves driving style classification (Moosavi et al., 2021). Moreover, integrating acceleration and brake events can increase classification accuracy by up to 10% according to Van Ly et al. (2013). Therefore, variable selection should align with the specific behavioural characteristics and heterogeneity concepts under investigation.

3.2.2. Feature selection for ML

Machine learning (ML) models rely on carefully selected traffic features to improve predictive accuracy and computational efficiency. Driving behaviour studies often generate extensive feature sets by incorporating various statistical descriptors such as maximum, minimum, and average values. For instance, one study derived 117 features from three acceleration signals (Vaitkus et al., 2014), while another extracted 58 brake-event-based features to classify driving behaviour



(a) Vehicle kinematic variables

(b) Vehicle dynamic variables

Fig. 4. Statistics of traffic variables used in literature.

Table 3
Techniques for pre-processing driving behaviour data.

Category	Technique	Characteristic
Outlier elimination	Regression (Sun et al., 2021)	- Identifies and adjusts anomalies by fitting a predictive model to the data.
	Cubic interpolation (Ma et al., 2021)	- Fills missing values by estimating them based on nearby data points, preserving dataset smoothness.
Filtering	Butterworth filter (Guyonvarch et al., 2018)	- Smooth response in the passband, preserving the true characteristics of driving data while effectively removing noise
	Savitzky-Golay filter (Lyu et al., 2022)	- Retains data distribution shape for pattern consistency
Data synchronisation	Up-sampling (Saleh et al., 2017)	- Increases the sampling rate in smaller datasets to capture more detailed information while maintaining consistency
	Down-sampling (Ma et al., 2021)	- Reduces the sampling rate in large-scale datasets, enhancing computational efficiency without significant data loss

Table 4
Feature selection techniques used for driving heterogeneity identification.

	Method	Pros (✓) & Cons (✗)	Reference
Statistical methods	FA DFT DTW WT PCA	✓ Computationally efficient ✓ Interpretable results ✗ Miss feature interactions ✗ Questionable assumptions	Zhang et al. (2021) Zhang et al. (2010), Zou et al. (2022) and Xue et al. (2019) Feng et al. (2019), Xue et al. (2019) and Eftekhari and Ghatee (2018) Zhang et al. (2010) and Zheng et al. (2022) Sun et al. (2021), Liu et al. (2020) and Deng et al. (2020)
Model-based methods	Tree-based GMM SFFS	✓ Capture feature interactions ✓ Yield better model performance ✗ Computationally intensive ✗ Risk of overfitting	Figueira and Larocca (2020) Wahab et al. (2009) Vaitkus et al. (2014)
Deep learning-based methods	Autoencoder RNN	✓ Handle complex patterns ✓ Good for high-dimensional data ✗ Computationally expensive ✗ Challengable interpretability	Guo et al. (2018) Moukafih et al. (2019) and Moosavi et al. (2021)

Abbreviations:
FA - Factor Analysis; GMM - Gaussian Mixture Method; SFFS - Sequential Forward Feature Selection - RNN - Recurrent Neural Network.

(Gahr et al., 2018). Given the complexity of high-dimensional datasets, feature selection techniques play a crucial role in refining inputs for ML models. These techniques can be broadly categorised into statistical methods, model-based approaches, and deep learning-based strategies, as summarised in Table 4.

Statistical methods, including Principal Component Analysis (PCA), Discrete Fourier Transform (DFT) (Tang, 2009), and Dynamic Time Warping (DTW), are widely applied in driving behaviour analysis. These techniques enhance computational efficiency while providing interpretable results. PCA, for example, transforms data into a new coordinate system, simplifying visualisation and feature ranking (Sun et al., 2021). Similarly, DFT analyses signals in the frequency domain to minimise information loss (Xue et al., 2019). Some studies integrate multiple techniques, such as combining Wavelet Transform (WT) with PCA (Zheng et al., 2022) or DFT with Discrete Wavelet Transform (DWT) (Xue et al., 2019), to improve feature selection accuracy. However, these methods often assume linear relationships in data, making them less effective in capturing complex feature interactions. Model-based methods, such as decision trees (DT), random forests (RF), and Gaussian Mixture Models (GMM), offer an alternative by directly assessing feature importance within predictive ML models. These approaches can identify non-linear dependencies between variables, leading to better model performance. However, they can be computationally intensive and susceptible to overfitting, particularly in small datasets. For high-dimensional and complex datasets, deep learning-based methods provide advanced feature selection capabilities. Techniques such as autoencoders and Recurrent Neural Networks (RNNs) effectively capture intricate relationships between features and adapt to evolving driving patterns (Guo et al., 2018; Moukafih et al., 2019). While these methods improve feature representation, they are computationally demanding and often lack interpretability. In a word, selecting the appropriate feature selection technique requires balancing computational efficiency, interpretability, and accuracy based on the specific objectives of driving heterogeneity identification.

3.3. Step 3: Identification methods of ML

The third step of the framework focuses on applying machine learning (ML) models to identify driving heterogeneity based on the traffic features selected in *Step 2*. In literature, ML techniques methods used for this purpose are generally classified into four categories: supervised learning (SL), unsupervised learning (USL), semi-supervised learning (SSL), and reinforcement learning (RL), which we elaborate further on below.

3.3.1. Supervised learning methods

Supervised learning (SL) techniques train models to learn the relationship between input features and output labels, allowing them to make predictions or decisions on new, unlabelled data. This process requires training data to be labelled in advance, which is obtained from expert knowledge. Some studies use rule-based strategies to label data by measuring physical variable changes, such as vehicle steering angle or brake/accelerator pedal positions (Wang et al., 2018). Threshold values for variables in rule-based labelling are typically determined by data analysts' prior knowledge and sometimes combined with other tools, such as driving style questionnaire (DSQ) (Wahab et al., 2009). K-means is also often employed for unsupervised learning labelling to group drivers and then label these clusters based on statistical analyses. For instance, Deng et al. (2020) classified 30 participants into cautious, moderate, and aggressive drivers based on the PCA and K-means clustering before training models for driving style recognition. In these labelling processes, strict thresholds are usually set to distinguish different groups. A downside of this is that it can result in inaccurate classifications since there are not always clear-cut boundaries between different driving profiles. To improve this, approaches such as fuzzy logic can be adopted in some studies (Eftekhari and Ghatee, 2018). Unlike the definitive nature of classical binary logic, fuzzy logic systems bridge inputs to outputs using a set of rules, which allows for establishments of conditions like $if(A\&B) \Rightarrow C$, where A, B, and C represent different driving profiles. Such an approach avoids the constraints of rigid categories, offering a more accurate classification of driving heterogeneity.

With labelled data, supervised learning classifiers are trained to identify driving heterogeneity. Commonly used traditional ML algorithms include Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbours (KNN), and Multi-Layer Perceptron (MLP), among others. Xue et al. (2019) employed SVM for driving style recognition and revealed its advantage over RF, KNN, and MLP with an accuracy of 91.7%. More recently, deep learning methods, such as ANNs, CNNs, and RNNs, have demonstrated superior performance in handling complex and high-dimensional driving data. According to Xie et al. (2021), the F1-score of CNN-based method is higher than both k-NN and RF-based methods in driving manoeuvre classification. Subsequently, enhanced CNN-based models, such as the adaptive regularised CNN (CNNAR) (Bejani and Ghatee, 2019), the parallel Convolutional Neural Network (PCNN) (Camlica et al., 2022), and the Residual Convolutional Network (RCN) (Abdennour et al., 2021) were introduced by boosting CNN's capability in driving pattern recognition, showing impressive performance by improving accuracy of 99.3% and reducing training time by two hours. Furthermore, Long Short-Term Memory (LSTM) networks are developed to overcome the vanishing gradient challenges of RNNs, exhibiting high accuracy in driving style classification, and unsafe driving behaviour detection, such as 91% as reported by Khodairy and Abosamra (2021) and 99% according to Saleh et al. (2017), which outperform traditional ML models like MLP and DT (Wijnands et al., 2018). Additionally, hybrid deep learning approaches have shown significant improvements in classification accuracy. For example, by taking CNN's ability to extract semantic driving patterns (e.g., turns) from input trajectories and employing an RNN on the sequential driving data to decode interrelationships among driving patterns, the proposed D-CRNN model presented improved accuracies of 8%–31% in driving style identification compared to CNN and RNN models (Moosavi et al., 2021).

Table 5 summarises SL applications in driving heterogeneity identification, detailing input data types, classifier choices, and output categories. Note that most SL studies focus on kinematic variables, with some integrating dynamic features to capture more driving behaviour feathers (Li et al., 2019; Khodairy and Abosamra, 2021). The output of SL models varies depending on the classification task. Some studies categorise drivers into styles-based groups (e.g., aggressive and normal) or risk-based groups (e.g., high, moderate, and low risk), while others identify specific behaviours such as braking or acceleration patterns (Xie et al., 2021). Additionally, some models focus on identifying drivers through driving states (Abdennour et al., 2021), while others detect unsafe behaviours like drowsy or distracted driving (Shahverdy et al., 2020).

3.3.2. Unsupervised learning methods

Unsupervised learning (UL) methods can derive driving profiles by directly examining unlabelled data, which is significantly less labour-intensive and reduces potential labelling biases. Table 6 summarises key studies that employ clustering techniques. Clustering methods such as K-means and Fuzzy C-means (FCM) group drivers based on similar driving styles, offering interpretable categorisations such as aggressive, normal, and defensive driving (Sun et al., 2021; Feng et al., 2019). More advanced clustering techniques like Federated Learning K-means (FL-K-means) and Gaussian Mixture Models (GMM) improve identification precision by handling scattered and sensitive data (Lu et al., 2023; Zhang et al., 2021). Topic models, particularly Latent Dirichlet Allocation (LDA) and its variants (T-LDA, mLDA, mHLDA), segment naturalistic trajectories into behavioural "topics", enabling fine-grained identification of cautious and radical driving styles (Xie et al., 2018; Qi et al., 2019). HMM-based approaches, such as sticky HDP-HMM and BP-AR-HMM, capture temporal dependencies by segmenting driving trajectories into hidden states, representing distinct driving states (Wang et al., 2019; Hamada et al., 2016). Similarly, DAA-based methods such as Double Articulation Analyser with Temporal Prediction (DAA-TP) and Nested Pitman–Yor Language Model (NPYLM) can decompose driving sequences into hierarchical structures, mirroring linguistic pattern recognition for driver identification (Taniguchi et al., 2014, 2015). Other studies employed deep learning models, such as Deep Sparse Autoencoder (DSAE) and Autoencoders with Self-Organised Maps (AESOM) to extract latent driving features, improving real-time recognition of high-risk and moderate-risk driving behaviours (Liu et al., 2017; Guo et al., 2018).

Similar to SL methods, USL techniques primarily rely on kinematic vehicle data, such as speed, acceleration, and braking patterns, with some studies incorporating dynamic variables like yaw rate and lateral acceleration (Hamada et al., 2016; Liu et al., 2017). Clustering and topic models work well with aggregated statistical features to distinguish different groups (e.g., aggressive, normal, risky), while HMM and deep learning-based models process sequential driving data, enabling better recognition of behavioural transitions (Wang et al., 2019).

3.3.3. Semi-supervised learning methods

Semi-supervised learning (SSL) methods train classifiers with a small amount of labelled data and a large volume of unlabelled data, making it a promising approach for identifying driving heterogeneity with reduced labelling efforts. For example, semi-supervised SVM (S3VM) has shown better performance than traditional SVM in driving style classification (Wang et al., 2017). Advanced SSL models, like the

Table 5
Identification of driving heterogeneity using supervised learning methods.

Paper	Input data[a]		ML models[b]	Output
	Kine.	Dyna.		
Xue et al. (2019)	✓		**SVM**, RF, KNN, MLP	Aggressive, and normal driving
Li et al. (2017)	✓		RF	High-, moderate-, and low-risk driving
Jafarnejad et al. (2017)	✓	✓	**AB**, GB, RF, ET, SVM	Aggressive/risky, and normal driving
Vaitkus et al. (2014)	✓		KNN	Aggressive, and normal driving
Silva and Eugenio Naranjo (2020)	✓		**SVM**, ANN, KNN, FL, KNN, RF	Aggressive, calm, and normal driving
Figueira and Larocca (2020)	✓		CART, SVM	High-, moderate-, and low-risk driving
Tango and Botta (2013)	✓	✓	**SVM**, ANFIS, LRNN, FFNN, LR	Typical and skillful driver
Li et al. (2019)	✓	✓	**CNN**, LSTM, pretrain-LSTM, SVM	High-, moderate-, and low-risk driving
Shahverdy et al. (2020)	✓	✓	2D CNN	Normal, aggressive, distracted, drowsy, and drunk driving
Xie et al. (2021)	✓		**CNN**, KNN, RF	Driving manoeuvres: lane keeping, braking, turning, acceleration, right lane change, and left lane change
Abdennour et al. (2021)	✓	✓	**DeepRCN**, DeepCNN, DT, RF, SVM, MLP	Driver recognition
Bejani and Ghatee (2019)	✓		**CNNAR**, SVM, MLP, KNN, DT	Cautious, moderate, and aggressive driving
Camlica et al. (2022)	✓		**PCNN**, CNN, LSTM, HMM, SVM	Aggressive, and non-aggressive driving
Khodairy and Abosamra (2021)	✓		**3-CCM-LSTM**, 2-CMM-LSTM	Normal, drowsy, and aggressive driving
Saleh et al. (2017)	✓	✓	**stacked-LSTM**, MLP, DT	Normal, aggressive, and drowsy driving
Wijnands et al. (2018)	✓		LSTM	Safe and unsafe driving
Moosavi et al. (2021)	✓	✓	**D-CRNN**, CNN, RNN, ARNet, VRAE, GBDT	Driver recognition
Moukafih et al. (2019)	✓	✓	**LSTM-FCN**, RF, LSTM, AB, ResNet	Aggressive and non-aggressive driving
Eftekhari and Ghatee (2018)	✓		ANFIS	Safe, aggressive, and semi-aggressive driving
Schlegel et al. (2021)	✓		**HDC-FFNN**, SNN, KNN, SVM, LSTM	Aggressive, and normal driving

[a] Table headings: Kine. - Vehicle kinematic variable; Dyna. - Vehicle dynamic variable;
Dis. - discrete, the output of ML model is distinct groups; Con. - continuous, the output of ML model is continuous trajectories.
[b] ML models: ET - Extra Trees; FL - Fuzzy Logic; CART - Classification and Regression Tree; ANFIS - Adaptive Neuro-fuzzy Inference Systems; 3-CCM - Three-class Classification Model; VRAE - Variational Recurrent Auto-Encoder; FFNN - Feed-forward Neural Networks; SNN - Spiking Neural Networks; LRNN - Layer Recurrent Neural Networks.

Table 6
Identification of driving heterogeneity using unsupervised learning methods.

Paper	Input data		ML models[a]	Output
	Kine.	Dyna.		
Higgs and Abbas (2013)	✓		K-means	Driving states
Sun et al. (2021)	✓		Fuzzy C-means	Aggressive, normal, and mild driving
Feng et al. (2019)	✓		SVC	Aggressive, normal, and defensive driving
Lu et al. (2023)	✓		IFL K-means, FL K-means, FL-GMM, FFCM, MA K-means	Aggressive, moderate, and calm driving
Zhang et al. (2021)	✓		HC-GMM, GMM, DBSCAN, HC, K-means	Aggressive and normal driving
Bender et al. (2015)	✓		LDA	Trajectory segmentation
Xie et al. (2018)	✓		T-LDA, LDA, pLSA	Cautious, normal, radical, very radical driving
Qi et al. (2019)	✓		mLDA, mHLDA	Extensive driving styles
Wang et al. (2019)	✓		sticky HDP-HMM	Driving primitives
Hamada et al. (2016)	✓	✓	BP-AR-HMM	Driving states
Taniguchi et al. (2014)	✓		DAA-TP	Driving states
Taniguchi et al. (2015)	✓		NPYLM	Driver identification
Liu et al. (2017)	✓	✓	DSAE	Driving states
Guo et al. (2018)	✓		AESOM	Slight, moderate, high risk driving

[a] ML models: IFL - Improved Federated Learning; FFCM - Federated Fuzzy C-means Method; pLSA - Probabilistic Latent Semantic Analysis; DSAE - Deep Sparse Autoencoder.

HDP-HSMM, outperform supervised counterparts such as HDP-HMM in extracting driving patterns from high-dimensional data (Wang et al., 2018). Similarly, Tri-CatBoost integrates pseudo-labelling through tri-training, achieving higher accuracy than both supervised and unsupervised baselines (Liu et al., 2020). Another approach, ARNet, leverages a limited number of labelled samples to guide a regularised autoencoder, improving accuracy by over 3% compared to traditional models. SSL methods are particularly useful when labelled data is scarce. Yet, their performance can be sensitive to noisy labels and data inconsistency. Moreover, their added complexity often increases computational requirements and implementation difficulty.

3.3.4. Reinforcement learning methods

Reinforcement Learning (RL) approaches driving behaviour as a Markov Decision Process (MDP), where agents learn to perform driving actions based on a system of rewards and penalties. Driving heterogeneity is identified by analysing variations in learned behaviours and reward responses. For example, different reward functions can represent different levels of driving aggressiveness (Vlachogiannis et al., 2020). However, the lack of standard reward design and difficulty in validating learned behaviours are key challenges. Inverse Reinforcement Learning (IRL) instead learns the reward functions directly from observed driver behaviour. Techniques such as MLIRL and LogReg-IRL recover style-related parameters from human driving data (Jiang et al., 2018; Kishikawa and Arai, 2021). More advanced methods, like SIRL (Rosbach et al., 2019) and NFACRL (Abbas et al., 2011), further enhance the robustness of driving style identification, particularly in dynamic or risky environments. While IRL offers deeper insights into individual driving preferences, its reliance on high-fidelity simulation environments, complex reward interpretation, and high computational cost limits its scalability in real-world applications.

3.3.5. Summary of ML methods

Each ML technique employs a distinct mechanism, as illustrated in Fig. 5. From a data processing perspective, SL, USL, and SSL focus on data-driven analysis, including classification and clustering (see Fig. 5(a)–(c)). In contrast, RL is primarily concerned with understanding and modelling the decision-making processes of drivers, see Fig. 5(d). Each ML technique has strengths and weaknesses and focuses on different aspects of driving heterogeneity, as summarised in Table 7. SL methods rely on labelled data and learn from historical labelled examples to classify driving behaviours into specific categories (e.g., aggressive vs. normal driving). They are predominantly used

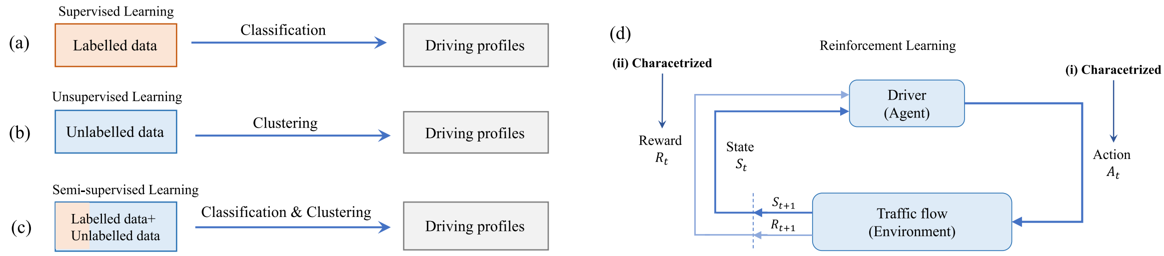


Fig. 5. Mechanism of different ML techniques.

Table 7
Comparison of ML techniques in driving heterogeneity identification.

ML technique	Main heterogeneity focus	Strengths	Weaknesses
SL	Inter, short-term, global	High interpretability, effective classification	Requires labelled data, less adaptable
USL	Intra, short-term, global, and special	Captures hidden structures, scalable	Lower interpretability
SSL	Inter, short-term, and global	Reduces need for labels, improves generalisation	Susceptible to misclassification
RL	Inter, short-term, global	Adaptive, useful for AV behaviour modelling	High computational cost, complex reward tuning

to characterise inter-driver heterogeneity, meaning variations among different drivers. They also frequently identify short-term and global heterogeneity, such as variations in acceleration or braking patterns across different traffic scenarios. USL methods identify patterns by clustering similar driving behaviours or segmenting trajectories based on statistical properties, which are particularly useful for identifying intra-driver heterogeneity (i.e., variations in an individual driver's behaviour over time). They also effectively capture short-term heterogeneity and global driving behaviour trends by analysing large-scale datasets without predefined categories. However, the lack of explicit labels makes their interpretability more challenging. SSL methods leverage both labelled and unlabelled data but can suffer from misclassification issues if the small labelled dataset does not represent the full heterogeneity of the driving population. RL-based models particularly emphasise short-term and global heterogeneity, making them valuable for adaptive driving systems and autonomous vehicle behaviour modelling.

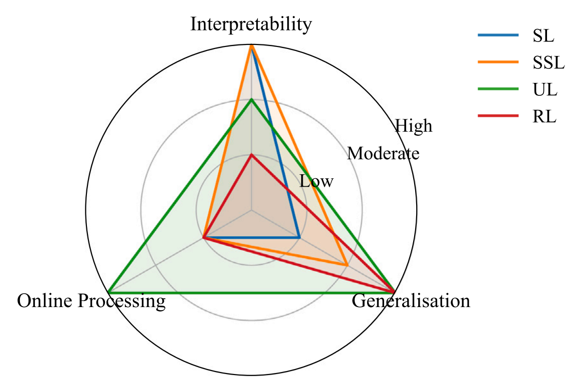


Fig. 6. Analysis of ML techniques in model implementation.

3.4. Step 4: Performance evaluation

The final step of the framework is performance evaluation which justifies a model's reliability, ensuring trustworthy and replicable outcomes. This is not only about model accuracy but also interpretability, generalisation, and online processing which displays the model's practical usability in real-world applications for ADAS, traffic management, and autonomous vehicle control.

3.4.1. Model accuracy

Evaluating model accuracy is crucial to finding the best performance for identifying driving heterogeneity. Classification models usually rely on Accuracy, Precision, Recall, F1-score, AUC-ROC, and Cohen's Kappa to measure alignment with ground-truth labels (Xue et al., 2019; Fung et al., 2017; Ma et al., 2018; Silva and Eugenio Naranjo, 2020; Abdennour et al., 2021; Zhang et al., 2014). Various models such as SVM, RF, and KNN achieve an accuracy surpassing 85% when used to classify driving skills, some even exhibit better exceeding 95% (Chandrasiri et al., 2016; Jafarnejad et al., 2017; Kwon et al., 2021). Ranking-based metrics like MRR and CRR assess the prioritisation of driving behaviours, crucial for driver feedback systems. MAE and MSE are used for continuous outcome predictions, where MSE minimises large errors while MAE offers straightforward model performance. For unsupervised learning, clustering performance is measured by the Silhouette Score, Davies–Bouldin Index, and Calinski–Harabasz Index, ensuring well-separated clusters (Higgs and Abbas, 2014). RL models use cumulative reward and convergence time to assess learning efficiency, essential for adaptive ADAS and traffic control.

Studies also employ benchmarking models from state-of-the-art to ensure performance validation, highlighting model strengths, and guiding the selection of optimal algorithms for real-world applications while enabling continuous refinement. This is usually done by using advanced deep learning models and traditional ML algorithms to conduct the same identification tasks, as seen for example with the proposed CNNAR model, which was compared with SVM, MLP, and KNN to demonstrate its superiority in identifying driving heterogeneity (Moosavi et al., 2021). Other studies compare their improved ML models with corresponding foundational counterparts to illustrate enhancements (Moukafih et al., 2019; Qi et al., 2019).

3.4.2. Model implementation

Interpretability, generalisation, and online processing are crucial factors for real-world applications, influencing how well models can be understood, adapted to diverse driving environments and implemented in real-time driving scenarios. Interpretability ensures that the model's predictions can be understood and trusted by researchers, policymakers, and industry stakeholders. Generalisation determines whether an ML model can maintain its accuracy across different road conditions, weather patterns, and driver populations. And online Processing allows ML models to process incoming traffic data in real-time, making them applicable to adaptive traffic control, driver monitoring systems, and autonomous vehicle decision-making. Each ML approach has distinct strengths and limitations across these three dimensions, as illustrated in Fig. 6, influencing its suitability for various driving heterogeneity identification tasks.

Interpretability: SL and SSL methods offer the highest interpretability, as they classify driving behaviours into well-defined categories, making them useful for safety assessments and driver feedback. USL and RL methods have lower interpretability because of no label, but their results can be analysed to have human-comprehensive meanings. For instance, interpretable identification results can be provided by conducting statistical analysis on a limited number of clusters and giving semantic meanings (Sun et al., 2021; Wang et al., 2018; Hamada et al., 2016).

Generalisation: SL struggles with new environments due to reliance on predefined labels, while SSL improves adaptability by leveraging unlabelled data. USL is highly generalisable, as it uncovers hidden driving patterns across diverse conditions. As presented by Ding et al. (2022), the proposed GMM-based driving style identification method demonstrated effectiveness when supplemented with new driving data. RL can generalise well but depends on carefully tuned reward functions, which can limit transferability to new scenarios.

Online processing: USL is best suited for real-time applications, as clustering can adapt incrementally without retraining. SL and SSL require batch processing, limiting their real-time use. For instance, incorporating more SVMs can distinguish more driving styles, while this complicates the algorithm and can overburden the computational capacity of on-board vehicle controllers (Chu et al., 2023). RL demands extensive training and updates, making it difficult for immediate deployment in adaptive traffic systems.

In total, effective ML models for driving heterogeneity must balance interpretability, generalisation, and online processing for better real-world applications in traffic management, driver profiling, and autonomous driving.

3.5. Summary

The proposed framework structures the ML-based identification process using four inherently connected steps. Each step includes multiple methods, offering flexibility in approach selection based on research objectives. By systematically comparing these techniques, the framework facilitates optimised identification, balancing model effectiveness with practical application needs.

4. Discussion

In this section, we discuss the main findings of the literature review and the proposed framework for driving heterogeneity analysis. Then we propose challenges and future recommendations towards implementing this framework for real-world applications.

4.1. Main findings

Driving heterogeneity identification involves three key aspects including applications, concepts, and methodologies. A clear objective of each aspect ensures reliable identification. The main insights from this study are summarised below.

4.1.1. Driver heterogeneity dimensions

Driving heterogeneity is categorised into three core concepts, with five identification tasks. **Inter-** and **intra-** driving heterogeneity refers to differences among drivers and variations within individual drivers' behaviour. Understanding driving heterogeneity from this perspective aids in improving traffic efficiency and road safety. Driving heterogeneity can be divided into **long-term** and **short-term** from a temporal perspective, which benefits the development of personalised ADAS. Additionally, **Global** and **special** driving heterogeneity are identified based on overall vehicle movements or specific driving events, which is important for AV design. The identification tasks include *driving style* classification, *risk level* evaluation, *driving skill* characterisation, *irregular behaviour* detection, and *driving pattern* recognition. Clearly defining these concepts and identification tasks helps comprehensively understand the essence of driving heterogeneity and enhances the interpretability of ML models.

4.1.2. ML-based heterogeneity identification

The ML-based driving heterogeneity identification process can be structured as a four-step framework, consisting of *Trajectory Data Preparation*, *Traffic Feature Selection*, *Identification Models of ML*, and *Performance Evaluation*. Each step includes multiple methods with unique strengths and limitations. Facilitating driving heterogeneity identification requires aligning them with the specific research objectives. Proper data collection, preprocessing, and feature selection are necessary to match the heterogeneity concept being studied. Since ML techniques differ in accuracy, interpretability, and real-time applicability, balancing these factors ensures an effective identification process, improving its practical relevance.

4.1.3. Applications of the identification framework

The proposed identification framework is adaptable to various datasets, integrates diverse ML techniques, and supports real-world applications. This flexibility allows for the incorporation of new models and data sources, enhancing identification performance. The framework emphasises interpretability and real-time recognition, encouraging researchers to evaluate methods across multiple dimensions. By guiding the implementation of ML-based driving heterogeneity identification, it supports traffic management, personalised ADAS, and human-like AV designs, ultimately improving transportation systems.

4.2. Key issues and future research recommendations

While ML-based methods show strong potential in driving heterogeneity identification, practical deployment, especially in real-time and automated driving systems requires improvements in both data and model design. This section highlights key challenges and outlines future directions to enhance the applicability of the proposed framework in real-world settings.

4.2.1. Enhancing data quality and availability

Real-time and high-resolution data collection: ML models are highly sensitive to the quality and granularity of input data (Zhu et al., 2018). Traditional data sources, including traffic images and basic in-vehicle sensors, often suffer from noise and low sampling resolution. Industry-grade data collection systems, such as those used by Waymo, Mobileye, and Aurora, combine LiDAR, radar, and vision sensors with sub-millisecond-accurate logging via CAN or Ethernet networks (Waymo, 2024; Mobileye, 2024). These multi-sensor platforms enable large-scale collection of naturalistic driving data across diverse environments.

Advanced preprocessing and anomaly detection: Noise filtering and outlier elimination remain essential for improving data reliability. However, commonly used filters such as Savitzky-Golay or Butterworth may smooth out useful behavioural variations. More adaptive preprocessing methods, including machine learning-based anomaly detection and dynamic filtering strategies, are needed to better preserve meaningful heterogeneity in raw data.

Fusion of heterogeneous data sources: Combining data from simulators, traffic cameras, GPS, IMUs, and floating car data can yield a more holistic view of driving behaviour. However, successful integration depends on the development of unified data formats (e.g., ROS, JSON), synchronisation protocols (e.g., timestamp alignment), and cross-platform interoperability standards. Research should focus on frameworks that enable robust data fusion for training consistent ML models.

Balancing dataset use and development: Public datasets like NGSIM (U.S. Department of Transportation, Federal Highway Administration, 2006), HighD (Krajewski et al., 2018), KITTI (Geiger et al., 2013), and Lyft5 (Wang et al., 2023b) are widely used due to their accessibility, but they vary in precision and collection context, which may introduce bias or limit generalisability. Future work should aim to balance the reuse of open datasets with the creation of context-specific datasets that better represent traffic conditions.

Ethical data use and privacy protection: The use of personalised driving data raises concerns regarding privacy and data protection. Researchers must prioritise secure data handling practices, including anonymisation techniques (e.g., differential privacy), encryption, and compliance with international regulations such as the GDPR and CCPA (Villegas-Ch and García-Ortiz, 2023). Future work should explore privacy-preserving learning approaches that allow effective model training without compromising individual privacy.

4.2.2. Improving model design and performance

Context-aware and flexible labelling: Traditional labelling strategies often rely on predefined thresholds or global statistics, potentially overlooking subtle, time-sensitive behavioural shifts (Sagberg et al., 2015). Recent industry practices emphasise event-driven and context-aware labelling techniques to capture the complexity of real-world driving behaviours. For instance, AI-powered systems analyse driver gaze, head movements, and body posture to detect distraction and drowsiness, enabling more nuanced labelling of driver states (Zhao et al., 2022). Future research should continue to explore such adaptive labelling methods to enhance model accuracy.

Feature representation and selection: High-dimensional data with redundant variables can hinder model performance. Attention mechanisms, embedding layers, and spatio-temporal encoders should be employed to capture the most informative features. Domain knowledge can also assist in selecting features that reflect heterogeneity across time, context, and driver type.

Model interpretability vs. accuracy: While deep learning models such as CNNs and LSTMs often achieve high accuracy, they can lack transparency. Techniques like SHAP (SHapley Additive exPlanations) values, attention visualisation, and hybrid rule-based models can improve interpretability without significant performance loss (Yao et al., 2023). Enhancing explainability is essential for increasing trust in ML models, particularly in safety-critical applications.

Cross-disciplinary inspiration: Other domains, such as natural language processing (NLP) and biological modelling of gene expression, offer insights into pattern recognition and behavioural inference. Developing a taxonomy of driving behaviours, similar to biological annotation databases, could support better labelling and model validation. For instance, techniques from NLP sentiment analysis have been adapted to understand driver emotions and intentions, enriching behaviour modelling (Taniguchi et al., 2015).

Adoption of Emerging AI Techniques: Recent advancements in AI models such as Vision Transformers (ViT), Graph Neural Networks (GNNs), and Large Language Models (LLMs) offer promising capabilities for driving behaviour analysis (Xiao et al., 2022). These models can capture long-range dependencies, learn contextual semantics, and reduce reliance on large labelled datasets through self-supervised or foundation model approaches. As these techniques gain traction in industry, they are increasingly used to detect nuanced and high-level patterns in driving heterogeneity. When integrated with the proposed framework, these models can significantly enhance the scalability, adaptability, and reliability of driving behaviour identification in complex, real-world traffic scenarios.

4.2.3. Addressing heterogeneity in human-automated traffic

The emergence of automated vehicles in traffic introduces new challenges for driving heterogeneity analysis. Interactions between human-driven vehicles (HDVs) and AVs create more complex behavioural dynamics, requiring the framework to adapt accordingly (Calvert and van Arem, 2020).

Heterogeneity of HDVs in the presence of AVs: Empirical studies show that HDVs often adjust their driving styles, such as maintaining smoother speeds, longer headways, and more cautious manoeuvres, when following AVs (Wen et al., 2022; Wang et al., 2023a). These behavioural shifts are further influenced by the external design of AVs (e.g., visibility of sensors) and the perceived assertiveness or caution in their driving style. Industrial companies such as Waymo and Cruise actively test human-AV interactions in mixed traffic using naturalistic testbeds and closed-loop simulations. Incorporating these behavioural adaptations as variables in heterogeneity models will improve their ability to reflect real-world traffic interactions.

Heterogeneity of human-driven AVs: Drivers of partially automated vehicles (e.g., SAE Level 2–3) exhibit diverse attitudes towards automation, with variation in trust, comfort, and takeover behaviour. Misalignment between AV system behaviour and driver expectations may result in frequent manual overrides, reduced system efficiency, and safety concerns (Lee and See, 2004; Ma and Zhang, 2021). Industry solutions, such as Ford's and Tesla's driver monitoring systems, track gaze direction, head pose, and hand position to evaluate readiness for control transitions (Lee et al., 2024). Future heterogeneity models should incorporate variables such as trust level, takeover frequency, and driver compliance to better model human-in-the-loop behaviours.

Overall, the proposed framework can be extended to address these evolving traffic conditions by integrating new feature variables (e.g., time headway to AVs, takeover intent), incorporating updated datasets from real-world or simulated mixed traffic scenarios, and refining model evaluation criteria to include human–system interaction dynamics. This adaptation will support the design of safer, more personalised, and behaviourally aligned automated driving systems, thus ensuring better interaction between AVs and a diverse range of human drivers.

5. Conclusion

This study provides a comprehensive review of machine learning (ML) techniques for analysing driving behaviour heterogeneity and introduces a structured framework for identifying and interpreting heterogeneity in real-world traffic scenarios. By synthesising key concepts and state-of-the-art methodologies, the proposed framework serves as a systematic guide for data collection, preprocessing, feature selection, modelling, and evaluation, facilitating a more rigorous and interpretable approach to driving heterogeneity identification. Additionally, the review serves as a roadmap for future research, encouraging further exploration of ML applications in traffic analysis with the potential to enhance traffic management, road safety, and vehicle automation. Specifically, a clear conceptualisation of driving heterogeneity deepens our understanding of driver behaviour and lays the foundation for the development of personalised driving assistance systems and human-like autonomous vehicles. By reviewing various ML methodologies and assessing their strengths, limitations, and applicability to different driving contexts, this study emphasises the need to balance accuracy, interpretability, and real-time recognition for effective heterogeneity identification. Recognising individual driving characteristics allows for adaptive traffic control strategies, leading to more intelligent and responsive transportation solutions.

CRediT authorship contribution statement

Xue Yao: Methodology, Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Simeon C. Calvert:** Methodology, Supervision, Writing – review & editing. **Serge P. Hoogendoorn:** Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Abbas, M., Chong, L., Higgs, B., Medina, A., Yang, C.D., 2011. Agent-based evaluation of driver heterogeneous behavior during safety-critical events. In: 2011 14th International IEEE Conference on Intelligent Transportation Systems. ITSC, IEEE, pp. 1797–1802.

Abdennour, N., Ouni, T., Amor, N.B., 2021. Driver identification using only the can-bus vehicle data through an rcn deep learning approach. Robot. Auton. Syst. 136, 103707.

Abou Elassad, Z.E., Mousannif, H., Al Moatassime, H., Karkouch, A., 2020. The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review. Eng. Appl. Artif. Intell. 87, 103312.

Azadani, M.N., Boukerche, A., 2021. Driving behavior analysis guidelines for intelligent transportation systems. IEEE Trans. Intell. Transp. Syst. 23 (7), 6027–6045.

Bejani, M.M., Ghatee, M., 2019. Convolutional neural network with adaptive regularization to classify driving styles on smartphones. IEEE Trans. Intell. Transp. Syst. 21 (2), 543–552.

Bender, A., Agamennoni, G., Ward, J.R., Worrall, S., Nebot, E.M., 2015. An unsupervised approach for inferring driver behavior from naturalistic driving data. IEEE Trans. Intell. Transp. Syst. 16 (6), 3325–3336.

Bouhsissin, S., Sael, N., Benabbou, F., 2023. Driver behavior classification: A systematic literature review. IEEE Access.

Calvert, S., van Arem, B., 2020. A generic multi-level framework for microscopic traffic simulation with automated vehicles in mixed traffic. Transp. Res. C: Emerg. Technol. 110, 291–311.

Camlica, Z., Quesenberry, J., Carballo, D., Crowley, M., 2022. Aggressive driver behavior detection using parallel convolutional neural networks on simulated and real driving data. In: 2022 9th International Conference on Internet of Things: Systems, Management and Security. IOTSMS, IEEE, pp. 1–8.

Chandrasiri, N.P., Nawa, K., Ishii, A., 2016. Driving skill classification in curve driving scenes using machine learning. J. Mod. Transp. 24 (3), 196–206.

Chen, X., Sun, J., Ma, Z., Sun, J., Zheng, Z., 2020. Investigating the long-and short-term driving characteristics and incorporating them into car-following models. Transp. Res. C: Emerg. Technol. 117, 102698.

Chu, H., Zhuang, H., Wang, W., Na, X., Guo, L., Zhang, J., Gao, B., Chen, H., 2023. A review of driving style recognition methods from Short-Term and Long-Term perspectives. IEEE Trans. Intell. Veh..

Deng, Z., Chu, D., Wu, C., Liu, S., Sun, C., Liu, T., Cao, D., 2020. A probabilistic model for driving-style-recognition-enabled driver steering behaviors. IEEE Trans. Syst. Man Cybern.: Syst. 52 (3), 1838–1851.

Ding, Z., Xu, D., Tu, C., Zhao, H., Moze, M., Aioun, F., Guillemard, F., 2022. Driver identification through heterogeneity modeling in car-following sequences. IEEE Trans. Intell. Transp. Syst..

Eftekhari, H.R., Ghatee, M., 2018. Hybrid of discrete wavelet transform and adaptive neuro fuzzy inference system for overall driving behavior recognition. Transp. Res. F: Traffic Psychol. Behav. 58, 782–796.

Eren, H., Makinist, S., Akin, E., Yilmaz, A., 2012. Estimating driving behavior by a smartphone. In: 2012 IEEE Intelligent Vehicles Symposium. IEEE, pp. 234–239.

Feng, Y., Pickering, S., Chappell, E., Iravani, P., Brace, C., 2019. A support vector clustering based approach for driving style classification. Int. J. Mach. Learn. Comput. 9 (3), 344–350.

Fernandes, P., Ferreira, E., Macedo, E., Coelho, M.C., 2024. Unraveling roundabout dynamics: Analysis of driving behavior, vehicle performance, and exhaust emissions. Transp. Res. D: Transp. Environ. 133, 104308.

Figueira, A.C., Larocca, A.P.C., 2020. Proposal of a driver profile classification in relation to risk level in overtaking maneuvers. Transp. Res. F: Traffic Psychol. Behav. 74, 375–385.

Fung, N.C., Wallace, B., Chan, A.D., Goubran, R., Porter, M.M., Marshall, S., Knoefel, F., 2017. Driver identification using vehicle acceleration and deceleration events from naturalistic driving of older drivers. In: 2017 IEEE International Symposium on Medical Measurements and Applications (MeMeA). IEEE, pp. 33–38.

Gahr, B., Ryder, B., Dahlinger, A., Wortmann, F., 2018. Driver identification via brake pedal signals—a replication and advancement of existing techniques. In: 2018 21st International Conference on Intelligent Transportation Systems. ITSC, IEEE, pp. 1415–1420.

Geiger, A., Lenz, P., Stiller, C., Urtasun, R., 2013. Vision meets robotics: The kitti dataset. Int. J. Robot. Res. 32 (11), 1231–1237.

Guo, J., Liu, Y., Zhang, L., Wang, Y., 2018. Driving behaviour style study with a hybrid deep learning framework based on GPS data. Sustainability 10 (7), 2351.

Guyonvarch, L., Hermitte, T., Duvivier, F., Val, C., Guillaume, A., 2018. Driving style indicator using UDRIVE NDS data. Traffic Inj. Prev. 19 (sup1), S189–S191.

Hamada, R., Kubo, T., Ikeda, K., Zhang, Z., Shibata, T., Bando, T., Hitomi, K., Egawa, M., 2016. Modeling and prediction of driving behaviors using a non-parametric Bayesian method with AR models. IEEE Trans. Intell. Veh. 1 (2), 131–138.

Higgs, B., Abbas, M., 2013. A two-step segmentation algorithm for behavioral clustering of naturalistic driving styles. In: 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013). IEEE, pp. 857–862.

Higgs, B., Abbas, M., 2014. Segmentation and clustering of car-following behavior: Recognition of driving patterns. IEEE Trans. Intell. Transp. Syst. 16 (1), 81–90.

Hoogendoorn, R., Van Arem, B., 2013. Driver workload classification through neural network modeling using physiological indicators. In: 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013). IEEE, pp. 2268–2273.

Jafarnejad, S., Castignani, G., Engel, T., 2017. Towards a real-time driver identification mechanism based on driving sensing data. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems. ITSC, IEEE, pp. 1–7.

Jiang, Y., Deng, W., Wang, J., Zhu, B., 2018. Studies on Drivers' Driving Styles Based on Inverse Reinforcement Learning. Technical Report, SAE Technical Paper.

Kaplan, S., Guvensan, M.A., Yavuz, A.G., Karalurt, Y., 2015. Driver behavior analysis for safe driving: A survey. IEEE Trans. Intell. Transp. Syst. 16 (6), 3017–3032.

Khan, M.N., Das, S., 2024. Advancing traffic safety through the safe system approach: A systematic review. Accid. Anal. Prev. 199, 107518.

Khodairy, M.A., Abosamra, G., 2021. Driving behavior classification based on oversampled signals of smartphone embedded sensors using an optimized stacked-LSTM neural networks. IEEE Access 9, 4957–4972.

Kim, I., Kim, T., Sohn, K., 2013. Identifying driver heterogeneity in car-following based on a random coefficient model. Transp. Res. C: Emerg. Technol. 36, 35–44.

Kishikawa, D., Arai, S., 2021. Estimation of personal driving style via deep inverse reinforcement learning. Artif. Life Robot. 26 (3), 338–346.

Krajewski, R., Bock, J., Kloeker, L., Eckstein, L., 2018. The highD dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems. In: 2018 21st International Conference on Intelligent Transportation Systems. ITSC, pp. 2118–2125. http://dx.doi.org/10.1109/ITSC.2018.8569552.

Kwon, S.K., Seo, J.H., Yun, J.Y., Kim, K.-D., 2021. Driving behavior classification and sharing system using cnn-lstm approaches and v2x communication. Appl. Sci. 11 (21), 10420.

Lee, J., Gershon, P., Domeyer, J., Mehler, B., Reimer, B., 2024. Understanding hands-off patterns while using Tesla Autopilot: Individual differences and their impact on hands-off duration. In: The 9th International Conference on Driver Distraction and Inattention. p. 26.

Lee, J., Jang, K., 2024. Characterizing driver behavior using naturalistic driving data. Accid. Anal. Prev. 208, 107779.

Lee, J.D., See, K.A., 2004. Trust in automation: Designing for appropriate reliance. Hum. Factors 46 (1), 50–80.

Li, G., Li, S.E., Cheng, B., Green, P., 2017. Estimation of driving style in naturalistic highway traffic using maneuver transition probabilities. Transp. Res. C: Emerg. Technol. 74, 113–125.

Li, G., Zhu, F., Qu, X., Cheng, B., Li, S., Green, P., 2019. Driving style classification based on driving operational pictures. IEEE Access 7, 90180–90189.

Liang, K., Zhao, Z., Li, W., Zhou, J., Yan, D., 2022. Comprehensive identification of driving style based on vehicle's driving cycle recognition. IEEE Trans. Veh. Technol. 72 (1), 312–326.

Lin, N., Zong, C., Tomizuka, M., Song, P., Zhang, Z., Li, G., et al., 2014. An overview on study of identification of driver behavior characteristics for automotive control. Math. Probl. Eng. 2014.

Liu, W., Deng, K., Zhang, X., Cheng, Y., Zheng, Z., Jiang, F., Peng, J., 2020. A semi-supervised tri-catboost method for driving style recognition. Symmetry 12 (3), 336.

Liu, H., Taniguchi, T., Tanaka, Y., Takenaka, K., Bando, T., 2017. Visualization of driving behavior based on hidden feature extraction by using deep learning. IEEE Trans. Intell. Transp. Syst. 18 (9), 2477–2489.

Lu, L., Lin, Y., Wen, Y., Zhu, J., Xiong, S., 2023. Federated clustering for recognizing driving styles from private trajectories. Eng. Appl. Artif. Intell. 118, 105714.

Lyu, N., Wang, Y., Wu, C., Peng, L., Thomas, A.F., 2022. Using naturalistic driving data to identify driving style based on longitudinal driving operation conditions. J. Intell. Connect. Veh. 5 (1), 17–35.

Ma, Y., Li, Z., Li, Y., Li, H., Malekian, R., 2019. Driving style estimation by fusing multiple driving behaviors: a case study of freeway in China. Clust. Comput. 22 (4), 8259–8269.

Ma, Y., Li, W., Tang, K., Zhang, Z., Chen, S., 2021. Driving style recognition and comparisons among driving tasks based on driver behavior in the online car-hailing industry. Accid. Anal. Prev. 154, 106096.

Ma, Z., Zhang, Y., 2021. Drivers trust, acceptance, and takeover behaviors in fully automated vehicles: Effects of automated driving styles and driver's driving styles. Accid. Anal. Prev. 159, 106238.

Ma, Y., Zhang, Z., Chen, S., Yu, Y., Tang, K., 2018. A comparative study of aggressive driving behavior recognition algorithms based on vehicle motion data. IEEE Access 7, 8028–8038.

Martinez, C.M., Heucke, M., Wang, F.-Y., Gao, B., Cao, D., 2017. Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey. IEEE Trans. Intell. Transp. Syst. 19 (3), 666–676.

Mei, P., Karimi, H.R., Ou, L., Xie, H., Zhan, C., Li, G., Yang, S., 2025. Driving style classification and recognition methods for connected vehicle control in intelligent transportation systems: A review. ISA Trans..

Mobileye, 2024. True Redundancy: Two independent perception subsystems. https://www.mobileye.com/technology/true-redundancy/. (Accessed 22 March 2024).
Moosavi, S., Mahajan, P.D., Parthasarathy, S., Saunders-Chukwu, C., Ramnath, R., 2021. Driving style representation in convolutional recurrent neural network model of driver identification. arXiv preprint arXiv:2102.05843.
Moukafih, Y., Hafidi, H., Ghogho, M., 2019. Aggressive driving detection using deep learning-based time series classification. In: 2019 IEEE International Symposium on INnovations in Intelligent SysTems and Applications. INISTA, IEEE, pp. 1–5.
Ossen, S., Hoogendoorn, S.P., 2011. Heterogeneity in car-following behavior: Theory and empirics. Transp. Res. C: Emerg. Technol. 19 (2), 182–195.
Ossen, S., Hoogendoorn, S.P., Gorte, B.G., 2006. Interdriver differences in car-following: A vehicle trajectory–based study. Transp. Res. Rec. 1965 (1), 121–129.
Priyadharshini, G., Josephin, J.F., 2020. A comprehensive review of various data collection approaches, features, and algorithms used for the classification of driving style. In: IOP Conference Series: Materials Science and Engineering. Vol. 993, IOP Publishing, 012098.
Qi, G., Wu, J., Zhou, Y., Du, Y., Jia, Y., Hounsell, N., Stanton, N.A., 2019. Recognizing driving styles based on topic models. Transp. Res. D: Transp. Environ. 66, 13–22.
Rosbach, S., James, V., Großjohann, S., Homoceanu, S., Roth, S., 2019. Driving with style: Inverse reinforcement learning in general-purpose planning for automated driving. In: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems. IROS, IEEE, pp. 2658–2665.
Sagberg, F., Selpi, Bianchi Piccinini, G.F., Engström, J., 2015. A review of research on driving styles and road safety. Hum. Factors 57 (7), 1248–1275.
Saleh, K., Hossny, M., Nahavandi, S., 2017. Driving behavior classification based on sensor data fusion using LSTM recurrent neural networks. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems. ITSC, IEEE, pp. 1–6.
Schlegel, K., Mirus, F., Neubert, P., Protzel, P., 2021. Multivariate time series analysis for driving style classification using neural networks and hyperdimensional computing. In: 2021 IEEE Intelligent Vehicles Symposium. IV, IEEE, pp. 602–609.
Shahverdy, M., Fathy, M., Berangi, R., Sabokrou, M., 2020. Driver behavior detection and classification using deep convolutional neural networks. Expert Syst. Appl. 149, 113240.
Shi, B., Xu, L., Hu, J., Tang, Y., Jiang, H., Meng, W., Liu, H., 2015. Evaluating driving styles by normalizing driving behavior based on personalized driver modeling. IEEE Trans. Syst. Man Cybern.: Syst. 45 (12), 1502–1508.
Silva, I., Eugenio Naranjo, J., 2020. A systematic methodology to evaluate prediction models for driving style classification. Sensors 20 (6), 1692.
Sun, Z., Yao, X., Qin, Z., Zhang, P., Yang, Z., 2021. Modeling car-following heterogeneities by considering leader–follower compositions and driving style differences. Transp. Res. Rec. 2675 (11), 851–864.
Tang, X., 2009. Driving skill recognition: new approaches and their comparison. In: 2009 American Control Conference. IEEE, pp. 420–425.
Tango, F., Botta, M., 2013. Real-time detection system of driver distraction using machine learning. IEEE Trans. Intell. Transp. Syst. 14 (2), 894–905.
Taniguchi, T., Nagasaka, S., Hitomi, K., Chandrasiri, N.P., Bando, T., Takenaka, K., 2015. Sequence prediction of driving behavior using double articulation analyzer. IEEE Trans. Syst. Man Cybern.: Syst. 46 (9), 1300–1313.
Taniguchi, T., Nagasaka, S., Hitomi, K., Takenaka, K., Bando, T., 2014. Unsupervised hierarchical modeling of driving behavior and prediction of contextual changing points. IEEE Trans. Intell. Transp. Syst. 16 (4), 1746–1760.
Taylor, J., Zhou, X., Rouphail, N.M., Porter, R.J., 2015. Method for investigating intradriver heterogeneity using vehicle trajectory data: A dynamic time warping approach. Transp. Res. B: Methodol. 73, 59–80.
Tselentis, D.I., Papadimitriou, E., 2023. Driver profile and driving pattern recognition for road safety assessment: Main challenges and future directions. IEEE Open J. Intell. Transp. Syst..
U.S. Department of Transportation, Federal Highway Administration, 2006. Next generation simulation (NGSIM) vehicle trajectories and supporting data. https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm. (Accessed 25 March 2022).
Vaitkus, V., Lengvenis, P., Žylius, G., 2014. Driving style classification using long-term accelerometer information. In: 2014 19th International Conference on Methods and Models in Automation and Robotics. MMAR, IEEE, pp. 641–644.
Van Ly, M., Martin, S., Trivedi, M.M., 2013. Driver classification and driving style recognition using inertial sensors. In: 2013 IEEE Intelligent Vehicles Symposium. IV, IEEE, pp. 1040–1045.
Villegas-Ch, W., García-Ortiz, J., 2023. Toward a comprehensive framework for ensuring security and privacy in artificial intelligence. Electronics 12 (18), 3786.
Vlachogiannis, D.M., Vlahogianni, E.I., Golias, J., 2020. A reinforcement learning model for personalized driving policies identification. Int. J. Transp. Sci. Technol. 9 (4), 299–308.
Wahab, A., Quek, C., Tan, C.K., Takeda, K., 2009. Driving profile modeling and recognition based on soft computing approach. IEEE Trans. Neural Netw. 20 (4), 563–582.
Wang, Y., Farah, H., Yu, R., Qiu, S., van Arem, B., 2023a. Characterizing behavioral differences of autonomous vehicles and human-driven vehicles at signalized intersections based on waymo open dataset. Transp. Res. Rec. 03611981231165783.
Wang, W., Han, W., Na, X., Gong, J., Xi, J., 2019. A probabilistic approach to measuring driving behavior similarity with driving primitives. IEEE Trans. Intell. Veh. 5 (1), 127–138.
Wang, Y., Han, Z., Xing, Y., Xu, S., Wang, J., 2023b. A survey on datasets for decision-making of autonomous vehicle. arXiv preprint arXiv:2306.16784.
Wang, W., Xi, J., Chong, A., Li, L., 2017. Driving style classification using a semisupervised support vector machine. IEEE Trans. Hum.- Mach. Syst. 47 (5), 650–660.
Wang, W., Xi, J., Zhao, D., 2018. Driving style analysis using primitive driving patterns with Bayesian nonparametric approaches. IEEE Trans. Intell. Transp. Syst. 20 (8), 2986–2998.
Waymo, 2024. The Waymo Driver: A comprehensive sensor suite for autonomous driving. https://waymo.com/waymo-driver/. (Accessed 22 March 2024).
Wen, X., Cui, Z., Jian, S., 2022. Characterizing car-following behaviors of human drivers when following automated vehicles using the real-world dataset. Accid. Anal. Prev. 172, 106689.
Wijnands, J.S., Thompson, J., Aschwanden, G.D., Stevenson, M., 2018. Identifying behavioural change among drivers using Long Short-Term Memory recurrent neural networks. Transp. Res. F: Traffic Psychol. Behav. 53, 34–49.
Xiao, W., Liu, H., Ma, Z., Chen, W., 2022. Attention-based deep neural network for driver behavior recognition. Future Gener. Comput. Syst. 132, 152–161.
Xie, J., Hu, K., Li, G., Guo, Y., 2021. CNN-based driving maneuver classification using multi-sliding window fusion. Expert Syst. Appl. 169, 114442.
Xie, L., Shi, Y., Li, Z., 2018. Driving pattern recognition based on improved LDA model. In: 2018 5th IEEE International Conference on Cloud Computing and Intelligence Systems. CCIS, IEEE, pp. 320–324.
Xie, D.-F., Zhu, T.-L., Li, Q., 2020. Capturing driving behavior heterogeneity based on trajectory data. Int. J. Model. Simul. Sci. Comput. 11 (03), 2050023.
Xue, Q., Wang, K., Lu, J.J., Liu, Y., 2019. Rapid driving style recognition in car-following using machine learning and vehicle trajectory data. J. Adv. Transp. 2019.
Yao, X., Calvert, S.C., Hoogendoorn, S.P., 2023. Identification of driving heterogeneity using Action-chains. In: 2023 IEEE 26th International Conference on Intelligent Transportation Systems. ITSC, pp. 6001–6006.
Yao, X., Calvert, S.C., Hoogendoorn, S.P., 2025. A novel framework for identifying driving heterogeneity through action patterns. IEEE Trans. Intell. Transp. Syst. 1–13. http://dx.doi.org/10.1109/TITS.2025.3560509.
Yao, X., Yan, Q., Sun, Z., Calvert, S.C., Hoogendoorn, S.P., 2024b. Investigation on car-following heterogeneity and its impacts on traffic safety and sustainability. Transp. A: Transp. Sci. 1–25.
Zhang, Y., Lin, W.C., Chin, Y.-K.S., 2010. A pattern-recognition approach for driving skill characterization. IEEE Trans. Intell. Transp. Syst. 11 (4), 905–916.
Zhang, J., Wang, Y., Lu, G., 2019. Impact of heterogeneity of car-following behavior on rear-end crash risk. Accid. Anal. Prev. 125, 275–289.
Zhang, X., Zhao, X., Rong, J., 2014. A study of individual characteristics of driving behavior based on hidden markov model. Sens. Transducers 167 (3), 194.
Zhang, C., Zhu, J., Wang, W., Xi, J., 2021. Spatiotemporal learning of multivehicle interaction patterns in lane-change scenarios. IEEE Trans. Intell. Transp. Syst. 23 (7), 6446–6459.
Zhao, D., Zhong, Y., Fu, Z., Hou, J., Zhao, M., 2022. A review for the driving behavior recognition methods based on vehicle multisensor information. J. Adv. Transp. 2022 (1), 7287511.
Zheng, X., Yang, P., Duan, D., Cheng, X., Yang, L., 2022. Real-time driving style classification based on short-term observations. IET Commun..
Zhu, B., Liu, Z., Zhao, J., Chen, Y., Deng, W., 2018. Driver behavior characteristics identification strategies based on bionic intelligent algorithms. IEEE Trans. Hum.-Mach. Syst. 48 (6), 572–581.
Zou, Y., Zhu, T., Xie, Y., Zhang, Y., Zhang, Y., 2022. Multivariate analysis of car-following behavior data using a coupled hidden Markov model. Transp. Res. C: Emerg. Technol. 144, 103914.