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Research article

Driving style classification and recognition methods for connected vehicle control in intelligent transportation systems: A review

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ABSTRACT

Advancements in intelligent vehicle technology have spurred extensive research into the impact of driving style (DS) on intelligent transportation systems (ITS), aiming to enhance vehicle safety, comfort, and energy efficiency. Accurate DS identification is pivotal for accelerating ITS adoption, especially in regions where its implementation is still in its infancy. This paper investigates the role of DS recognition methods, particularly clustering and classification techniques, in influencing connected vehicle control and optimizing speed planning within ITS. While traditional speed planning approaches focus on general traffic models, this study emphasizes the critical role of DS in shaping personalized and adaptive speed planning. The paper highlights three primary DS recognition approaches: rule-based, model-based, and learning-based methods, and introduces a framework for integrating DS recognition with speed planning, addressing aspects such as data collection, preprocessing, and classification techniques. This focus provides a novel perspective on leveraging DS recognition to enhance ITS adaptability.

1. Introduction

With the continuous progress of the global economy, there has been a consistent annual increase in the number of motor vehicles [1,2]. As the country with the most significant number of vehicles, China needs to prioritize research on the transportation system of its capital, Beijing [3]. By 2022, the national motor vehicle population is projected to reach 417 million [4]. By September 2022, Beijing's motor vehicle count has reached 7.08 million [5]. Though this number showcases the capital's growth and prosperity, it highlights pressing challenges like traffic congestion, increased resource use, and environmental pollution. In recent years, ITS has emerged as a solution to mitigate the burden of traffic congestion and establish a smart city [6,7].

ITS now recognizes networking as a critical area of research [8]. In this framework, connected vehicles use intelligent systems to promote information exchange between vehicles, associated equipment, and their surrounding environment [9,10]. The United States has emerged as a trailblazer in developing the connected vehicle industry [11]. Research into connected vehicle technology began in 2011, and its official implementation and promotion started in 2012. The Federal Highway Administration conducted a study employing Internet of Vehicles technology to validate enhanced driving efficiency and safety performance within an interconnected environment. The U.S. Highway Traffic Safety Administration firmly believes that the Internet of Vehicles can provide vehicle consumers with superior services encompassing safety, efficiency, and convenience [12]. Regarding safety, vehicles utilizing networked information can avert 70% to 80% of traffic accidents [13]. Regarding efficiency, road congestion can be reduced by 60% [13]. Moreover, in terms of convenience, there can be a 30% reduction in the number of stops, leading to a decrease in driving time by 13% to 45% [14]. As the birthplace of modern automobiles, Europe has consistently regarded connected vehicles as a key development objective. The connected vehicle industry has been strategically deployed by issuing the "ITS Development Action Plan" [15]. Simultaneously, the European Union introduced a comprehensive framework

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Nomenclature

ACC	Adaptive cruise control
ADAS	Advanced driver assistance systems
ARI	Adjusted rand index
AVs	Autonomous vehicles
BSS	Between-cluster sum of squares
CNN	Convolutional neural networks
CQI	Clustering quality indice
DBSCAN	Density-based spatial clustering of applications with noise
DFT	Discrete Fourier transform
DS	Driving style
DWT	Discrete wavelet transform
EMQTT	Erlang message queuing telemetry transport
EV	Electric vehicle
GMM	Gaussian mixture model
HEV	Hybrid electric vehicle
ITS	Intelligent transportation systems
KMO	Kaiser–Meyer–Olkin
KNN	K nearest neighbors
MLP	Multilayer perceptron
PCA	Principal component analysis
PSO	Particle swarm optimization
RF	Random forest
RNN	Recurrent neural networks
ROC	Receiver operating characteristic
ROS	Robot operating system
S3VM	Semi-supervised support vector machine
SOM	Self-organizing maps
SPAT	Signal phase and timing
SQL	Structured query language
SVM	Support vector machine
V2I	Vehicle to infrastructure
V2V	Vehicle to vehicle
V2X	Vehicle to everything
WSS	Within-cluster sum of squares

plan in 2014, providing robust support for traffic safety, networking, and collaborative intelligent transportation systems [16]. The ultimate goal is to establish seamless interconnectivity between vehicles and transportation infrastructure and between vehicles themselves [17–19].

1.1. Motivation

Connected vehicle speed planning has gained increasing importance with the growing popularity of ITS [20]. However, traditional speed planning methods have limitations, as they often overlook the individual driver's personality and habits, resulting in low universality [21]. Existing methods, while ensuring regular driving operation, may neglect the driver's unique DS, leading to deviations from expected driving trajectories [22,23].

Recognizing the significance of incorporating DS into speed planning, this paper aims to address these shortcomings and contribute to advancing personalized speed planning methods. The integration of DS into speed planning not only enhances the driving experience for individuals but also has positive implications for fuel efficiency and overall vehicle performance. By tailoring speed planning to individual DS, drivers can experience a more personalized and comfortable journey, aligning with their preferences and habits. This approach not only improves the accuracy of predicted driving trajectories but also contributes to more efficient fuel consumption. Moreover, the consideration of DS in speed planning is expected to foster greater confidence and trust among drivers using connected vehicles.

Therefore, by analyzing a database of 432 articles, this paper aims to provide a comprehensive review of DS classification and recognition methods, with a focus on their applications in connected vehicle environments. While the original motivation mentions speed planning, the central theme of this paper is to explore how DS-based clustering and classification techniques can contribute to various aspects of connected vehicles, including speed control, traffic flow optimization, and safety enhancement. These methods, although primarily focused on driving behavior analysis, have significant implications for speed planning and other decision-making processes in dynamic traffic conditions.

1.2. DS related terms

At present, there are two prevailing subjective interpretations of DS [24]. One commonly used approach involves the administration of a subjective questionnaire, where drivers are requested to complete a specific form. Another method, known as level rules, categorizes drivers based on predetermined thresholds of their operational behaviors, like jerk and throttle position. Yet, depending solely on these assessment methods might lead to some subjectivity, hindering a truly objective characterization of DS.

The driver's specific operation directly reflects their DS in the actual driving process. It is widely accepted that drivers with different styles may exhibit varying driving behaviors when confronted with the same driving situation [25,26]. These differences include the reaction time, the intensity with which they press the pedals, and the angles at which they turn the steering wheel [27]. The current definition of DS encompasses the following aspects: (1) DS refers to how a driver carries out a driving task, influenced by factors such as driver type, driver condition, driving situation, and purpose of travel [28]. (2) DS represents a relatively consistent, long-term, and inherent behavioral tendency of a driver, resulting from synthesizing their psychological mindset and behavioral patterns [29]. (3) DS encompasses a collection of personal driving habits that develop gradually as a driver gains experience over time [30]. (4) DS encompasses the behavioral characteristics of a driver during the act of driving, manifesting in their input to the vehicle and the resultant response of the entire vehicle throughout the driving process [31].

In the context of DS analysis, the terms "classification" and "recognition" are closely related but serve distinct purposes. Clarifying these terms is essential for understanding the methodologies applied in intelligent vehicle systems and their implications for driving behavior analysis. Classification refers to the process of grouping driving behaviors into predefined categories based on observable data. DS analysis involves training algorithms to assign each driving behavior to one of several predefined driving styles, such as aggressive, cautious, or normal driving. Recognition refers to the identification of driving behaviors or styles in real-time or from previously unseen data. While classification places behaviors into predefined categories, recognition involves dynamically detecting and identifying behaviors as they occur. Recognition typically implies that the system not only classifies the behavior but also interprets its significance in context, such as recognizing a sudden change from cautious to aggressive driving.

In intelligent vehicle systems, both classification and recognition play important but different roles: Classification helps segment different driver types or behaviors for system learning and long-term analysis, improving features like personalized driving assistance. Recognition enables real-time safety measures by detecting risky or unusual driving behaviors as they occur, allowing systems to adjust adaptive cruise control, braking, or steering assistance.

Table 1
A review of existing driving styles.

References	Description	Application
[32]	Give suggestions to select methods and parameters for DS better.	Driving conditions prediction and DS recognition in HEV control strategies
[33]	Focused on investigating the requirements and methods involved in automatic DS recognition using vehicle and trip data.	Intelligent context-adaptive driving assistance applications
[34]	Identify the machine learning and artificial intelligence algorithms employed in current systems for analyzing driver behavior and driving styles.	Intelligent vehicle controls
[35]	It explores analyzing and identifying DS, explicitly focusing on machine learning techniques that leverage present and emerging trends.	Advanced driver assistance systems
[36]	A review of HMM for driving behavior recognition, proposing improvements for driving assistance systems.	Vehicle insurance branch of the ADAS system
[37]	A review of DS recognition methods, proposing a context-adaptive application based on recognized DS.	ITS
[38]	It explores recent advancements in the field of DS recognition across both short- and long-term pipelines.	Smart vehicles
[39]	A review of driver behavior classification to identify and prevent dangerous driving behaviors using AI.	Road safety and traffic management
[31]	Emphasizing personalized driving behavior modeling to improve safety in mixed traffic environments for intelligent vehicles	Automotive
This paper	It explores the key factors and approaches for DS recognition in ITS, highlighting its role in enhancing vehicle safety, comfort, and energy efficiency.	Connected vehicle

1.3. Review of existing surveys

This paper summarizes previous review papers to understand the current state of development in this field. The specific details are outlined in Table 1. Wang et al. [32] present a summary of the methods and parameters used to achieve this goal, as well as the corresponding results. From these insights, researchers can make more informed choices regarding selecting methods and parameters to enhance driving conditions prediction and the recognition of driving styles, thereby improving the control strategy of hybrid electric vehicles.

Martinez et al. [35] offer a survey that explores the characterization and recognition of driving styles by revising numerous algorithms. The survey specializes in machine learning techniques that align with current and upcoming trends. Additionally, the survey briefly touches upon the applications of driving style recognition in intelligent vehicle controls and includes expert predictions regarding future advancements in this field.

Deng et al. [36] review Hidden Markov Models (HMM) for predicting and recognizing driving behaviors, which are important for ADAS. It examines how HMM handles time series data and state transitions in driving behavior models. The review covers factors affecting driving behaviors, HMM methods used in studies, and these models' limitations and future potential. It concludes with suggestions for improving driving assistance and vehicle control systems.

Nai et al. [37] present a comprehensive review of automatic DS recognition methods. They also provide an initial outline for a context-adaptive application, which can be described through three sequential steps. Firstly, the DS is automatically classified into predefined classes learned from historical driving and trip data. Secondly, a context-adaptive driving application is proposed based on DS recognition. Lastly, the system incorporates a serious game theoretic approach to reward eco-safe and cooperative driving behavior.

To support the implementation of driving styles in the automotive field, Chu et al. [38] conducted a comprehensive examination of recent advancements in DS recognition across both short-term and long-term pipelines. Initially, they provided clear definitions for short-term and long-term DS, followed by a detailed description of the input data utilized by recognition models, as well as relevant data-processing techniques. Additionally, they revisited evaluation metrics currently in use for various recognition algorithms. Lastly, they delved into the potential applications of DS recognition in intelligent vehicles.

Bouhsissin et al. [39] examine driver behavior, which is critical due to the high number of road accidents. Human behavior is often the main cause of accidents, making it essential to detect and classify aggressive or abnormal driving. Automatic detection helps prevent dangerous situations and supports corrective actions. It reviews studies on classifying driver behavior, looking at behavior types, data sources, features, and AI algorithms. It highlights key findings, challenges, and suggests future research directions for improving driver behavior classification and road safety.

Bolovinou et al. [31] emphasize the importance of personalization in driving behavior research for intelligent vehicles to coexist safely with human-driven cars in mixed traffic. By considering diverse driving behaviors, personalized models improve predictions and traffic balance. The review categorizes personalized driving behaviors, explores relevant datasets and modeling techniques, and highlights how intelligent vehicles need to adapt to human drivers' complex behaviors for safer and more efficient traffic.

Unlike previous studies, this paper establishes a novel connection between DS and speed planning, emphasizing their strong interdependent relationship. While machine learning algorithms are commonly used for DS identification and classification, current technological limitations prevent these algorithms from being executed directly on in-vehicle systems. To address this, the paper introduces a vehicle–cloud integration approach to overcome the computational constraints of vehicle-based systems. Additionally, it explores the feasibility of leveraging cloud platforms to perform speed planning using reinforcement learning, offering a new perspective on optimizing speed planning in intelligent transportation systems.

1.4. Contributions of this survey

Despite significant progress in driving behavior recognition, current research has yet to fully integrate speed planning with driving characteristics. This comprehensive review fills that gap by exploring the connection between these two aspects, specifically for connected vehicles. More uniquely, it is the first survey to address the challenge of predicting optimal target vehicle speed. The key contributions of this review are summarized as follows:

(1) Bridging the Gap Between DS Recognition and Speed Planning: This survey establishes a novel framework that links DS recognition to speed planning, highlighting how personalized driving behavior can directly influence vehicle trajectory optimization. Unlike prior studies,

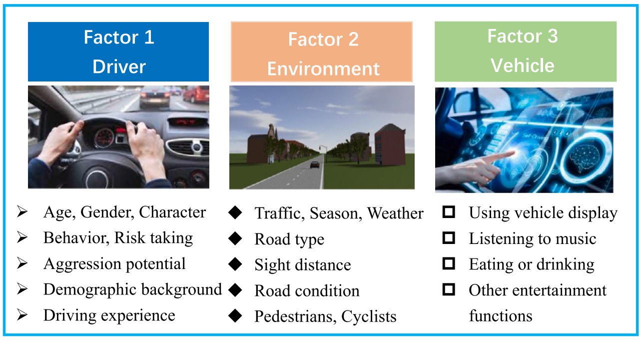


Fig. 1. Influencing factors of DS.

which treated these areas independently, this work emphasizes their interdependence and provides a comprehensive evaluation of clustering and classification techniques in this context.

(2) Comprehensive Review of DS Recognition Methods: The paper categorizes and evaluates three primary approaches to DS recognition: rule-based, model-based, and learning-based methods. By systematically analyzing their advantages, limitations, and applications, it provides a clear understanding of how these methods contribute to speed planning, enhancing vehicle safety, efficiency, and adaptability.

(3) Proposing a Vehicle–Cloud Collaboration Framework: Recognizing the computational challenges in real-time DS recognition and speed planning, this paper introduces a vehicle–cloud collaboration framework. This approach leverages cloud computing to handle intensive DS recognition tasks, enabling connected vehicles to achieve real-time adaptability and optimization.

2. DS classification

Before planning speed based on driving characteristics, it is essential to identify the DS. In practical scenarios, most sensor data is unlabeled. Thus, classifying DS forms the foundation of this research. This section begins by introducing long-term and short-term driving styles. It then delves into the factors influencing DS, followed by describing the sensor data sources and their processing. Lastly, the DS classification algorithm and evaluation criteria are analyzed.

2.1. DS analysis

2.1.1. Short-term or long-term

DS can be mainly categorized into two main types [38]: short-term and long-term. Short-term DS pertains to the driver's specific decisions in different scenarios. This classification is based on brief intervals of driving data unique to a particular situation. Factors like the driver's intended destination, driving habits, and immediate traffic conditions influence this style. Conversely, long-term DS refers to the consistent driving behavior of a driver over an extended period, regardless of individual driving scenarios. This style is shaped by an extensive compilation of driving data over time and is predominantly affected by personal driving habits, remaining stable and consistent throughout. To ensure the study's validity, the number of labels designated for short-term and long-term DS varies. For instance, short-term styles receive different labels based on specific circumstances. A driver usually displaying a standard style at high speeds might exhibit aggressive behavior at a traffic light intersection. Meanwhile, after a thorough evaluation, long-term DS can be classified under distinct labels, such as 'standard' or 'aggressive'.

2.1.2. Driving style classification methods

The classification of driving styles is generally divided into two methods: through continuous indexing and through discrete classes [35].

Through continuous indexing [40]: this approach quantifies driving styles by introducing a continuous variable, such as relative fuel consumption or an efficiency index. This continuous variable can later be transformed into discrete categories using threshold algorithms. Continuous indices are commonly utilized to evaluate the overall energy efficiency of driving behavior, providing a detailed and nuanced representation of driving styles.

Through discrete classes [41]: the discrete classification method directly divides driving styles into a finite number of categories (e.g., mild, normal, aggressive), usually based on specific characteristics or behaviors. This method simplifies algorithm design and enhances user understanding. Additionally, multidimensional classifications have been proposed, focusing on safety-related behaviors such as reckless, anxious, or patient driving.

While continuous indexing offers higher precision, discrete class classification is more prevalent due to its intuitiveness and ease of use, especially in user-friendly driving style analysis applications.

2.2. Influencing factors on DS classification

Drawing upon the relevant theoretical framework, the authors in [42] provide an integrated analysis of the factors affecting driving behavior, as depicted in Fig. 1. They also introduce the driver–vehicle–environment model to elucidate this framework. The factors that influence DS are grouped into three categories, which will be detailed in the following sections.

2.2.1. Drivers' own factors

The drivers' long-term and short-term DS are influenced by their skill levels, behaviors, and individual characteristics. Factors such as driving moods, current driving tasks, the duration of continuous driving, and other situational elements are subject to fluctuations during a drive and primarily affect drivers' short-term DS [43]. Personal character and driving competence primarily shape an individual's long-term DS. In particular, driving behavior can be attributed to four key factors: physiological state, psychological state, driver profile, and driving events, all contributing to its influence [44].

The physiological state refers to the condition or functioning of a driver's body when operating a vehicle, which includes factors such as fatigue, stress, and posture [45]. Detecting or predicting the physiological state can be achieved by observing the driver's positions and actions, such as eye activity, facial expressions, head movements, and body posture. These are considered vital indicators of the driver's perception and concentration.

The psychological state relates to the mental or emotional well-being of the driver, encompassing emotions such as happiness, anger, sadness, distraction, and more [46]. Monitoring physiological parameters such as heart rate, breathing rate, and other indicators can provide insights into the driver's psychological state. When there is a significant change in these parameters, the driver may experience difficulty controlling their thought processes and ability to make accurate judgments [47].

Driver profile pertains to the characteristics associated with the driver, which include demographic factors such as gender, age, education, and income, as well as driving history such as years of experience on the road and record of violations, as highlighted in the current study [42]. Driving events refer to the necessary driving actions undertaken by the driver while operating the vehicle, resulting in changes in the vehicle's motion or state. Examples of driving events include turning, tailgating, and flashing headlights.

The assessment of DS is heavily influenced by environmental conditions, as emphasized in the studies conducted by [48,49]. The environmental context encompasses various characteristics that significantly

Table 2
The input of driving styles classification.

References	Factors to consider
[54,55]	Jerk feature
[56,57]	3-axis accelerometer
[58,59]	Vehicle speed and throttle opening
[60,61]	Longitudinal acceleration, lateral acceleration, yaw rate
[40,62]	Speed, longitudinal acceleration, and lateral acceleration

impact both vehicle performance and driver capabilities. As a result, the complexity of analyzing DS increases as more factors are considered. These characteristics include detailed information about road geometry (e.g., curvature, gradient, lane width, shoulder width), road conditions (e.g., dry, wet, snowy, icy), road types (e.g., asphalt, concrete, gravel, dirt), weather conditions (e.g., clear, rainy, foggy, snowy, windy), light conditions (e.g., daylight, nighttime), and traffic conditions (e.g., traffic lights, traffic flow, disruptions) [50].

2.2.2. Vehicle factors

Naturalistic driving studies, such as those by Pitts et al. [51], have revealed that vehicle interactions play a crucial role in driving style classification. Engaging in complex visual-haptic tasks, like using in-car touchscreens or adjusting entertainment systems, significantly increases crash risk, particularly when visual attention is diverted from the road for more than two seconds within a six-second period. Furthermore, Horberry et al. [52] emphasized that distractions—visual, auditory, and haptic—either individually or in combination, can deteriorate driver performance.

Expanding this, recent advancements in vehicle technology, such as ADAS, further complicate driver–vehicle interaction. For instance, adaptive cruise control and lane-keeping systems necessitate continuous monitoring from drivers, which could either mitigate or exacerbate distraction risks depending on the system design. Hence, a thorough investigation into the interplay between the vehicle's technological features and driver responses is vital to improving safety and optimizing DS classification algorithms.

2.2.3. External environmental factors

External factors like road geometry, traffic density, and weather conditions profoundly influence short-term driving styles. Shi et al. [53] have highlighted that road types (e.g., urban streets vs. highways) and weather (e.g., rain or snow) temporarily alter driving behavior, affecting braking intensity, steering angles, and speed variability. While these influences primarily shape short-term driving styles, their cumulative effects could also contribute to long-term patterns.

Future expansions in this field should consider integrating real-time traffic and weather data with DS recognition models. This integration would enhance the adaptability of these models, making them robust in varying environments and providing a dynamic framework for ITS applications.

2.3. Data acquisition and preprocessing

Given the numerous sensors incorporated within the vehicle, including GPS, cameras, radar, and more, the study [63] have consolidated all these components into a comprehensive diagram, as depicted in Fig. 2. The analysis of vehicle data yields vast information encompassing a wide range of data. However, delving into the intricate details of driving style's typical characteristics is a formidable task. Therefore, it is necessary to process the characteristic parameters of all vehicles entering and leaving the station, followed by applying the principal component analysis (PCA) algorithm to reduce the high-dimensional parameters to low-dimensional ones [64]. This approach enables a more manageable and comprehensive analysis. Scholars have different expressions for the input of DS classification, as shown in Table 2.

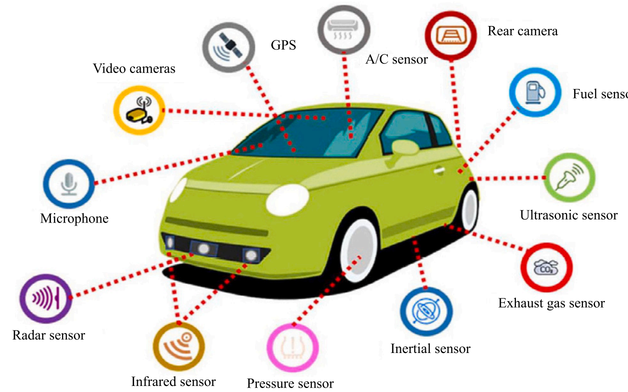


Fig. 2. Schematic diagram of the vehicle sensor.

Before conducting principal component analysis, Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were conducted. A KMO value greater than 0.8 indicates that the data is highly suitable for principal component analysis. It is considered moderately suitable if the KMO value falls between 0.7 and 0.8. Principal component analysis can still be performed if the KMO value ranges from 0.6 to 0.7. However, if the KMO value is below 0.6, the data is unsuitable for principal component analysis. Additionally, for the data to be suitable for principal component analysis, the p-value of Bartlett's sphericity test should be less than 0.05 [65].

To perform cluster analysis based on principal component scores, it is essential to calculate the scores of multiple principal components. The calculation process involves determining factor loads and eigenvalues using the following formula to calculate the principal component loads [66]:

$$U_{ij} = \frac{a_{ij}}{\sqrt{\lambda_i}} \tag{1}$$

where U_{ij} represents the jth principal component loading coefficient, and a_{ij} denotes the factor loading coefficient of the ith principal component. Additionally, λ_i represents the eigenvalue of the ith principal component.

In order to eliminate dimensional differences, the original feature parameter matrix is standardized using the following formula:

$$Z_{nj} = \frac{x_{nj} - \frac{1}{n}\sum x_{nj}}{\sqrt{\frac{1}{n-1}\sum \left(x_{nj} - \frac{1}{n}\sum x_{nj}\right)^2}} \tag{2}$$

where Z_{nj} represents the normalized result of the original characteristic parameter data, following a Gaussian distribution with a mean value of 0 and a variance of 1. On the other hand, x_{nj} represents the original data.

The principal component score is calculated using the following formula:

$$F_{ni} = \sum U_{ij} Z_{nj} \tag{3}$$

where F_{ni} represents the ith principal component score of the nth sample.

2.4. DS clustering algorithms

2.4.1. K-means

The k-means clustering algorithm is an iterative analysis technique that groups data points into K clusters. By iteratively updating the cluster centers and reassigning objects, the k-means algorithm aims to minimize the variance within each cluster and maximize the separation between clusters. This iterative process helps in identifying patterns and grouping similar data points [67]. The primary goal of the clustering

Table 3
Comparison of commonly used clustering algorithms.

Algorithms	Efficiency	Sensitivity to noise	Sensitivity to the order in which data is entered	Cluster shape	High dimensionality	Scalability
K-means	Higher	Sensitive	Insensitive	Spherical	Good	Good
K-medoids	Normal	Insensitive	Insensitive	Spherical	Normal	Bad
DBSCAN	Modesty	Insensitive	Sensitive	Any shape	Normal	Good
GMM	Modesty	Insensitive	Insensitive	Any shape	Good	Good
SOM	Low	Sensitive	Sensitive	Any shape	Good	Good

algorithm being considered is to divide a set of n-given patterns, where each pattern is represented as a d-dimensional vector, into K groups. The objective is to minimize the total within-cluster variation in this partition.

K-means is one of the most widely used clustering algorithms for DS classification due to its simplicity and computational efficiency. Studies like [25] have successfully used K-means to group driving data into predefined clusters such as aggressive, moderate, and conservative driving styles. However, its reliance on spherical cluster shapes and the need to predefine the number of clusters limit its adaptability to complex or overlapping DS patterns. Moreover, K-means is sensitive to noise and outliers, which may distort cluster centroids in real-world driving data.

2.4.2. K-medoids

The K-medoids clustering algorithm is a technique for grouping data into K distinct partitions centered around K representative objects. Unlike the K-means clustering algorithm, K-medoids select K natural objects from the dataset to serve as the central points of the clusters while assigning the remaining objects to the cluster whose center point is most similar to theirs [68]. This algorithm evaluates the clustering quality by calculating the sum of distances between objects within each cluster. The clustering quality is defined as follows [69]:

$$E(w) = \sum_{i=1}^{K} \sum_{p \in c_i} |p - o_i| \tag{4}$$

where p is the object of cluster c_i, and o_i is the cluster center, among which p and o_i are multi-dimensional objects.

K-medoids clustering is similar to K-means but instead of using centroids, it selects actual data points as the cluster centers. This makes K-medoids more robust to outliers. In DS classification, the algorithm can group data points such as speed, throttle input, or acceleration patterns into different DS by repeatedly selecting new medoids that minimize the total distance between data points and their nearest medoids. K-medoids provides a more accurate clustering of DS in the presence of outliers or irregular cluster shapes but comes at the cost of higher computational complexity. It is better suited for smaller datasets or scenarios where data integrity (resistance to noise) is more critical than speed.

2.4.3. DBSCAN

DBSCAN has been widely applied in DS classification due to its ability to identify clusters of arbitrary shapes and to label low-density regions as noise [70]. Studies like [71] used DBSCAN to detect erratic driving behaviors based on acceleration and throttle input data. Its ability to handle noisy data and avoid the need to predefine the number of clusters makes it ideal for real-world scenarios. However, its performance is highly sensitive to parameter tuning (e.g., epsilon and minimum points), which could affect clustering outcomes in datasets with varying densities.

2.4.4. GMM

GMM is a probabilistic clustering method that models DS as a mixture of Gaussian distributions, enabling soft clustering where a data point can belong to multiple clusters with varying probabilities [72]. Miao et al. [73] applied GMM to classify overlapping driving styles such as cautious-aggressive transitions. GMM's flexibility in modeling complex datasets is a significant advantage, but its computational complexity and potential overfitting require careful parameter optimization.

2.4.5. SOM

SOM, an artificial neural network used for clustering and visualizing high-dimensional data, has been applied in DS analysis for pattern discovery [74]. Siami et al. [75] utilized SOM to map driving behaviors based on vehicle speed, acceleration, and braking data. While SOM excels in visualizing relationships between driving styles, its high computational requirements and sensitivity to initialization limit its use in real-time applications.

In evaluating the clustering algorithms, we considered factors such as efficiency, sensitivity to noise, cluster shape, and scalability. K-means and K-medoids perform well in terms of computational efficiency, with K-means being particularly suitable for real-time applications. DBSCAN and K-medoids demonstrate robustness to noise, outperforming K-means in handling outliers. While DBSCAN and GMM excel in identifying clusters of arbitrary shapes, K-means is limited to spherical clusters. Additionally, K-means and GMM are scalable for larger datasets, whereas SOM is better suited for offline analysis. These considerations are summarized in Table 3 of the revised manuscript, providing a comprehensive comparison of the algorithms.

2.5. Algorithm evaluation metrics

2.5.1. Internal indices

Five widely utilized internal clustering quality indices (CQIs) and one external CQI are employed to assess the ability of clustering algorithms to identify cluster structures [76].

(1) The Silhouette index

The calculation of the Silhouette coefficient [77], denoted as s(i), for each instance, i is performed in the following manner:

$$s(i) = \frac{b(i) - a(i)}{\max(b(i), a(i))} \tag{5}$$

where $a(i)$ denotes the distance of the ith vector to all other points within the same cluster, and the minimum average dissimilarity to instances in each cluster that differ from cluster C is denoted as $b(i)$. The average Silhouette is computed by taking the average of all output values, which ultimately represents the final result within the range of [−1, 1]. A higher value indicates the presence of high-quality clusters.

(2) The Calinski index

Calinski et al. [78] aim to identify well-isolated clusters and relies on two measures that assess separation and cohesion. The between-cluster sum of squares (BSS) evaluates the separation, while the within-cluster sum of squares (WSS) evaluates the cohesion.

$$CH = \frac{BSS_K(K-1)}{WSS_K(N-K)} \tag{6}$$

where K represents the number of clusters, and N represents the total number of instances. The objective is to identify a value of K that maximizes the index, indicating the presence of well-isolated and cohesive clusters.

(3) The C-index

The C-index is defined as follows [79]:

$$C_{\text{index}} = \left(\frac{d_w - \min(d_w)}{\max(d_w) - \min(d_w)} \right) \tag{7}$$

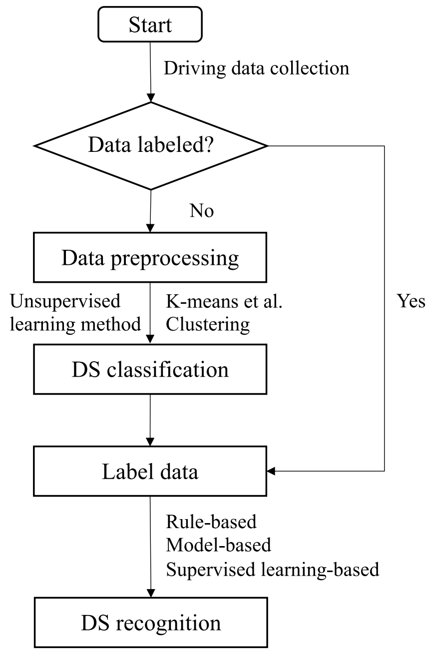


Fig. 3. Flow chart of DS recognition.

where d_w represents the sum of distances between all pairs of instances within the same cluster. If there are p pairs of instances in the same cluster, $\max(d_w)$ denotes the sum of the p largest distances, while $\min(d_w)$ represents the sum of the p smallest distances, considering all pairs of instances. It is desirable to minimize this index, which is bounded within the interval [0, 1].

(4) The Davies–Bouldin index

The calculation of the Davies–Bouldin index involves averaging each pair of clusters, which is expressed as follows [80]:

$$DB = \frac{1}{K}\sum_{i=1, i\neq j}^{K} \max\left(\frac{d_i + d_j}{d\left(c_i, c_j\right)}\right) \tag{8}$$

where K represents the total number of clusters. d_i and d_j refer to the average distances of all instances within each cluster to their respective cluster centers, c_i and c_j. The term $d(c_i, c_j)$ represents the distance between the cluster centers. The desired outcome for the Davies–Bouldin index is a small value, as it indicates the presence of compact and well-separated clusters.

(5) The Gamma index

This measure, also referred to as the Baker and Hubert's index [81], is defined as follows:

$$G = \left(\frac{s(+) - s(-)}{s(+) + s(-)}\right) \tag{9}$$

where $s(+)$ represents the number of consistent comparisons, while $s(-)$ represents the number of inconsistent comparisons. Comparisons are made between all pairs of clusters and dissimilarities between clusters. A comparison is considered consistent if the within-cluster distance is smaller than the between-cluster distance; otherwise, it is inconsistent. The objective of this index is to maximize its value, which is bounded by 1, indicating well-separated and distinct clusters.

2.5.2. External index

The Adjusted Rand Index (ARI) [82] was developed as an enhancement to the Rand index [83]. The Rand index can be expressed as follows:

$$\text{Rand} = \frac{a+d}{a+b+c+d} \tag{10}$$

where a represents the number of pairs of objects in the same group in both partitions S and T. b denotes the number of pairs of objects that are in the same group in partition S but not in T. Similarly, c represents the number of pairs of objects in the same group in partition T but not in S, and d represents the number of pairs of objects in different groups in both partitions S and T. Note that considering a set of N objects, S and T represent two distinct partitions to be compared.

The Rand index encounters an issue when comparing two random partitions as it does not have a minimum value of zero. To address this limitation, the Adjusted Rand Index (ARI) was introduced, specifically designed for random partitions. Similar to the Rand index, the ARI ranges between 0 and 1, where 1 represents identical partitions. The ARI can be calculated as follows:

$$ARI = \frac{\binom{n}{2}(a+d) - [(a+b)(a+c) + (c+d)(b+d)]}{\binom{n}{2}^2 - [(a+b)(a+c) + (c+d)(b+d)]} \tag{11}$$

where $\binom{n}{k}$ with k ≤ n refers to a k-combination of n.

2.6. Key issues in DS classification

DS classification mainly focuses on classifying DS into several specific categories. This classification is precious for understanding driver behavior habits, safety assessment, insurance pricing, etc. However, research and practical applications in this area also face various bottlenecks and challenges:(1) Lack of standardized classification criteria: No uniform standard currently defines "aggressive" or "conservative" driving. This subjectivity makes study results challenging to replicate and compare. (2) Difficulty in data labeling: Manually labeling large amounts of driving data is challenging, especially regarding ambiguous or borderline DS. (3) Feature selection and extraction: Proper selection and extraction of features decisive for classification is critical, but this usually requires extensive domain knowledge and experience. (4) Model complexity and overfitting: More complex models may be used to obtain more accurate classification results, but this may lead to overfitting or poor generalization ability of the model in practical applications.

3. DS recognition

With labeled data types identified, the research on DS recognition can proceed. DS identification relies on labeled data obtained through cluster analysis, with various methods employed to ensure accurate characterization of driving behaviors. Commonly used approaches include rule-based, model-based, and machine learning-based techniques [35]. Fig. 3 presents a flowchart outlining the stages and processes involved in DS recognition, providing a clear overview of the identification workflow. Additionally, Fig. 4 offers a comprehensive summary of the diverse methods utilized for DS recognition, highlighting their key features and applications.

3.1. Rule-based algorithm

Among these, the rule-based method is the simplest form of recognition. Specific rules are defined for particular characteristics, and by using predefined threshold values, driving characteristics can be categorized accordingly. Stoichkov et al. [89] developed a rule-based algorithm to identify driving behaviors for six specific events: acceleration/deceleration, left/right turns, and lane changes. Murphey et al. [54] used the cumulative number of aggressive behaviors during driving to classify overall driving characteristics into calm, normal, and aggressive types.

While the rule-based method is straightforward and practical, it has limitations regarding the number of input parameters it can handle. Many researchers have focused on studying a single parameter, which necessitates improving the accuracy and robustness of the algorithm.

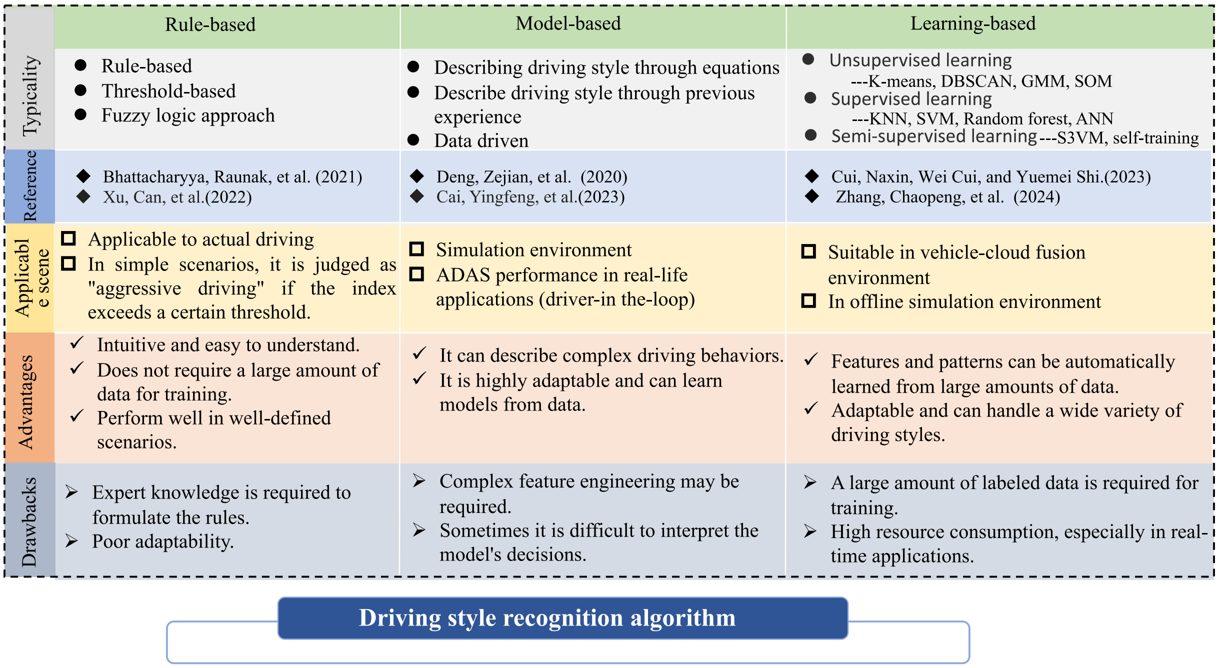


Fig. 4. DS recognition algorithms review in the literature [84–88].

To address the complexity arising from an increased number of variables, fuzzy logic can be employed as a replacement, offering better stability. Dorr et al. [90] utilized a real-time fuzzy logic algorithm that considered factors like road type and vehicle distance. This algorithm achieved a classification accuracy of 68% without external factors. However, these algorithms face limitations in terms of variability and generalization, and therefore, data-driven algorithms may be necessary to complement them during the development phase.

3.2. Model-based algorithm

Model-based algorithms define DS using pre-set equations characterizing specific traits [91]. The models are tailored to each DS by adjusting parameters to match the data that informed them, typically through data-driven techniques. The application's needs dictate the complexity of these models and directly affect the accuracy of the DS representation. Adopting these DS models is driven by the need to curtail time-consuming and costly data collection and testing [92]. Moreover, sophisticated driver models can supplant classification algorithms by mapping real-world driving scenarios into pre-defined categories. However, the primary challenge with driver modeling is establishing the accuracy of the outcomes. Besides, model-based methods also need to compare and verify the built model with real drivers [35].

3.3. Learning-based algorithm

Machine learning-based methods offer significant improvements in classification accuracy compared to traditional classification methods [93]. While supervised learning methods are commonly employed for driving characteristics classification, they often require a substantial amount of labeled training data. After conducting an analysis, Abou et al. [42] tallied the frequency with which previous scholars utilized machine learning techniques for DS recognition. The results revealed that SVM emerged as the most commonly employed method, closely followed by Neural Networks. Furthermore, it was observed that 65.85% of scholars employed accuracy as the primary metric for evaluating DS, while recall was utilized by 35.36% of researchers.

Xue et al. [94] applied the K-means algorithm to label driving characteristics, and subsequently extracted features from vehicle trajectories. The labeled data was then classified using a support vector Machine (SVM), which outperformed other algorithms such as random forest (RF), K Nearest Neighbors (KNN), and Multilayer Perceptron (MLP), achieving an accuracy of 91.7%. However, manually labeling large datasets is time-consuming due to the variability in driver behavior. To address this, Wang et al. [95] proposed a semi-supervised approach, semi-supervised support vector machine (S3VM), which reduces the labeling effort by using a small amount of labeled data. In their approach, K-means clustering was first applied to select data clusters, which were manually labeled. A specialized loss function was then used to label the remaining data, improving classification accuracy by approximately 10% while reducing labeling workload.

Moreover, several advanced classification methods have gained popularity, offering significant improvements over traditional techniques. Among these, XGBoost and LightGBM [96], both gradient boosting frameworks, are widely recognized for their ability to handle large datasets efficiently and provide accurate results in classification tasks. XGBoost, in particular, has been shown to outperform many classical machine learning models in terms of accuracy and speed.

Furthermore, deep learning techniques [97,98], such as MLP, recurrent neural networks (RNN), convolutional neural networks (CNN), and transformer models, have made substantial strides in various domains, including driving style classification. MLPs, with their multiple hidden layers, are capable of modeling complex, non-linear relationships. RNNs are well-suited for sequential data, such as time-series driving behavior data, while CNNs can extract hierarchical features, often applied to sensor data and images in ADAS. Recently, transformer-based models, known for their self-attention mechanisms, have shown promise in processing long-range dependencies in sequential data, making them highly suitable for applications in ITS [99].

A comparison of three different algorithms is shown in Fig. 4. The rule-based method is the most widely used algorithm in practice. It is simple, practical, and does not require much training data. However, it requires prior experience and is not universally applicable. In simple scenarios, it is judged as "aggressive driving" if the index exceeds a certain threshold. The advantage of model-based algorithms is that they can describe complex driving behaviors. It is highly adaptable and can learn models from data. It is often possible to provide probabilistic estimates of driving behavior. Its disadvantage is that it requires enough data to train the model, may require complex feature engineering,

Table 4
DS recognition algorithms.

References	Algorithm
[55,100]	Fuzzy logic
[38,101]	Rule-based
[41,102]	Adaptive fuzzy
[103,104]	kNN, RF
[35,105]	GMM, k-means, SVM
[88,106]	NN

and sometimes makes explaining the model's decisions difficult. Model-based methods are usually applied in a simulation environment. The advantage of learning-based algorithms is that they can automatically learn features and patterns from large amounts of data. It is adaptable, can handle various DS, and can use deep learning to extract meaningful features automatically. The disadvantage is that a large amount of labeled data is required for training, and resource consumption is high, especially in real-time applications. The applicable environment is usually an offline environment or a vehicle–cloud integration environment.

3.4. Algorithm evaluation

The existing evaluation metrics can be broadly categorized into accuracy metrics and time metrics [107]. Accuracy metrics assess the recognition accuracy of an algorithm and include measures such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. However, these metrics only apply when ground truth data is available for comparison.

On the other hand, time metrics focus on the recognition speed of an algorithm and typically involve calculating the average computation time of the recognition process. These metrics provide insights into the efficiency of the algorithm.

In addition to accuracy and time metrics, other performance metrics can be considered. One such metric is interpretability, which quantifies the difficulty level in understanding a model's internal logic and workings. This metric can be helpful for assessing the transparency and explainability of the algorithm. Fig. 5 presents an overview of the evaluation metrics commonly employed in DS recognition algorithms.

3.4.1. Accuracy metrics

(1) Accuracy

The accuracy rate in DS recognition represents the proportion of correctly identified samples among all subjects. It can be calculated using the following formula:

$$A = \frac{TP}{TP + FP} \tag{12}$$

where A denotes accuracy; TP and FP are determined by the count of correctly predicted positive samples divided by the sum of correctly predicted positive samples and incorrectly predicted positive samples.

(2) Precision, recall and F1-score

The accuracy of DS recognition indicates the proportion of correctly predicted samples out of all the samples. It can be expressed as follows:

$$P = \frac{TP + TN}{TP + FP + TN + FN} \tag{13}$$

where TN and FN denote the number of negative samples that were correctly predicted and incorrectly predicted, respectively.

The recall rate (Recall) measures the proportion of true positive examples the classifier correctly predicts as positive. It assesses the classifier's ability to identify positive examples. The recall can be calculated using the following formula:

$$R = \frac{TP}{TP + FN} \tag{14}$$

The F1 score is a metric commonly used in classification tasks that combines precision and recall into a single value. It provides a balanced measure of the classifier's performance by considering both the ability to correctly identify positive examples and the ability to find all positive ones. The F1 score is a metric that falls from 0 to 1, with a higher value indicating superior performance. It can be calculated as follows:

$$F1_{score} = \frac{P * R}{P + R} \tag{15}$$

3.4.2. Time metrics

The evaluation of DS recognition algorithms must not only focus on accuracy but also on computational efficiency, especially for real-time applications. Time-related metrics, such as average computation time per sample, play a crucial role in assessing the feasibility of deploying these algorithms in connected vehicles. High computational complexity could hinder the implementation of DS recognition systems in scenarios requiring rapid decision-making, such as adaptive cruise control or emergency braking.

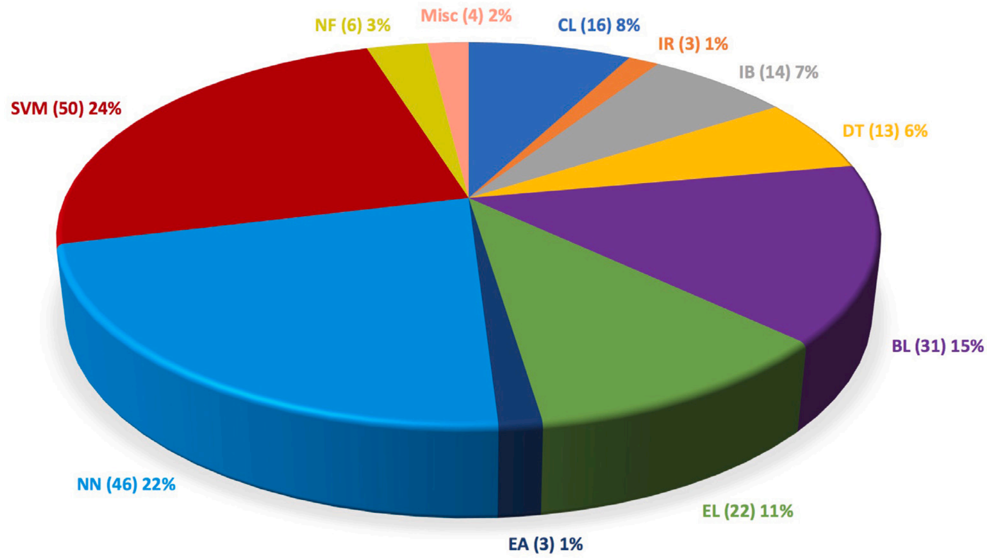
To address this, future research should explore lightweight algorithms or hardware acceleration techniques, such as edge computing or the use of GPUs, to ensure real-time performance. Metrics such as average training time per epoch and average prediction time per sample could be expanded to include comparisons across different algorithmic frameworks (e.g., rule-based, model-based, and learning-based approaches). This would offer a comprehensive understanding of trade-offs between accuracy and speed, especially under dynamic driving conditions (see Fig. 6 [108] and Table 4).

3.5. Key issues in DS recognition

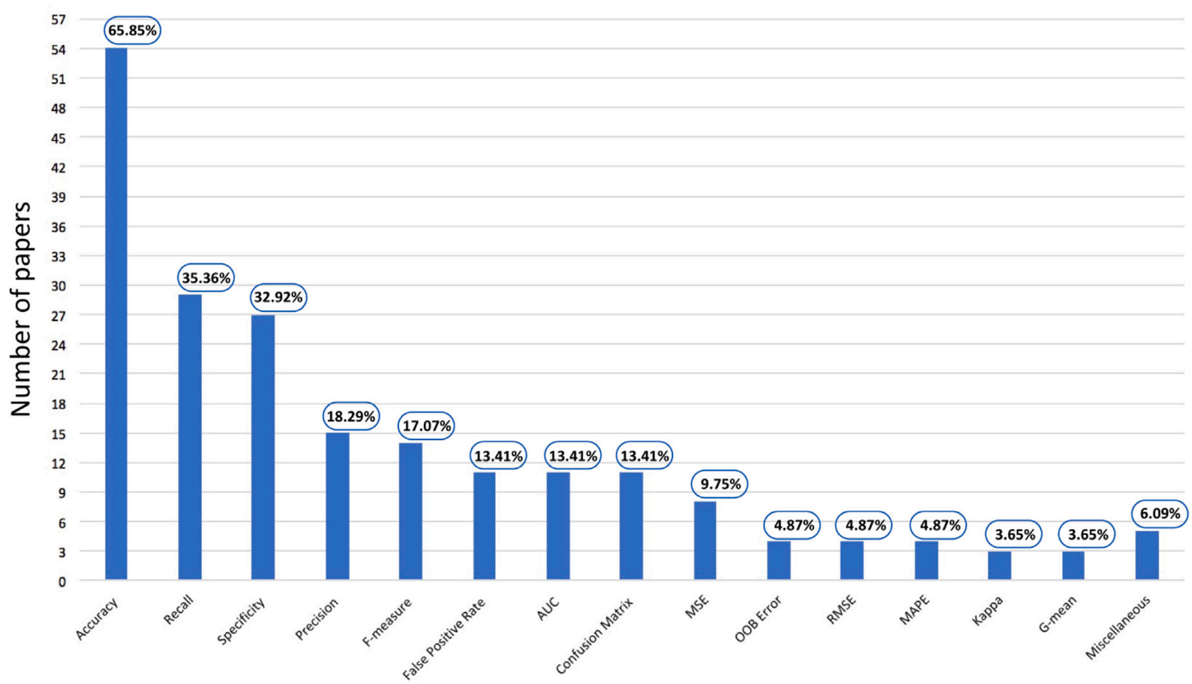
In recent years, DS recognition has been a research hotspot because it can be used in driver assistance systems, in-vehicle information systems, safety assessment, insurance pricing, and many other fields. However, research and application in this area still face some bottlenecks and challenges: (1) Data collection: The collection of driving data requires high-precision sensors and long-term data collection in real road environments, which makes large-scale data collection very expensive and challenging. (2) Data diversity: DS is influenced by multiple factors such as culture, geography, weather, road conditions, vehicle type, etc. Therefore, the trained model may not be accurate enough in some specific environments or scenarios. (3) Feature Engineering: Extensive feature engineering is still required to define and extract features useful for DS recognition, requiring expert knowledge and experience. (4) The generalization ability of the model: Even a model trained on a large amount of data may fail in some specific scenarios or new environments. (5) Real-time requirements: For some applications, such as driver assistance systems, the model needs to work in real-time or near real-time conditions, which puts forward higher requirements for computing resources and algorithm efficiency.

4. Implications for intelligent transportation systems and vehicle control

Once DS have been classified and identified, speed planning can be customized for specific types. Connected vehicles have also emerged as a promising solution for realizing future intelligent transportation systems. The performance of connected vehicle control strategies—measured in terms of safety, fuel efficiency, and passenger comfort—is significantly influenced by environmental factors, driving conditions, and drivers' DS [109]. However, the relationship between connected vehicle control and DS recognition has not been comprehensively revealed because of complex application conditions and the mixed traffic of vehicles with different autonomous driving levels.



(a) Distribution of the studies over type of ML technique.



(b) Distribution of the studies over performance metric.

Fig. 5. Statistics for machine learning algorithms [42].

4.1. Utilizing DS recognition in vehicle control systems

4.1.1. Human-like autonomous driving through DS recognition

With the advancement of autonomous driving technology, the integration of driving style recognition into autonomous vehicle control systems is essential for creating a more natural and human-like driving experience [110]. Human-like driving behavior is a key factor in improving driver–vehicle interaction and promoting trust between human drivers and autonomous vehicles. By incorporating DS recognition, AVs can adapt their driving styles to align more closely with those of human drivers, ensuring smoother, more comfortable, and intuitive driving experiences [111].

The incorporation of human-like driving styles into AV systems allows these vehicles to better mimic human drivers, making their behavior more predictable and relatable. Zhao et al. [112] develops a human-like trajectory planning model for automated driving, focusing on curve conditions where the lane centerline serves as a reference. Thirty-two skilled drivers were involved in collecting data under various curve conditions using a driver-in-the-loop system. The data were processed with dynamic time warping to align trajectories and remove anomalies. The study compared left and right turning trajectories, exploring drivers' performance demands and visual attention mechanisms.

Anthropomorphism in autonomous driving is not only about replicating human-like driving behaviors but also ensuring that the vehicle's behavior is predictable and aligned with user expectations. DS recognition enables AVs to exhibit a range of behaviors that are contextually appropriate, similar to how a human driver would adjust their behavior in response to traffic conditions, road types, and environmental

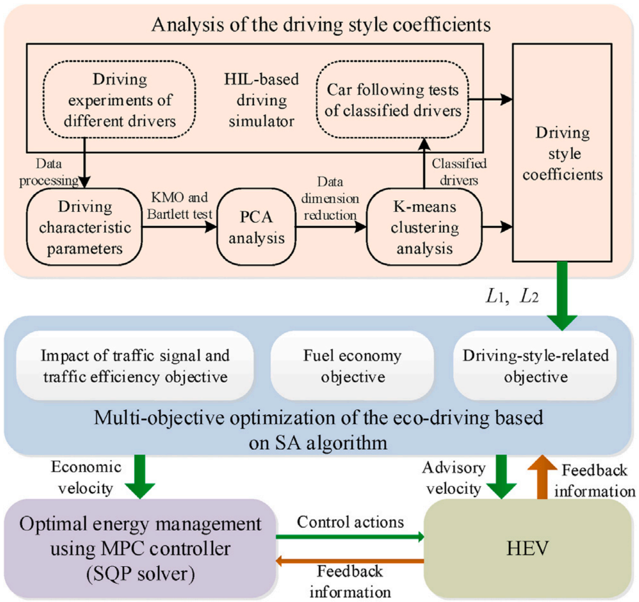


Fig. 6. Schematic diagram for DS recognition [108].

factors [113].

4.1.2. Adaptive cruise control

The adaptive cruise control (ACC) system is a widely adopted feature in modern vehicles as part of advanced driver assistance systems [114]. It plays a crucial role in the advancement of smart vehicles towards highly automated driving. ACC enables longitudinal driving in specific situations, encompassing functions such as maintaining a constant speed and following the vehicle ahead. Additionally, it must react to various conditions, such as the departure of the leading vehicle or the entry of a vehicle from the side. ACC stands as the most commonly utilized function among existing in vehicles ADAS features [115]. By effectively integrating acceleration by braking, it alleviates the pressure on the driver's feet to a certain extent, contributing to enhanced driving comfort [116].

Zhu et al. [117] introduce a novel data-driven approach for developing a Personalized Adaptive Cruise Control (PACC) system. The first step involves establishing a platform to acquire driving data, followed by collecting a substantial amount of real-world driving data from 84 human drivers. Subsequently, an unsupervised clustering algorithm is implemented to group the drivers into three distinct clusters. Next, a practical PACC structure is designed based on the grouped driving data, considering different driving characteristics. This structure primarily focuses on speed control, distance control, and the switching rule. Real-vehicle experiments are conducted to validate the effectiveness of the proposed PACC algorithm. The results demonstrate its capability to accurately capture and reflect different DS.

Gao et al. [118] proposes a PACC system employing DS recognition and MPC techniques. The objective is to accommodating diverse DS while ensuring effective car-following, comfort, and fuel economy. Real vehicle experiments are conducted, collecting driving data from 66 randomly selected drivers. This data is then subjected to unsupervised machine-learning techniques to cluster and group the experimental data. Subsequently, a DS classifier is developed using supervised machine learning methods to recognize the DS of drivers in real-time. The simulation results demonstrate that the proposed personalized ACC system caters to different DS while maintaining various performance metrics.

By integrating the results of DS recognition into the ACC control system, it is possible to design an ACC control algorithm that considers the driver's style, thereby enhancing safety and promoting smoother driving on the road.

4.1.3. New energy vehicle regenerative braking control

Regenerative braking holds excellent significance in automotive energy-saving technology. The variation in regenerative braking intensity arises from the diverse rules governing accelerator pedal usage under different driving conditions and styles. Adapting the energy recovery intensity to match these variables can enhance energy efficiency. To address this, the study [119] proposes an intelligent connected vehicle regenerative braking control strategy (RBCS) that considers the interconnected impact of driving conditions and styles, focusing on the accelerator pedal. Specifically, a modified approach is introduced for determining DS characteristic parameters that accounts for the influence of driving conditions. Subsequently, the authors established the regenerative braking control strategy, which relies on the accelerator pedal and corrects the intensity accordingly using correction coefficients. Next, collect driving data through driver-in-the-loop experiments, enabling us to refine the DS characteristic parameters. Lastly, a vehicle simulation model and a hardware-in-the-loop experiment platform are developed to validate the RBCS. The results showcase a further enhancement in the vehicle's economy.

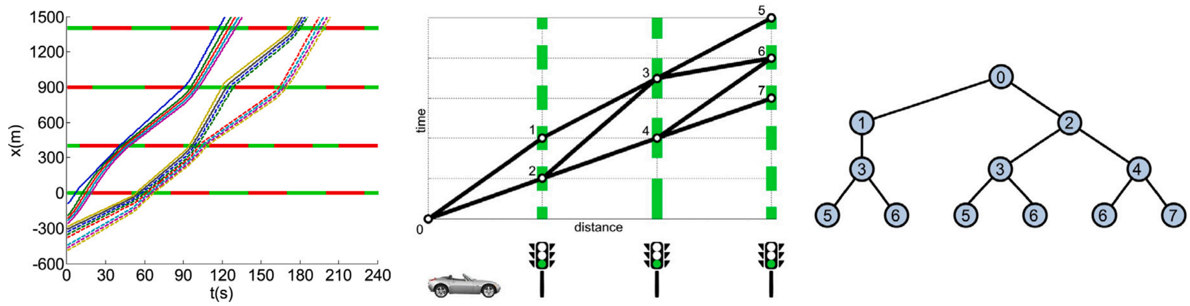
Therefore, considering the interplay between congestion type and DS, the optimization of regenerative braking strategy can be significantly improved. This can be achieved by integrating regenerative braking technology with intelligent networked vehicles, thereby leveraging traffic information and the driver's braking intentions to their fullest extent.

4.1.4. HEV energy optimal control

Implementing tailored energy management strategies for HEVs based on the driver's DS can effectively enhance fuel efficiency. The study [120] introduce an adaptive equivalent consumption minimization strategy (AECMS-style), focusing on DS to enhance fuel economy in HEVs. A novel approach is developed to adjust the optimal equivalent factor for the AECMS style, and the motor braking strategy is redesigned for driving charging mode, considering various DS. Experimental findings demonstrate that the AECMS style improves fuel economy and charging sustainability in HEVs. Tian et al. [121] proposed an adaptive energy management system comprising offline and online components to enhance the energy efficiency of a parallel hybrid electric bus. The online portion executes the energy management strategy, integrating the driver's DS into the ECMS. Through simulation, it is demonstrated that the proposed strategy outperforms ECMS regarding charging sustainability and equivalent fuel consumption, catering to both aggressive and conservative drivers. Thus, the practical significance and theoretical value of incorporating DS recognition into the real-time energy management strategy of HEVs are evident.

4.2. Vehicle speed planning control

By utilizing V2I to gather traffic condition information and V2V to obtain speed and position data of surrounding vehicles, along with various other data sources such as the vehicle's own speed and energy consumption, it becomes possible to plan the optimal driving speed for the vehicle in the upcoming period. Wang et al. [108] developed a road scene and HEV fuel consumption model, introducing a rule-based method to determine target speed by considering road speed limits and SPaT information. This approach reduced red-light stops and improved traffic efficiency. They further formulated a multi-objective optimization problem addressing fuel economy, DS, and safety, solved using the Particle Swarm Optimization (PSO) algorithm to optimize HEV platoon speed. Building on this, Xin et al. [122] proposed a hierarchical ecological driving system utilizing V2X communication to



(a) Driving trajectory. (b) Available paths to cross intersections on the green. (c) Decision tree of possible paths.

Fig. 7. Schematic diagram of speed planning considering driving behavior [122,123]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

integrate DS, optimizing vehicle speed through traffic signal data and driving behavior. This reduced red-light waiting times and improved fuel efficiency, highlighting a progression from foundational modeling to advanced real-time optimization. The study [123] aim to identify a driving pace that optimizes fuel consumption and time of arrival while ensuring the driver's comfort is not compromised.

As depicted in Fig. 7(a), the x-axis represents time duration, the y-axis represents the driving distance of the vehicle, and the red and green lines correspond to the duration of red and green lights, respectively. It is evident that while connected vehicles can attain consistent speeds at traffic light intersections through V2X communication, there are notable variations in the driving trajectories among drivers with distinct DS. Fig. 7(b) presents an example of a simple, straight route with three upcoming traffic lights, with intersection crossing nodes labeled on the graph. To evaluate all available pace choices, they can represent them in the form of a decision tree (refer to Fig. 7(c)). The algorithm aims to optimize the driving pace by comparing all possible options and selecting the one with the lowest cost function. However, it is essential to consider the driver's response at intersection crossings. Deviations from the driver's preferred style can negatively impact compliance, so any recommendations must take this into account.

In multi-vehicle platoon driving, optimizing target vehicle speed involves factors like fuel economy, traffic smoothness, vehicle ride comfort, and the consideration of relative distances under different DS. This consideration ensures the safety of the multi-vehicle platoon. Therefore, the acceleration and distance required for multi-vehicle platoon driving with different DS are expressed as follows [108,124]:

$$\begin{cases} a_{\mathrm{d}} = L_1\left(s - S_{\mathrm{d}}\right) + L_2\left(v_1 - v_2\right) \\ S_{\mathrm{d}} = S_0 + t_{\mathrm{h}} v_2 + \frac{v_2\left(v_2 - v_1\right)}{2\sqrt{a_{\mathrm{int}}\ b_{\mathrm{int}}}} \end{cases} \tag{16}$$

where L_1 and L_2 are correction coefficients of DS. To incorporate the influence of DS on the optimal solution, the objective function is defined as follows:

$$\min \sum_{t=0}^{T-\Delta t} \begin{bmatrix} \omega_1 f\left[v_m(t), a_m(t)\right] \Delta t + \omega_2(t)\left(a_m(t) - a_{md}(t)\right)^2 \\ +\omega_3\left(v_m(t+\Delta t) - v_{\mathrm{target}}^m\ (t+\Delta t)\right)^2 \end{bmatrix} \tag{17}$$

$$\begin{cases} f\left[v_m(t), a_m(t)\right] = \frac{\dot{m}_{\mathrm{ful}}(t)}{D(t)} \\ \dot{m}_{\mathrm{fiul}}(t) = \frac{P_{\mathrm{rrm}}(t)}{\eta H}\Delta t \\ D(t) = v_{\mathrm{m}}(t)\Delta t + \frac{1}{2}a_{\mathrm{m}}^2(t)\Delta t \\ P_{\mathrm{req}}(t) = \frac{1}{2}\rho_{\mathrm{a}} C_{\mathrm{D}} A_{\mathrm{m}} v_{\mathrm{m}}^3(t) + \mu M_{\mathrm{m}} g v_{\mathrm{m}}(t) \\ \qquad + M_{\mathrm{m}} g\theta v_{\mathrm{m}}(t) + M_{\mathrm{m}} v_{\mathrm{m}}(t) a_{\mathrm{m}}(t) \\ \omega_2(t) = \alpha e^{-\beta\left(s_n(t) - s_m(t) - S_0\right)} \\ a_{md}(t) = L_1 R_{mn}(t) + L_2\left(v_n(t) - v_m(t)\right) \\ R_{mn}(t) = s_n(t) - s_m(t) - S_{mn}(t) \\ S_{mn}(t) = S_0 + t_{\mathrm{h}} v_m(t) + \frac{v_m(t)\left[v_m(t) - v_{\mathrm{m}}(t)\right]}{2\sqrt{a_{\mathrm{int},m,m} b_{\mathrm{min},m}}} \end{cases} \tag{18}$$

where F_t means the vehicle's driving force, F_f denotes the frictional rolling resistance, F_w is the air resistance, F_i represents the gradient resistance, and F_j is the acceleration resistance; all units are N. In the objective function, the weight coefficients for various optimization items are denoted as ω_1, ω_2, and ω_3. The time window for model predictive control is represented by T. The position of the HEV is denoted as s, while v represents the vehicle's speed. The target speed of the HEV is indicated by v_{target}. The acceleration of the vehicle is denoted as a, and Δt represents the simulation calculation step. By utilizing the aforementioned formula, DS can be translated into a factor that influences the process of speed planning. Hence, recognizing the driver's DS is crucial in speed planning. It is essential to incorporate driving behavior into the speed planning process as it greatly contributes to improving fuel economy. Accurately recognizing driving behavior requires machine learning techniques, which present a significant challenge for the current onboard computing units of connected vehicles.

4.3. Key issues in vehicle speed planning

In summary, Wang et al. [108] have extended the application of driving behavior recognition to speed planning. They have successfully developed an optimal vehicle speed planning approach by incorporating DS recognition in the presence of traffic lights. This approach has further facilitated energy management in hybrid vehicles. However, it is essential to note that the DS recognition in this study relies on a hardware-in-the-loop platform, which unfortunately does not enable real-time recognition of the driver's DS. In addition, as artificial intelligence evolves, reinforcement learning is anticipated to emerge as the optimal method for speed planning [125]. However, with the current technology, it is restricted to simulations on designated platforms.

Indeed, accurate estimation of DS recognition faces significant challenges due to complex real-world scenarios, demanding working conditions, and limited onboard computing power. To address these issues, the paper proposes establishing a digital twin model for vehicles and implementing vehicle–cloud integrated management and control [126,127]. Leveraging the computational and storage capabilities of the cloud, essential feature information such as DS can be deeply analyzed to facilitate optimal path planning. Combining the benefits of cloud computing and machine learning on a cloud platform presents innovative directions for subsequent research endeavors.

5. Conclusion

This paper provides a comprehensive overview of the current state, implications, and opportunities in driving behavior research, along with recent advancements in intelligent transportation systems. The

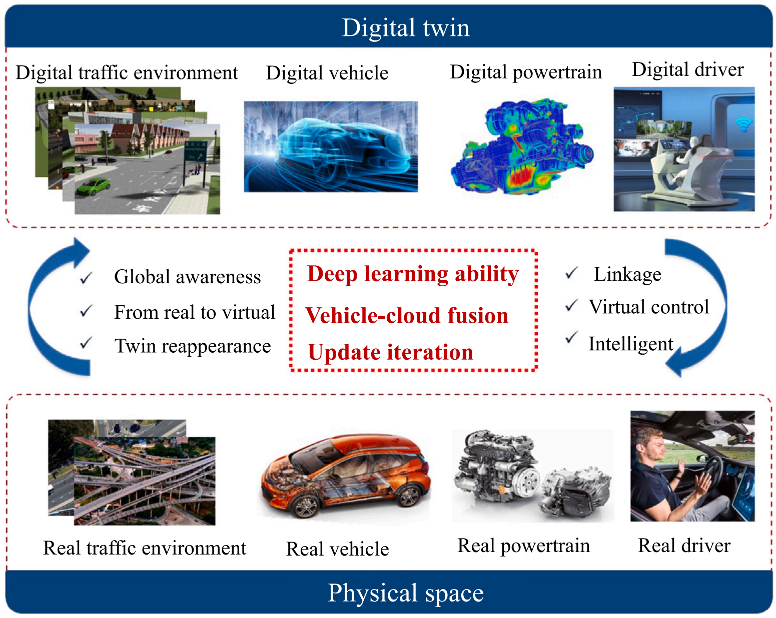


Fig. 8. The schematic diagram for vehicle–cloud collaboration.

opening section outlines the research motivation for driving behavior classification and recognition, summarizes prior progress in the field, categorizes factors influencing driving behavior, and highlights the key contributions of this study. Subsequently, the paper delves into driving behavior classification, examining both long-term and short-term influencing factors and data processing techniques. It also reviews unsupervised learning algorithms for analyzing unlabeled data and outlines evaluation metrics for these methods. The discussion then extends to rule-based and learning-based algorithms for driving behavior recognition, with a focus on evaluation indicators such as time efficiency and accuracy. Furthermore, the paper explores the impact of DS on optimal vehicle speed planning, addressing both single-vehicle and multi-vehicle scenarios within a networked environment. This analysis offers novel insights and sets the stage for future research in speed planning optimization.

6. Future directions

With the rapid development of modern transportation systems, integrating in-vehicle systems and cloud computing is becoming increasingly possible [128]. So far, many studies have shown the feasibility of the idea of vehicle–cloud collaboration. Dong et al. [129] combined mixed reality with digital twin integrating the virtual and physical spaces into a cohesive environment where physical entities coexist and interact with virtual entities through their digital counterparts. The cloud unit, hosting the mixed experimental platform, plays a crucial role in fusing multi-platform information and issuing control instructions.

The cloud control platform system placement is established upon the comprehensive analysis of real-time data from smart vehicles, employing extensive data computation. This approach enables the seamless correlation of various elements, such as vehicles, traffic conditions, and environmental factors within the physical and informational domains [2], as shown in Fig. 8. Fig. 9 depicts the cloud platform architecture comprising the application, network, platform, and terminal layers [130]. Among these layers, the platform layer offers enhanced computing and storage capabilities, enabling efficient processing and analysis of large volumes of data.

Leveraging the cloud platform's computational power, the DS recognition and speed planning method can transmit vehicle state data to the platform for streamlined data processing and analysis. Additionally, the cloud platform can store historical data, facilitating trend analysis and evolution patterns of vehicle states. Moreover, the cloud platform enables multi-vehicle coordination by integrating and analyzing vehicle status data. This coordinated state estimation method provides a comprehensive view of the fleet's status and trends, enabling better vehicle speed planning. In summary, harnessing the cloud platform's capabilities for driving behavior recognition and vehicle speed planning research holds significant potential and promising prospects. Based on the advantages of cloud platforms, future development trends can be summarized in the following points.

DS recognition and classification method based on vehicle–cloud fusion Under the current technology, DS classification and recognition based on vehicle–cloud integration is still in its infancy. Advanced artificial intelligence algorithms and intense learning models can be integrated to improve the accuracy of DS recognition further. However, this technology has specific challenges in information security and data transmission. Because some vehicle information data may leak the driver's privacy, and the data transmission may be affected by the Internet, there will be an unavoidable delay [131].

Recent advancements in vehicle–cloud collaboration, particularly through federated learning, have transformed DS classification and recognition. Unlike traditional methods that require local data processing or uploads to centralized servers—posing risks to data privacy and bandwidth—federated learning enables vehicles to train models locally and share only model updates with a central server, thereby protecting sensitive information. This decentralized approach enhances data privacy, reduces bandwidth use by transmitting less data, and improves model generalization by aggregating updates from diverse vehicles. Applications include real-time DS recognition and personalized driver assistance systems, but challenges such as system heterogeneity, communication overhead, and effective model aggregation persist. Ultimately, integrating federated learning with vehicle–cloud collaboration is expected to enhance driving safety and efficiency, especially for autonomous vehicles, while respecting driver privacy [132].

In future development, for information security issues, technologies such as encryption, identity verification, and data signature will be

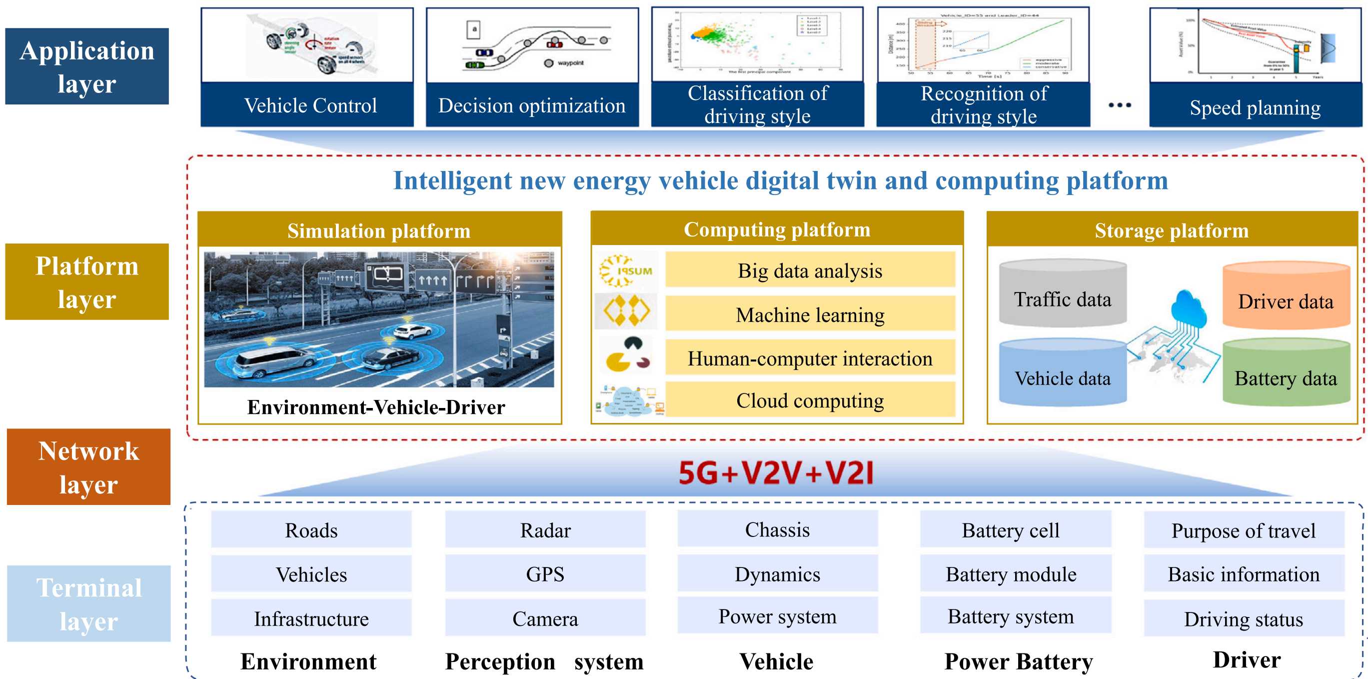


Fig. 9. The schematic diagram for the cloud platform architecture.

introduced to enhance the security of vehicle–cloud communication and protect data from unauthorized access and tampering. Secondly, part of the computing and processing work is transferred from the cloud to the vehicle itself, reducing its dependence on network delay and improving real-time performance. Third, promote the formulation of a unified vehicle–cloud collaborative communication security standard to ensure system security and interoperability. Finally, use artificial intelligence technology to monitor and identify abnormal behaviors and give early warning of potential security risks.

6.1. Personalized speed planning

Accurately identifying DS and planning speed accordingly gives drivers a more personalized driving experience. High-quality data is critical to accurately identifying DS. However, continuous, real-time data collection can involve many sensors and processing power, adding cost and complexity. Therefore, using the cloud platform to build a digital twin model and train and predict it based on a large amount of historical driving data and limited real-time data can reduce costs [133]. If multiple vehicles can plan speed based on DS, the entire traffic system may be smoother and reduce traffic congestion.

6.2. Multimodal DS recognition

The data sources for DS recognition will be more extensive in the future, including video and sensor data, etc [38]. Fusing these data will increase the complexity of the cloud model to a certain extent. On certain occasions, real-time identification and feedback on DS are required. A large amount of data will increase the difficulty of calculation and storage, and the accuracy and robustness will also face challenges. New materials and multi-sensor fusion algorithms will be considered for sensor hardware in future development. Based on the results of multimodal DS recognition, future driving assistance systems can be more intelligent and personalized to meet drivers' needs better. In addition to DS, multimodal data can monitor driver emotions and behaviors, providing more information to improve driving safety.

6.3. DS classification for driver-automation shared control in intelligent vehicles

In the context of intelligent vehicles, DS classification plays a crucial role in optimizing driver-automation shared control, enhancing safety, and improving the overall driving experience [134]. By identifying states like manual control, partial automation, and full automation, the system dynamically allocates control based on the driver's behavior and engagement levels.

Driving state classification in intelligent vehicles will enable smoother transitions between manual and automated control by adjusting to the driver's behavior, such as aggressive or calm driving, and enhancing safety through real-time interventions like adaptive cruise control or lane-keeping assist [135]. Continuous monitoring of driver states, such as distraction or fatigue, will allow proactive safety measures, including automatic emergency braking during critical moments. Future systems will balance automation with driver comfort by tailoring responses to individual DS, ensuring smoother transitions and a more intuitive experience. As systems evolve, they will offer DS-based personalization, learning from and adapting to the driver's preferences for a more seamless shared control experience. In complex traffic scenarios, driving state classification will assist drivers in navigating mixed traffic conditions, fostering safer interactions between human-driven and automated vehicles. Over time, continuous monitoring will enable long-term adaptation to the driver's habits, improving the synergy between human and automation, ultimately leading to more personalized, safe, and efficient vehicle control systems.

CRediT authorship contribution statement

Peng Mei: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Hamid Reza Karimi:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Lei Ou:** Writing – review & editing, Validation, Software, Methodology, Formal analysis, Data curation. **Hehui Xie:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Chong Zhan:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis, Data curation. **Guangyuan Li:** Writing – review & editing, Visualization, Investigation, Formal analysis, Conceptualization. **Shichun Yang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization.

Declarations

This paper is neither under consideration nor has been published in any other venue.

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.

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References

[1] Dziejarski Bartosz, Krzyżyńska Renata, Andersson Klas. Current status of carbon capture, utilization, and storage technologies in the global economy: A survey of technical assessment. Fuel 2023;342:127776.

[2] Mei Peng, Karimi Hamid Reza, Xie Jiale, Chen Fei, Ou Lei, Yang Shichun, Huang Cong. Battery state estimation methods and management system under vehicle–cloud collaboration: A Survey. Renew Sustain Energy Rev 2024;206:114857.

[3] Si Fangyuan, Du Ershun, Zhang Ning, Wang Yi, Han Yinghua. China's urban energy system transition towards carbon neutrality: challenges and experience of Beijing and Suzhou. Renew Sustain Energy Rev 2023;183:113468.

[4] Wang Haopeng, Zhao Zhenzhi, Ma Yingying, Wu Hao, Bao Fei. Sustainable road planning for trucks in urbanized areas of Chinese cities using deep learning approaches. Sustainability 2023;15(11):8763.

[5] Yan Wei, Wang Xiao, Liu Ying, Zhang Xu-mei, Jiang Zhi-gang, Huang Lin. A stochastic programming approach for EOL electric vehicle batteries recovery network design under uncertain conditions. Sci Rep 2024;14(1):876.

[6] Haque AKM Bahalul, Bhushan Bharat, Dhiman Gaurav. Conceptualizing smart city applications: Requirements, architecture, security issues, and emerging trends. Expert Syst 2022;39(5):e12753.

[7] Huang Cong, Ding Weiping, Gao Ruifeng, Mei Peng, Karimi Hamid Reza. Distributed state-of-charge estimation for lithium-ion batteries with random sensor failure under dynamic event-triggering protocol. Inf Fusion 2023;95:293–305.

[8] Peelam Mritunjay Shall, Gera Mehul, Chamola Vinay, Zeadally Sherali, et al. A review on emergency vehicle management for intelligent transportation systems. IEEE Trans Intell Transp Syst 2024.

[9] Huang Cong, Coskun Serdar, Wang Jun, Mei Peng, Shi Quan. Robust H_∞ dynamic output-feedback control for CACC with ROSSs subject to RODAs. IEEE Trans Veh Technol 2021;71(1):137–47.

[10] Chen Fei, Mei Peng, Xie Hehui, Yang Shichun, Xu Bin, Huang Cong. Reinforcement learning-based energy management control strategy of hybrid electric vehicles. In: 2022 8th international conference on control, automation and robotics. ICCAR, IEEE; 2022, p. 248–52.

[11] Anderson James M, Nidhi Kalra, Stanley Karlyn D, Sorensen Paul, Samaras Constantine, Oluwatola Oluwatobi A. Autonomous vehicle technology: A guide for policymakers. Rand Corporation; 2014.

[12] Yang Yang, Hua Kun. Emerging technologies for 5G-enabled vehicular networks. IEEE Access 2019;7:181117–41.

[13] Berhanu Yetay, Alemayehu Esayas, Schröder Dietrich, et al. Examining car accident prediction techniques and road traffic congestion: a comparative analysis of road safety and prevention of world challenges in low-income and high-income countries. J Adv Transp 2023;2023.

[14] Majstorović Željko, Tišljarić Leo, Ivanjko Edouard, Carić Tonči. Urban traffic signal control under mixed traffic flows: Literature review. Appl Sci 2023;13(7):4484.

[15] Chai Zhanxiang, Nie Tianxin, Becker Jan, Chai Zhanxiang, Nie Tianxin, Becker Jan. Infrastructure: echoing with autonomous driving. Auton Driv Chang Futur 2021;99–135.

[16] An Sheng-hai, Lee Byung-Hyug, Shin Dong-Ryeol. A survey of intelligent transportation systems. In: 2011 third international conference on computational intelligence, communication systems and networks. IEEE; 2011, p. 332–7.

[17] Guerrero-Ibanez Juan Antonio, Zeadally Sherali, Contreras-Castillo Juan. Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies. IEEE Wirel Commun 2015;22(6):122–8.

[18] Chhabra Rishu, Singh Saravjeet, Khullar Vikas. Privacy enabled driver behavior analysis in heterogeneous IoV using federated learning. Eng Appl Artif Intell 2023;120:105881.

[19] Lu Lin, Lin Yao, Wen Yuan, Zhu Jinxiong, Xiong Shengwu. Federated clustering for recognizing driving styles from private trajectories. Eng Appl Artif Intell 2023;118:105714.

[20] Lakhan Abdullah, Mohammed Mazin Abed, Abdulkareem Karrar Hameed, Deveci Muhammet, Marhoon Haydar Abdulameer, Nedoma Jan, Martinek Radek. A multi-objectives framework for secure blockchain in fog-cloud network of vehicle-to-infrastructure applications. Knowl-Based Syst 2024;111576.

[21] Yang Shuo, Zheng Hongyu, Wang Junmin, El Kamel Abdelkader. A personalized human-like lane-changing trajectory planning method for automated driving system. IEEE Trans Veh Technol 2021;70(7):6399–414.

[22] Li Daofei, Pan Hao. Two-lane two-way overtaking decision model with driving style awareness based on a game-theoretic framework. Transp A: Transp Sci 2023;19(3):2076755.

[23] Alhaek Fares, Liang Weichao, Rajeh Taha M, Javed Muhammad Hafeez, Li Tianrui. Learning spatial patterns and temporal dependencies for traffic accident severity prediction: A deep learning approach. Knowl-Based Syst 2024;286:111406.

[24] Rakauskas Michael E, Gugerty Leo J, Ward Nicholas J. Effects of naturalistic cell phone conversations on driving performance. J Saf Res 2004;35(4):453–64.

[25] Mei Peng, Karimi Hamid Reza, Huang Cong, Yang Shichun, Chen Fei. A learning-based driving style classification approach for intelligent vehicles. In: International conference on sensor systems and software. Springer; 2022, p. 179–90.

[26] Zhou Shaodong, Ju Zhiyang, Liu Yue, Zhang Hui, Karimi Hamid Reza. Driver state detection for driver-automation shared control with fuzzy logic. Control Eng Pract 2022;127:105294.

[27] Kim Young Woo, Ji Yong Gu, Yoon Sol Hee. Control interface for next generation vehicles: What is the best way to drive four-wheel independent steering vehicles? Int J Hum– Comput Interact 2024;40(7):1586–99.

[28] Azadani Mozhgan Nasr, Boukerche Azzedine. Driving behavior analysis guidelines for intelligent transportation systems. IEEE Trans Intell Transp Syst 2021;23(7):6027–45.

[29] Watson-Brown Natalie, Truelove Verity, Senserrick Teresa. Self-regulating compliance to enhance safe driving behaviours. Transp Res F: Traffic Psychol Behav 2024;105:437–53.

[30] Miotti Marco, Needell Zachary A, Ramakrishnan Sankaran, Heywood John, Trancik Jessika E. Quantifying the impact of driving style changes on light-duty vehicle fuel consumption. Transp Res D: Transp Environ 2021;98:102918.

[31] Liao Xishun, Zhao Zhouqiao, Barth Matthew J, Abdelraouf Amr, Gupta Rohit, Han Kyungtae, Ma Jiaqi, Wu Guoyuan. A review of personalization in driving behavior: Dataset, modeling, and validation. IEEE Trans Intell Veh 2024.

[32] Wang Rui, Lukic Srdjan M. Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles. In: 2011 IEEE vehicle power and propulsion conference. 2011, p. 1–7.

[33] Bolovinou Anastasia, Amditis Angelos, Bellotti Francesco, Tarkiainen Mikko. Driving style recognition for co-operative driving: A survey. In: The sixth international conference on adaptive and self-adaptive systems and applications. Citeseer; 2014, p. 73–8.

[34] Meiring Gys Albertus Marthinus, Myburgh Hermanus Carel. A review of intelligent driving style analysis systems and related artificial intelligence algorithms. Sensors 2015;15(12):30653–82.

[35] Martinez Clara Marina, Heucke Mira, Wang Fei-Yue, Gao Bo, Cao Dongpu. Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey. IEEE Trans Intell Transp Syst 2017;19(3):666–76.

[36] Deng Qi, Söffker Dirk. A review of HMM-based approaches of driving behaviors recognition and prediction. IEEE Trans Intell Veh 2021;7(1):21–31.

[37] Nai Wei, Yang Zan, Wei Yinzhen, Sang Jierui, Wang Jialu, Wang Zhou, Mo Peiyu. A comprehensive review of driving style evaluation approaches and product designs applied to vehicle usage-based insurance. Sustainability 2022;14(13):7705.

[38] Chu Hongqing, Zhuang Hejian, Wang Wenshuo, Na Xiaoxiang, Guo Lulu, Zhang Jia, Gao Bingzhao, Chen Hong. A review of driving style recognition methods from short-term and long-term perspectives. IEEE Trans Intell Veh 2023.

[39] Bouhsissin Soukaina, Sael Nawal, Benabbou Faouzia. Driver behavior classification: a systematic literature review. IEEE Access 2023;11:14128–53.
[40] Mohammadnazar Amin, Arvin Ramin, Khattak Asad J. Classifying travelers' driving style using basic safety messages generated by connected vehicles: Application of unsupervised machine learning. Transp Res C 2021;122:102917.
[41] Liang Kaichong, Zhao Zhiguo, Li Wenchang, Zhou Jiawei, Yan Danshu. Comprehensive identification of driving style based on vehicle's driving cycle recognition. IEEE Trans Veh Technol 2022;72(1):312–26.
[42] Abou Elassad Zouhair Elamrani, Mousannif Hajar, Al Moatassime Hassan, Karkouch Aimad. The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review. Eng Appl Artif Intell 2020;87:103312.
[43] Chen Xiaoyun, Sun Jian, Ma Zian, Sun Jie, Zheng Zuduo. Investigating the long- and short-term driving characteristics and incorporating them into car-following models. Transp Res C 2020;117:102698.
[44] Galovski Tara E, Blanchard Edward B. Road rage: a domain for psychological intervention? Aggress Violent Behav 2004;9(2):105–27.
[45] Biondi Francesco, Alvarez Ignacio, Jeong Kyeong-Ah. Human–vehicle cooperation in automated driving: A multidisciplinary review and appraisal. Int J Hum–Comput Interact 2019;35(11):932–46.
[46] Charles Susan Turk. Strength and vulnerability integration: a model of emotional well-being across adulthood.. Psychol Bull 2010;136(6):1068.
[47] Zhang Qi, Wu Qingtian, Zhou Yimin, Wu Xinyu, Ou Yongsheng, Zhou Huazhang. Webcam-based, non-contact, real-time measurement for the physiological parameters of drivers. Measurement 2017;100:311–21.
[48] Taubman-Ben-Ari Orit, Mikulincer Mario, Iram Amit. A multi-factorial framework for understanding reckless driving—appraisal indicators and perceived environmental determinants. Transp Res F: Traffic Psychol Behav 2004;7(6):333–49.
[49] de Zepeda Maria Valentina Niño, Meng Fanlin, Su Jinya, Zeng Xiao-Jun, Wang Qian. Dynamic clustering analysis for driving styles identification. Eng Appl Artif Intell 2021;97:104096.
[50] Tannant Dwayne, Regensburg Bruce. Guidelines for mine haul road design. 2001.
[51] Pitts Matthew J, Burnett Gary, Skrypchuk Lee, Wellings Tom, Attridge Alex, Williams Mark A. Visual–haptic feedback interaction in automotive touchscreens. Displays 2012;33(1):7–16.
[52] Horberry Tim, Mulvihill Christine, Fitzharris Michael, Lawrence Brendan, Lenné Mike, Kuo Jonny, Wood Darren. Human-centered design for an in-vehicle truck driver fatigue and distraction warning system. IEEE Trans Intell Transp Syst 2021.
[53] Shi Daqian, Liu Ziwei, Fu Jie, Yu Hongwei. The impact of drivers' short-term exposure to air pollution on traffic deaths. Environ Sci Pollut Res 2022;29(40):61323–33.
[54] Murphey Yi Lu, Milton Robert, Kiliaris Leonidas. Driver's style classification using jerk analysis. In: 2009 IEEE workshop on computational intelligence in vehicles and vehicular systems. IEEE; 2009, p. 23–8.
[55] Pachêco Gomes Iago, Wolf Denis Fernando. Driving style recognition using interval type-2 fuzzy inference system and multiple experts decision-making. Int J Fuzzy Syst 2024;26(2):553–71.
[56] Jiang Shuo, Strout Zach, He Bin, Peng Daiyan, Shull Peter B, Lo Benny PL. Dual stream meta learning for road surface classification and riding event detection on shared bikes. IEEE Trans Syst Man Cybern: Syst 2023.
[57] Vaitkus Vygandas, Lengvenis Paulius, Žylius Gediminas. Driving style classification using long-term accelerometer information. In: 2014 19th international conference on methods and models in automation and robotics. MMAR, IEEE; 2014, p. 641–4.
[58] Yang Qing, Wu Guangqiang, Zhang Shaozhe. Research on DCT shift strategy for various driving style based on "driver-vehicle-cloud" machine learning. Proc Inst Mech Eng D 2024;09544070241246605.
[59] Karrouchi Mohammed, Nasri Ismail, Rhiat Mohammed, Atmane Ilias, Hirech Kamal, Messaoudi Abdelhafid, Melhaoui Mustapha, Kassmi Kamal. Driving behavior assessment: a practical study and technique for detecting a driver's condition and driving style. Transp Eng 2023;14:100217.
[60] Brombacher Patrick, Masino Johannes. Driving event detection and driving style classification using artificial neural networks. In: 2017 IEEE international conference on industrial technology. ICIT, IEEE; 2017, p. 997–1002.
[61] Cheng Kun, Sun Dongye, Qin Datong, Cai Jing, Chen Chong. Deep learning approach for unified recognition of driver speed and lateral intentions using naturalistic driving data. Neural Netw 2024;179:106569.
[62] Zhu Yuanfang, Jiang Meilan, Yamamoto Toshiyuki, Ding Naikan, Shinkai Hiroko, Aoki Hirofumi, Shimazaki Kan. A framework for combining lateral and longitudinal acceleration to assess driving styles using unsupervised approach. IEEE Trans Intell Transp Syst 2023.
[63] Zaidan Ruqayah Alaa, Alamoodi Abdullah Hussein, Zaidan BB, Zaidan AA, Albahri Osamah Shihab, Talal Mohammed, Garfan Salem, Sulaiman Suliana, Mohammed Ali, Kareem Zahraa Hashim, et al. Comprehensive driver behaviour review: Taxonomy, issues and challenges, motivations and research direction towards achieving a smart transportation environment. Eng Appl Artif Intell 2022;111:104745.
[64] Tahaei Narges, Yang Jidong J, Chorzepa Mi Geum, Kim S Sonny, Durham Stephan A. Machine learning of truck traffic classification groups from weigh-in-motion data. Mach Learn Appl 2021;6:100178.
[65] Shrestha Noora. Factor analysis as a tool for survey analysis. Am J Appl Math Stat 2021;9(1):4–11.
[66] Raychaudhuri Soumya, Stuart Joshua M, Altman Russ B. Principal components analysis to summarize microarray experiments: application to sporulation time series. In: Biocomputing 2000. World Scientific; 1999, p. 455–66.
[67] Krishna K, Murty M Narasimha. Genetic K-means algorithm. IEEE Trans Syst Man Cybern B 1999;29(3):433–9.
[68] Fachada Nuno, de Andrade Diogo. Generating multidimensional clusters with support lines. Knowl-Based Syst 2023;277:110836.
[69] Park Hae-Sang, Jun Chi-Hyuck. A simple and fast algorithm for K-medoids clustering. Expert Syst Appl 2009;36(2):3336–41.
[70] Sander Jörg, Ester Martin, Kriegel Hans-Peter, Xu Xiaowei. Density-based clustering in spatial databases: The algorithm gdbscan and its applications. Data Min Knowl Discov 1998;2:169–94.
[71] Cui Fuhai, Wang Xinkuang, Wu Zhongcheng. A driving style recognition method for battery electric vehicle drivers. In: 2023 IEEE 8th international conference on intelligent transportation engineering. ICITE, IEEE; 2023, p. 383–9.
[72] Patel Eva, Kushwaha Dharmender Singh. Clustering cloud workloads: K-means vs gaussian mixture model. Procedia Comput Sci 2020;171:158–67.
[73] Miao Qing, Wu Xiaohe, Xu Chao, Ji Yanli, Zuo Wangmeng, Guo Yiwen, Meng Zhaopeng. Learning with noisy labels using collaborative sample selection and contrastive semi-supervised learning. Knowl-Based Syst 2024;111860.
[74] Carpenter Gail A, Grossberg Stephen. The ART of adaptive pattern recognition by a self-organizing neural network. Computer 1988;21(3):77–88.
[75] Siami Mohammad, Naderpour Mohsen, Lu Jie. A mobile telematics pattern recognition framework for driving behavior extraction. IEEE Trans Intell Transp Syst 2020;22(3):1459–72.
[76] Guerra Luis, Robles Víctor, Bielza Concha, Larrañaga Pedro. A comparison of clustering quality indices using outliers and noise. Intell Data Anal 2012;16(4):703–15.
[77] Aranganayagi S, Thangavel Kuttiyannan. Clustering categorical data using silhouette coefficient as a relocating measure. In: International conference on computational intelligence and multimedia applications. ICCIMA 2007, Vol. 2, IEEE; 2007, p. 13–7.
[78] Caliński Tadeusz, Harabasz Jerzy. A dendrite method for cluster analysis. Comm Statist Theory Methods 1974;3(1):1–27.
[79] Hubert Lawrence J, Levin Joel R. A general statistical framework for assessing categorical clustering in free recall.. Psychol Bull 1976;83(6):1072.
[80] Davies David L, Bouldin Donald W. A cluster separation measure. IEEE Trans Pattern Anal Mach Intell 1979;(2):224–7.
[81] Baker Frank B, Hubert Lawrence J. Measuring the power of hierarchical cluster analysis. J Amer Statist Assoc 1975;70(349):31–8.
[82] Hubert Lawrence, Arabie Phipps. Comparing partitions. J Classification 1985;2:193–218.
[83] Rand William M. Objective criteria for the evaluation of clustering methods. J Amer Statist Assoc 1971;66(336):846–50.
[84] Bhattacharyya Raunak, Jung Soyeon, Kruse Liam A, Senanayake Ransalu, Kochenderfer Mykel J. A hybrid rule-based and data-driven approach to driver modeling through particle filtering. IEEE Trans Intell Transp Syst 2021;23(8):13055–68.
[85] Xu Can, Zhao Wanzhong, Liu Jinqiang, Wang Chunyan, Lv Chen. An integrated decision-making framework for highway autonomous driving using combined learning and rule-based algorithm. IEEE Trans Veh Technol 2022;71(4):3621–32.
[86] Deng Zejian, Chu Duanfeng, Wu Chaozhong, Liu Shidong, Sun Chen, Liu Teng, Cao Dongpu. A probabilistic model for driving-style-recognition-enabled driver steering behaviors. IEEE Trans Syst Man Cybern: Syst 2020;52(3):1838–51.
[87] Cui Naxin, Cui Wei, Shi Yuemei. Deep reinforcement learning based PHEV energy management with co-recognition for traffic condition and driving style. IEEE Trans Intell Veh 2023;8(4):3026–39.
[88] Zhang Chaopeng, Wang Wenshuo, Ju Zhiyang, Chen Zhaokun, Venture Gentiane, Xi Junqiang. An embedded driving style recognition approach: Leveraging knowledge in learning. IEEE Trans Intell Veh 2024.
[89] Stoichkov Radoslav. Android smartphone application for driving style recognition. Dep Electr Eng Inf Technol Inst Media Technol 2013.
[90] Dörr Dominik, Grabengiesser David, Gauterin Frank. Online driving style recognition using fuzzy logic. In: 17th international IEEE conference on intelligent transportation systems. ITSC, IEEE; 2014, p. 1021–6.
[91] Zhou Yang, Ravey Alexandre, Péra Marie-Cécile. A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles. J Power Sources 2019;412:480–95.
[92] Xu Jiawei, Pan Sicheng, Sun Poly ZH, Park Seop Hyeong, Guo Kun. Human-factors-in-driving-loop: Driver identification and verification via a deep learning approach using psychological behavioral data. IEEE Trans Intell Transp Syst 2022;24(3):3383–94.
[93] Kotsiantis Sotiris B, Zaharakis Ioannis, Pintelas P, et al. Supervised machine learning: A review of classification techniques. Emerg Artif Intell Appl Comput Eng 2007;160(1):3–24.

[94] Xue Qingwen, Wang Ke, Lu Jian John, Liu Yujie. Rapid driving style recognition in car-following using machine learning and vehicle trajectory data. J Adv Transp 2019;2019.
[95] Wang Wenshuo, Xi Junqiang, Chong Alexandre, Li Lin. Driving style classification using a semisupervised support vector machine. IEEE Trans Hum-Mach Syst 2017;47(5):650–60.
[96] Zhang Yunchao, Chen Yanyan, Gu Xin, Sze NN, Huang Jianling. A proactive crash risk prediction framework for lane-changing behavior incorporating individual driving styles. Accid Anal Prev 2023;188:107072.
[97] Sengupta Saptarshi, Basak Sanchita, Saikia Pallabi, Paul Sayak, Tsalavoutis Vasilios, Atiah Frederick, Ravi Vadlamani, Peters Alan. A review of deep learning with special emphasis on architectures, applications and recent trends. Knowl-Based Syst 2020;194:105596.
[98] Yu Yue, He Youqian, Karimi Hamid Reza, Gelman Len, Cetin Ahmet Enis. A two-stage importance-aware subgraph convolutional network based on multi-source sensors for cross-domain fault diagnosis. Neural Netw 2024;106518.
[99] Gao Jianqiang, Yu Bo, Chen Yuren, Bao Shan, Gao Kun, Zhang Lanfang. An ADAS with better driver satisfaction under rear-end near-crash scenarios: A spatio-temporal graph transformer-based prediction framework of evasive behavior and collision risk. Transp Res C 2024;159:104491.
[100] Kalra Nidhi, Goyal Raman Kumar, Parashar Anshu, Singh Jaskirat, Singla Gagan. Driving style recognition system using smartphone sensors based on fuzzy logic.. Comput Mater Contin 2021;69(2).
[101] Manzoni Vincenzo, Corti Andrea, De Luca Pietro, Savaresi Sergio M. Driving style estimation via inertial measurements. In: 13th international IEEE conference on intelligent transportation systems. IEEE; 2010, p. 777–82.
[102] Li Ji, Zhou Quan, He Yinglong, Williams Huw, Xu Hongming. Driver-identified supervisory control system of hybrid electric vehicles based on spectrum-guided fuzzy feature extraction. IEEE Trans Fuzzy Syst 2020;28(11):2691–701.
[103] Wang Ke, Lu Jian John. A two-layer risky driver recognition model with context awareness. IEEE Access 2021;9:138483–95.
[104] Silva Iván, Eugenio Naranjo José. A systematic methodology to evaluate prediction models for driving style classification. Sensors 2020;20(6):1692.
[105] Zang Yingbang, Wen Licheng, Cai Pinlong, Fu Daocheng, Mao Song, Shi Botian, Li Yikang, Lu Guangquan. How drivers perform under different scenarios: ability-related driving style extraction for large-scale dataset. Accid Anal Prev 2024;196:107445.
[106] Xu Li, Hu Jie, Jiang Hong, Meng Wuqiang. Establishing style-oriented driver models by imitating human driving behaviors. IEEE Trans Intell Transp Syst 2015;16(5):2522–30.
[107] Tanha Jafar, Abdi Yousef, Samadi Negin, Razzaghi Nazila, Asadpour Mohammad. Boosting methods for multi-class imbalanced data classification: an experimental review. J Big Data 2020;7(1):1–47.
[108] Wang Shaohua, Yu Pengfei, Shi Dehua, Yu Chengquan, Yin Chunfang. Research on eco-driving optimization of hybrid electric vehicle queue considering the driving style. J Clean Prod 2022;343:130985.
[109] Talebpour Alireza, Mahmassani Hani S. Influence of connected and autonomous vehicles on traffic flow stability and throughput. Transp Res C 2016;71:143–63.
[110] Kolekar Sarvesh, De Winter Joost, Abbink David. Human-like driving behaviour emerges from a risk-based driver model. Nat Commun 2020;11(1):1–13.
[111] Li Guofa, Yang Liang, Li Shen, Luo Xiao, Qu Xingda, Green Paul. Human-like decision making of artificial drivers in intelligent transportation systems: An end-to-end driving behavior prediction approach. IEEE Intell Transp Syst Mag 2021;14(6):188–205.
[112] Zhao Jian, Song Dongjian, Zhu Bing, Sun Zhuo, Han Jiayi, Sun Yuhang. A human-like trajectory planning method on a curve based on the driver preview mechanism. IEEE Trans Intell Transp Syst 2023;24(11):11682–98.
[113] Liao Haicheng, Li Zhenning, Shen Huanming, Zeng Wenxuan, Liao Dongping, Li Guofa, Xu Chengzhong. Bat: Behavior-aware human-like trajectory prediction for autonomous driving. In: Proceedings of the AAAI conference on artificial intelligence. Vol. 38, 2024, p. 10332–40.
[114] Desjardins Charles, Chaib-Draa Brahim. Cooperative adaptive cruise control: A reinforcement learning approach. IEEE Trans Intell Transp Syst 2011;12(4):1248–60.
[115] Bevly David, Cao Xiaolong, Gordon Mikhail, Ozbilgin Guchan, Kari David, Nelson Brently, Woodruff Jonathan, Barth Matthew, Murray Chase, Kurt Arda, et al. Lane change and merge maneuvers for connected and automated vehicles: A survey. IEEE Trans Intell Veh 2016;1(1):105–20.
[116] Vahidi Ardalan, Eskandarian Azim. Research advances in intelligent collision avoidance and adaptive cruise control. IEEE Trans Intell Transp Syst 2003;4(3):143–53.
[117] Zhu Bing, Jiang Yuande, Zhao Jian, He Rui, Bian Ning, Deng Weiwen. Typical-driving-style-oriented personalized adaptive cruise control design based on human driving data. Transp Res C 2019;100:274–88.
[118] Gao Bingzhao, Cai Kunyang, Qu Ting, Hu Yunfeng, Chen Hong. Personalized adaptive cruise control based on online driving style recognition technology and model predictive control. IEEE Trans Veh Technol 2020;69(11):12482–96.
[119] Qiu Mingming, Yu Wei, Wang Lei, Zhang Bingzhan, Zhao Han. A regenerative braking control strategy for ICVs considering the coupling effect of driving conditions and driving styles. IEEE Trans Veh Technol 2023;72(6):7195–210.
[120] Yang Sen, Wang Wenshuo, Zhang Fengqi, Hu Yuhui, Xi Junqiang. Driving-style-oriented adaptive equivalent consumption minimization strategies for HEVs. IEEE Trans Veh Technol 2018;67(10):9249–61.
[121] Tian Xiang, Cai Yingfeng, Sun Xiaodong, Zhu Zhen, Xu Yiqiang. An adaptive ECMS with driving style recognition for energy optimization of parallel hybrid electric buses. Energy 2019;189:116151.
[122] Xin Qi, Fu Rui, Yuan Wei, Liu Qingling, Yu Shaowei. Predictive intelligent driver model for eco-driving using upcoming traffic signal information. Phys A 2018;508:806–23.
[123] Butakov Vadim A, Ioannou Petros. Personalized driver assistance for signalized intersections using V2I communication. IEEE Trans Intell Transp Syst 2016;17(7):1910–9.
[124] Hu Jianjun, Li Zhibo, Zhu Pengxing, Xiao Feng. Speed trajectory optimization method for electric vehicles based on driving style. IEEE Trans Transp Electrif 2022.
[125] Lee Heeyun, Kim Kyunghyun, Kim Namwook, Cha Suk Won. Energy efficient speed planning of electric vehicles for car-following scenario using model-based reinforcement learning. Appl Energy 2022;313:118460.
[126] Yang Daoguang, Karimi Hamid Reza, Kaynak Okyay, Yin Shen. Developments of digital twin technologies in industrial, smart city and healthcare sectors: A survey. Complex Eng Syst 2021;1(1):3.
[127] Mei Peng, Karimi Hamid Reza, Chen Fei, Yang Shichun, Huang Cong, Qiu Song. A learning-based vehicle-cloud collaboration approach for joint estimation of state-of-energy and state-of-health. Sensors 2022;22(23):9474.
[128] Ali Mohammed Hasan, Jaber Mustafa Musa, Abd Sura Khalil, Alkhayyat Ahmed, Albaghdadi Mustafa Fahem. Big data analysis and cloud computing for smart transportation system integration. Multimedia Tools Appl 2022;1–18.
[129] Dong Jianghong, Xu Qing, Wang Jiawei, Yang Chunying, Cai Mengchi, Chen Chaoyi, Liu Yu, Wang Jianqiang, Li Keqiang. Mixed cloud control testbed: Validating vehicle-road-cloud integration via mixed digital twin. IEEE Trans Intell Veh 2023.
[130] Mei Peng, Karimi Hamid Reza, Huang Cong, Chen Fei, Yang Shichun. Remaining driving range prediction for electric vehicles: Key challenges and outlook. IET Control Theory Appl 2023.
[131] Hu Xiaoya, Huang Guojun, Ning Yuqiao, Wang Licheng, Suo Jingwen, Ota Kaoru, Zhang Juyuan. A lightweight and confidential communication scheme for on-vehicle ECUs. IEEE Netw 2024.
[132] Chellapandi Vishnu Pandi, Yuan Liangqi, Brinton Christopher G, Żak Stanislaw H, Wang Ziran. Federated learning for connected and automated vehicles: A survey of existing approaches and challenges. IEEE Trans Intell Veh 2023.
[133] Shichun Yang, Zheng Zuo, Bin Ma, Yifan Zheng, Sida Zhou, Mingyan Liu, Yu Lu, Qiangwei Li, Xinan Zhou, Mengyue Zhang, et al. Essential technics of cybersecurity for intelligent connected vehicles: Comprehensive review and perspective. IEEE Internet Things J 2023.
[134] Nakade Tomohiro, Fuchs Robert, Bleuler Hannes, Schiffmann Jürg. Haptics based multi-level collaborative steering control for automated driving. Commun Eng 2023;2(1):2.
[135] Oudainia Mohamed Radjeb, Sentouh Chouki, Nguyen Anh-Tu, Popieul Jean-Christophe. Adaptive cost function-based shared driving control for cooperative lane-keeping systems with user-test experiments. IEEE Trans Intell Veh 2023.