Accident Analysis and Prevention 185 (2023) 107022

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

Feature selection for driving style and skill clustering using naturalistic driving data and driving behavior questionnaire

Yao Chen, Ke Wang *, Jian John Lu

College of Transportation Engineering, Tongji University, Key Laboratory of Road and Traffic Engineering of the State Ministry of Education, Shanghai 201804, China

ARTICLE INFO

Keywords:
Driving behavior
Feature selection
Cluster analysis
Driving behavior questionnaire
Driving skill
Driving style

ABSTRACT

Driver's driving style and driving skill have an essential influence on traffic safety, capacity, and efficiency. Through clustering algorithms, extensive studies explore the risk assessment, classification, and recognition of driving style and driving skill. This paper proposes a feature selection method for driving style and skill clustering. We create a supervised machine learning model of driver identification for driving behavior data with no ground truth labels on driving style and driving skill. The key features are selected based on permutation importance with the underlying assumption that the key features for clustering should also play an important role in characterizing individual drivers. The proposed method is tested on naturalistic driving data. We introduce 18 feature extraction methods and generate 72 feature candidates. We find five key features: longitudinal acceleration, frequency centroid of longitudinal acceleration, shape factor of lateral acceleration, root mean square of lateral acceleration, and standard deviation of speed. With the key features, drivers are clustered into three groups: novice, experienced cautious, and experienced reckless drivers. The ability of each feature to describe individuals' driving style and skill is evaluated using the Driving Behavior Questionnaire (DBQ). For each group, the driver's response to DBQ key questions and their distribution of key features are analyzed to prove the validity of the feature selection result. The feature selection method has the potential to understand driver's characteristics better and improve the accuracy of driving behavior modeling.

1. Introduction

Driving behavior is the performance of drivers to operate vehicles based on their perceptions, decisions, and maneuvers under the specific environmental context (Chen et al., 2019; Khattak et al., 2021; Ahmad et al., 2021; Mohammadnazar et al., 2021). It is a complex process involving interaction between drivers and the environment and dramatically impacts traffic safety and transport efficiency. Driving behavior is affected by many factors, such as roadway type, land use, traffic volume, and weather conditions. (Amata et al., 2009; Hamdar et al., 2016; Zhao et al., 2019; Khattak et al., 2021; Ahmad et al., 2021). Previous studies have shown that the proportion of committing driving errors varies by roadway type, land use, and environmental surroundings, even related to demographics (Khattak et al., 2021; Ahmad et al., 2021; Ahmad et al., 2023). Not only are there a wide variety of combinations in the driving context, but also diversity among drivers. Moreover, drivers are regarded as the most significant component causing traffic accidents, which is supported by numerous research (Lombardi et al., 2017; Song et al., 2021). Before the implementation of fully automated driving, human drivers are still the host of vehicles to control the driving state through their decisions and actions. However, the diversity of drivers in their abilities to process all kinds of information and the way of control the vehicle or respond to emergencies led to various behaviors (Elander et al., 1993; Miyajima et al., 2007; Amata et al., 2009; Chen et al., 2019). Such discrepancy leads to heterogeneity in traffic flow, which brings disorder to the traffic system, causes a decrease in mobility, and increases crash risk. Besides, the interaction mechanism between human drivers and the environment is the core of automated and connected vehicles. Personal driving characteristics are taken into account in designing intelligent vehicles and driving assistance systems, which can improve comfort and safety by customizing drivers' habits and expectations (Miyajima et al., 2007; Lin et al., 2014; Chen et al., 2019).

Research has been conducted on the modeling of specific types of short-term driving maneuvers or behaviors, such as following, overtaking, and lane-change (Yang et al., 2018; Xue et al., 2019; Yang et al., 2019; Hess et al., 2020; Mahmud et al., 2022). Meanwhile, statistical feature extraction and machine learning methods are also predominant

* Corresponding author.
E-mail address: ucwangke@gmail.com (K. Wang).

https://doi.org/10.1016/j.aap.2023.107022
Received 8 July 2022; Received in revised form 2 March 2023; Accepted 4 March 2023
Available online 15 March 2023
0001-4575/

in analyzing and modeling driving behavior, and driving style and driving skill are often used as two sides to explain driving characteristics. Statistical features, such as mean, median, maximum, variance, and standard deviation of speed or acceleration, are used to capture overspeed and slam acceleration (Van Ly et al., 2013; Feng et al., 2018; Figueredo et al., 2019). Nevertheless, these features are susceptible to the varying driving environments and window size for calculation. For example, the style of cautious drivers may take aggressive actions for the sake of avoiding a collision, while aggressive drivers may operate careful style in the condition of bad weather. Therefore, it is valuable to introduce different feature extraction methods to characterize individual driving behaviors and compare their performance with traditional statistical methods in driving behavior analysis. However, feature selection may be difficult for clustering analysis of driving style and driving skill since there is no universal feature importance calculation method for unsupervised machine learning algorithms.

Through clustering algorithms, extensive studies explore the risk assessment, classification, and recognition of driving style and driving skill. This paper proposes a feature selection method for driving style and skill clustering, which has been overlooked in the literature. Without the ground truth labels on driving style and skill, we create a supervised machine learning model to predict the driver's ID because it is naturally included in driving behavior data. Features for driving style and skill clustering are selected by ranking the feature importance in the well-trained driver identification model. With the help of driver self-reported questionnaires, we can evaluate the selected features separately and answer four questions: 1) Whether the proposed feature selection method is valid for driving style and skill clustering? 2) What feature extraction methods are the most efficient for individual driver identification? 3) What characteristics of individual driving behavior can be intuitively expressed by these features? 4) How do drivers' driving styles and skills influence these features?

The rest of this paper is organized as follows. Section 2 overviews related work. Section 3 describes the data collection process. Section 4 describes the methodology. Analysis results are presented in Section 5. Section 6 summarizes the conclusions.

2. Literature review

2.1. Driving style

Driving style has been considered a reflection of driving preference and it is measurable to describe some characteristics of driving behavior (Wang et al., 2017; Wang et al., 2018; Li et al., 2019; Xue et al., 2019; Mohammadnazar et al., 2021). It is often derived from self-assessment reports or objective evaluations (Sagberg et al., 2015; Mohammadnazar et al., 2021). Widely used self-assessment reports are the Driver Behavior Inventory (DBI), Driver Behavior Questionnaire (DBQ), Driver Style Questionnaire (DSQ), and Multi-dimensional Driving Style Inventory (MDSI) (Gulian et al., 1989; West et al., 1993; Reason et al., 1990; French et al., 1993; Taubman-Ben-Ari et al., 2004). The objective evaluation mainly obtains driving data through driving simulators or in-vehicle sensors and clusters of driving styles based on analysis of driving parameters using statistical and machine learning methods (Li et al., 2019; Wang et al., 2019; Xue et al., 2019; Lyu et al., 2021; Ma and Zhang, 2021).

Driving style can be classified at multiple levels (Sagberg et al., 2015). Regarding traffic safety, driving styles can be divided into two categories such as safe and unsafe (David, 2021), non-aggressive and aggressive (Johnson and Trivedi, 2011), and aggressive and normal (Wang et al., 2017). For specific driving behavior analysis, it concludes more driving styles, such as aggressive, deviant and risky, defensive, distress-reduction, and dissociative driving styles (Ma and Zhang, 2021; David, 2021). The most used is the global style proposed by Taubman - Ben-Ari et al. (2004): the reckless and careless driving style; the anxious driving style; the angry and hostile driving style; and the patient and careful driving style. Others classify driving styles into three or four categories: such as aggressive, normal, and cautious (Ma et al., 2021), or high-risk, moderate risk, and low-risk (Li et al., 2019), or safe, low-risk, high-risk, and dangerous (Xue et al. 2019).

Regardless of the categories of driving style, studies based on vehicle motion data show that it can vary with circumstances (Dörr et al., 2014; Yang et al., 2018; Mohammadnazar et al., 2021). Furthermore, the result from the self-reported assessment may differ from actual behaviors due to the self-knowledge of test drivers (Mohammadnazar et al., 2021). Therefore, this paper integrates two methods to evaluate the driving style of individual drivers. We cluster drivers based on vehicle motion into three categories and use the information from the self-reported assessment to verify the clustering result.

2.2. Driving skill

Driving skills are related to experience and knowledge for processing information under different driving tasks (Sundström, 2008). The primary method for measuring driving skills is self-assessment, such as Driving Appraisal Inventory (Cutler et al., 1993), Driver Behaviour Questionnaire (Kosuge et al., 2021), and the most commonly used is the Driver Skill Inventory (Lajunen and Summala, 1995). It consists of two aspects: perceptual motor skills, such as decision-making processes and technical driving skills to control a vehicle; safety skills, such as crash avoidance and attitudes towards safe driving. Items in Driver Skill Inventory have been validated and used in many countries. However, previous studies pointed out that some drivers have biased perceived driving skills by comparing themselves to group average or peers (Sundström, 2008; Martinussen et al., 2013; Martinussen et al., 2014). Another measurement method is driving simulators, providing a safe and objective assessment of driving skills (de Winter et al., 2009; Martinussen et al., 2017). Analysis of driver skills can be conducted on behavioral, eye-related measures, and cognitive workload (Qu et al., 2015). Nevertheless, the reliability of the result conducted by simulators depends on the accuracy of reproducing the real action. It is hard to simulate situations with all complexity and diversity in the real world (Groeger and Murphy, 2020; Mohammadnazar et al., 2021). So, this paper collected data from the field test with the questionnaire to conduct a more reliable assessment of driving skills.

2.3. Driving features related to driving skill and driving style

Driving behavior is usually measured by these driving parameters: vehicle speed, lateral and longitudinal acceleration, angular velocity, steering angle, and yaw angle (Wang et al., 2017; Eftekhari and Ghatee, 2018; Chen et al., 2019; Li et al., 2019). Specific driving events are also analyzed for driver style and skills, such as acceleration, brake, turn, lane changes, and car-following (Johnson and Trivedi, 2011; Bagdadi, 2013; Van Ly et al., 2013; Vaiana et al., 2014; Xue et al., 2019). Based on features extracted from these data, drivers were classified into different groups of driving style and skill levels.

Statistical characteristics, such as mean, standard deviation, maximum, and minimum of the driving parameters, are commonly used to characterize driving behavior, driving skill, and driving style. Eboli et al. (2017) used the 50th and 80th percentile speeds and average speeds to classify the drivers into three types. Hong et al. (2014) extract driving behavior features at five levels, including the maximum, average, and standard deviation of the speed, speed change, longitudinal acceleration, lateral acceleration, RPM, and throttle position. Xue et al. (2019) combined seven features for three different dimensions from time series of trajectory data for driving style recognition, and vehicles were divided into four levels for the consideration of car-following safety. Li et al. (2019) used seven statistical functions of six driving parameters to construct operational driving pictures as the input of neural network algorithms for driving style classification. Although these features are widely used in driving behavior studies, the threshold of these features for different driving styles has not yet been universally formed. Using feature extraction methods from statistics may ignore hidden information in the frequency domain.

The driving data collected from the vehicle can be considered as time series and analyzed by methods in signal processing. The commonly used include Fourier transform, wavelet transform, Dynamic Time Warping, and spectral analysis (Johnson and Trivedi, 2011; Chan et al., 2019; Kwak et al., 2020). Eftekhari and Ghatee (2018) extracted features by Discrete Wavelet Transform (DWT) to recognize safe, semi-aggressive, and aggressive driving. Kwak et al. (2020) extracted three features from wavelet and splitting time windows and achieved high accuracy of driving-pattern analysis for each driver. Features in the frequency domain of physiological signals are regarded as objective markers of the human brain and body in response to surrounding conditions and are effective features for detecting driving state, especially in driving fatigue (Yang et al., 2019). Moreover, there are connections between driving style and features in biological signals. Aggressive driving styles were reported to have a higher heart rate (Meseguer et al., 2018), and brain features of drivers were different in normal and angry driving (Yan et al., 2018). Nervous and anxious drivers have large alterations in biological behavior, while reckless drivers undergo minimum change (Habibifar and Salmanzadeh, 2022). However, wearable sensors are commonly used approaches for these signal collections, making it challenging for large-scale implementation.

Therefore, an appropriate feature extraction approach for driving behavior analysis is essential for further improving accuracy in driving style and driving skill characterization.

2.4. Driving style and driving skill clustering

Although many studies provide valuable insights on driving style and skills, there is no agreed definition in the literature (Martinez et al., 2018; Lyu et al., 2021; Zepeda et al., 2021). Clustering is an unsupervised method to mine inherent characteristics to build differentiable groups, and it has the advantages of reasonable interpretation and scalability (Zepeda et al., 2021). Clustering methods like K-means and hierarchical cluster analysis are often utilized to classify drivers into different groups (Kalsoom and Halim, 2013; Shirmohammadi et al., 2019; Deng et al., 2022). Data clustering tasks can convert into a graph partitioning problem by the spectral clustering algorithm, Pan et al. (2009) applied this method to divide drivers into three types of driving styles related to velocity and acceleration. The Density-Based Spatial Clustering of Application with Noise (DBSCAN) also can be applied to cluster the driving features if the density of observations is heterogeneous (Zhang et al., 2019; Zepeda et al., 2021).

Clustering is also crucial for assisting classification approaches to create data labels for identifying driving styles and skills. Campo et al. (2018) proposed a driving style classification approach using a data-driven extreme learning machine algorithm. Hierarchical clustering analysis was used to group drivers into discrete classes and assign suitable labels to each class. Feng et al. (2018) applied Delaunay Diagram as the cluster-labeling algorithm to classify driving events into different driving style groups. Xue et al. (2019) used four machine learning methods to recognize the driving style from the NGSIM trajectory data labeled by the K-means clustering algorithm.

Validation of clustering algorithm is tricky compared to supervised machine learning algorithm as clustering process does not contain ground truth labels. Widely applied measurements of clustering quality include Silhouette Coefficient, Calinski-Harabasz Index, and Davies-Bouldin Index. These measurements may work well to quantify cohesion in each cluster and separation between clusters; they can not answer whether the clustering result reflects an individual's driving style and driving skill. Moreover, the number of features and features with distinct values may improve the clustering validity index; however, it does not necessarily generate better driving style and driving skill clustering results.

2.5. Unsupervised feature selection

Unsupervised feature selection is always a challenging task due to the absence of label information that can be used to evaluate features in supervised feature selection. Existing unsupervised feature selection methods are categorized into filter models and wrapper models. A wrapper model searches for the best feature subsets to improve the quality of clustering. For example, Deepthi and Thampi (2015) presented a wrapper model that uses Particle Swarm Optimization (PSO) to search for the best subset of features and evaluates the subsets using the K-means clustering. Filter model does not rely on clustering algorithms to evaluate features, instead, they use criteria that reflect the structure of features, such as entropy (Dash and Liu, 1999) and Laplacian score (Saxena et al., 2010).

Extreme data, often revealed in small samples or large samples with high dimensions in feature space and imbalanced classes, invalidates traditional unsupervised feature selection methods (Cai et al., 2018). Due to the time series nature of driving behavior data, we propose a feature selection method that transfers time series data to time-window slices and converts unsupervised feature selection to supervised feature selection with driver's ID as the pseudo labels.

3. Data collection

There are several ways to collect driving data, including field tests, driving simulators, On Board Diagnostics, and other sensors such as smartphones. Previous studies using driving simulators design various driving scenes to derive diverse driving data. However, there is still a gap in fully reproducing real-world conditions with complex interactions (Mohammadnazar et al., 2021). Data that comes from field tests more closely resemble real-world driving conditions (Wang et al., 2022). Despite the validity of the On Board Diagnostics, the cost of installation for an extensive application is high and may cause concerns related to user privacy. Smartphones are also used in data collection for their convenience in containing information covering a diverse population of drivers. However, depending on the accuracy, the installation steadiness and transmission stability might cause biased data (Mohammadnazar et al., 2021). The Inertial Measurement Unit (IMU) was mounted with one gyro and one accelerometer along the axis of vehicle motion to output the yaw rate, acceleration, and heading angle. With its small size, low cost, and ease of implementation, IMU has been widely used in driving behavior for data collection (Martinez et al., 2018; Wang and Cheng, 2021). Therefore, this paper implements a field experiment by a test car with feasible and low-cost equipment to finish the data collection.

3.1. In-vehicle sensors

Naturalistic driving data were collected from field experiments by a data acquisition system consisting of a test vehicle, Inertial Measurement Unit (IMU), GPS, and two cameras. The direction of the installation is shown in Fig. 1, as the vehicle moves in the Y-axis, the lateral movement is on the X-axis, the vertical movement is on the Z-axis, and the heading angles are roll, pitch, and yaw, respectively. Vehicle speed is obtained from the GPS, and cameras record the driving context in front of the car and the driver's state. All sensor data were recorded synchronously at a sampling rate of 10 Hz.

To eliminate the influence of different vehicle types on driver's preference and error brought by calibration on several sensors. All equipment was installed on one test vehicle, and all experiments were implemented by the test vehicle. The model of the test vehicle is BYD Qin plug-in hybrid sedan 2015 with a maximum engine power of 223 kW. Automated vehicle features like adaptive cruise control system and automatic emergency braking system are absent to avoid the influence of these features on driving behavior.

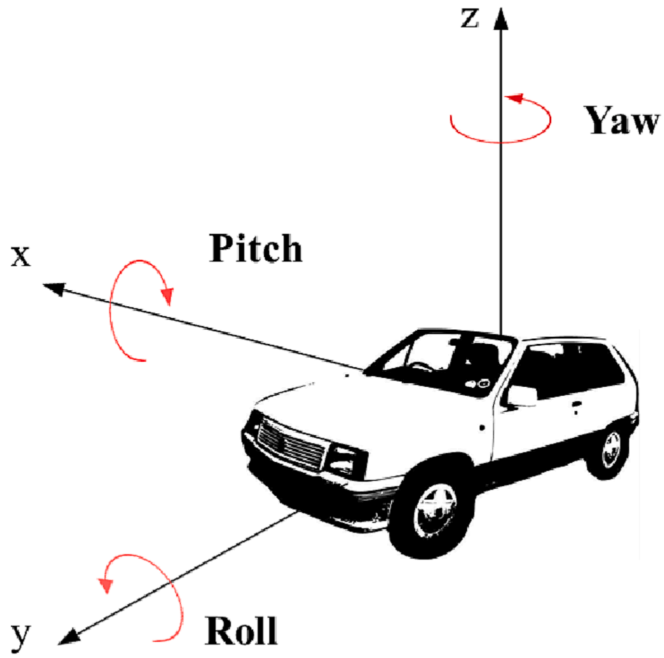

Fig. 1. Three-axle motions of the vehicle.

3.2. Experiment participants

Nineteen licensed and adult drivers were recruited for a naturalistic driving experiment between April 2021 and June 2021. Before the experiment, each participant completed and endorsed information consent for data acquisition and analysis. Each driver received a reasonable remuneration for participation in research. Before driving on the field, each driver received an introduction to the driving route and vehicle operations. They were then given a 15-minute drive test to familiarize themselves with the experiment vehicle.

Drivers were required to complete a driving behavior questionnaire (DBQ) before the field driving. Data on driver demographics, attitudes, behaviors, and habits were collected. The questionnaire has 33 questions in total. The first seven items are related to demographic information, including age, gender, income, education, marital state, how long the driver has had a license, and miles are driven per year. The remaining 26 items measure specific driving behavior reflecting the driving style and driving skill (e.g., “be nervous of driving on the highway or in peak hours”, “be impatient while driving”, and “speed up to prevent others overtaking”) on a 5-point scale (1 = never, 2 = seldom, 3 = occasionally, 4 = usually, 5 = always). All items in the questionnaire are attached in Appendix A.

3.3. Experiment route and time

The experimental road is a circular route starting from the southwest gate of the Tongji University campus with a total length of 14 km (shown in Fig. 2). The route consists of arterials, local roads with mild curves, and road slopes. All experiments were performed on dry roads with good visibility. The test time was between 10:00 AM and 4:00 PM without extreme traffic. In total, 42 loops of driving data were collected, and the total mileage is 588 km. Savitzky-Golay filtering was used to process the driving data collected from the in-vehicle sensors.

4. Methodology

Fig. 3 shows the research framework consisting of feature selection and evaluation. The feature selection process is based on naturalistic driving data, consisting of driving parameter selection, feature extraction, handling multicollinearity, driver identification model, and feature importance ranking, introduced in Sections 4.1-4.3. Section 4.4 introduces the feature evaluation, validating the selected features separately using the DBQ data.

4.1. Driving parameter selection

IMU obtains vehicle triaxial acceleration and angular velocity, and GPS records vehicle speed. Literature shows that accelerations in the x-axis and y-axis could be used to characterize the driver’s acceleration/deceleration maneuvers and the operations of the steering wheel

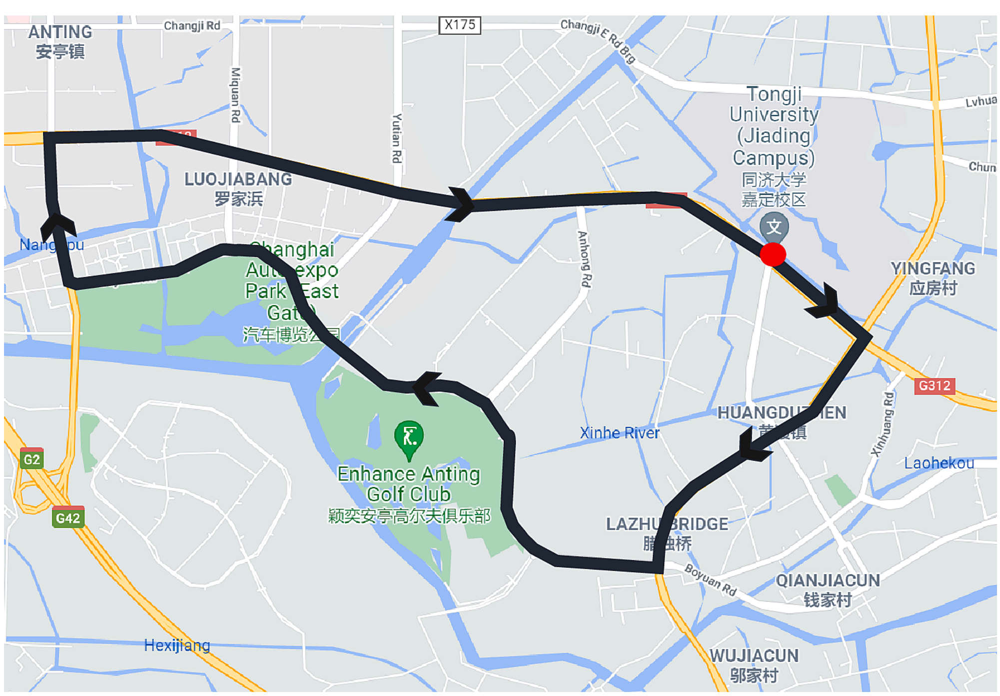

Fig. 2. Naturalistic driving experiment route.

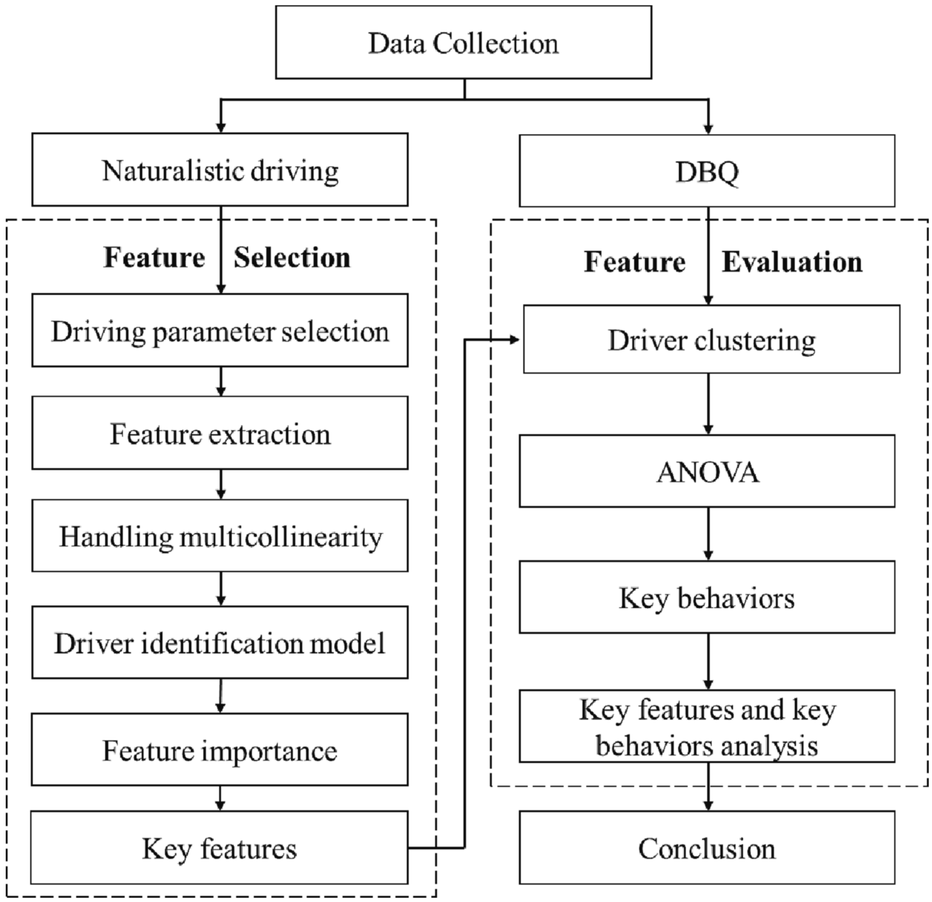

Fig. 3. Research framework.

(Vaiana et al., 2014; Dörr et al., 2014; Hamdar et al., 2016). The acceleration in Z-axis is not considered in this paper since there is no abrupt change in slope over our experimental route. The angular velocity of the x-axis and y-axis is discarded since the rollover or overturn of the vehicle is not observed during our experiment. Therefore, we select four driving parameters for later analysis in this paper: longitudinal (y-axis) acceleration, lateral (x-axis) acceleration, yaw rate (z-axis angular velocity), and speed.

4.2. Feature extraction

Driving parameters are recorded ten times per second during the experiment. To describe any meaningful characteristics of driving behavior, we need to extract features (for example, average speed) from the time series of driving parameters. Statistical features are essential data characteristics that reflect the distribution and work in analyzing and recognizing driving behavior. Frequency features from time series are related to vibration, and those parameters can represent the magnitude of fluctuation. In the International Organization for Standardization (ISO) 2631-1 of evaluating human exposure to whole-body vibration, the crest factor and root mean square is widely used in the comfort assessment (Paddan and Griffin, 2002; Campo et al., 2018). From the concept of dissipation in automotive ride comfort, the more switches between different states with a larger span, the more excellent value of dissipation, which means poorer comfort and stationarity (Liu et al., 2000). Due to the vibration captured by IMU related to driving stability, this paper added frequency features in the analysis to select key features to characterize drivers with more interpretability.

We introduce 18 time-based and frequency-based feature extraction methods in this paper: maximum (max), minimum (min), mean (mean), variance (va), standard deviation (std), kurtosis (ku), skewness (sk), peak-peak (pk), average rectified value (arv), root mean square (rms), shape factor (sf), crest factor (cf), impulse factor (if), margin factor (mf), average amplitude (aa), frequency centroid (fc), frequency variance (fv), and spectral entropy (se). Given a time series $T = (t_1, \ldots, t_n)$, the feature extraction of each method is shown in Table 1.

There are 14 time-based feature extraction methods and four frequency-based methods in Table 1. No. 1–7 are statistical measures widely used in driving behavior analysis and modeling, such as maximum, minimum, and standard deviation. No. 8–18 are feature extraction methods proven to be useful in signal processing but new to driving behavior studies. We briefly introduce them below.

Peak-peak measures the maximum-to-minimum difference. The Average Rectified Value (ARV) of a time series is the average of its absolute value. Root Mean Square (RMS) value is defined as the square root of the mean square. Both ARV and RMS are suitable for time series or signals containing positive and negative values.

Shape factor, crest factor, impulse factor, and margin factor are four dimensionless time-domain features. Shape factor, also known as form factor, is the ratio of the root mean square value to the average rectified value. The shape factor refers to a value that is affected by the shape of an object but is independent of its dimensions (Yiakopoulos et al., 2011; Caesarendra and Tjahjowidodo, 2017). The crest factor is the ratio of maximum value to the root mean square value and measures the extent of impact present in the vibration signals (Yu, 2011). It is particularly suitable for acute signals that characterize some behavior (Shidore et al., 2021). The impulse factor is the ratio of the maximum value to the average rectified value. The margin factor, or clearance factor, is the ratio of maximum value to the squared mean value of the square roots of the absolute values of time series. Both impulse factor and margin factor

Table 1
Feature extraction methods.

No.	Feature	Abbreviation	Definition	No.	Feature	Abbreviation	Definition
Time-based feature extraction method							
1	Maximum	max	$T_{\max} = \max(T)$	8	Peak-peak	pk	$T_{pk} = T_{\max} - T_{\min}$
2	Minimum	min	$T_{\min} = \min(T)$	9	Average rectified value	arv	$T_{arv} = \frac{1}{n}\sum_{i=1}^{n} \lvert t_i \rvert$
3	Mean	mean	$T_{mean} = \frac{1}{n}\sum_{i=1}^{n} t_i$	10	Root mean square	rms	$T_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} t_i^2}$
4	Variance	va	$T_{va} = \frac{1}{n}\sum_{i=1}^{n}(t_i - T_{mean})^2$	11	Shape factor	sf	$T_{sf} = \frac{T_{rms}}{T_{arv}}$
5	Standard deviation	std	$T_{std} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(t_i - T_{mean})^2}$	12	Crest factor	cf	$T_{cf} = \frac{T_{\max}}{T_{rms}}$
6	Kurtosis	ku	$T_{ku} = \frac{\sum_{i=1}^{n}(x_i - T_{mean})^4}{(n-1)T_{std}^4}$	13	Impulse factor	if	$T_{if} = \frac{T_{\max}}{T_{arv}}$
7	Skewness	sk	$T_{sk} = \frac{\sum_{i=1}^{n}(x_i - T_{mean})^3}{(n-1)T_{std}^3}$	14	Margin factor	mf	$T_{mf} = \frac{T_{\max}}{\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert t_i \rvert}\right)^2}$
Frequency-based feature extraction method							
15	Average amplitude	aa	$T_{aa} = \frac{1}{m}\sum_{k=1}^{m} X(k)$	17	Frequency variance	fv	$T_{fv} = \frac{\sum_{k=1}^{m}(f_k - T_{fc})^2 X(k)}{\sum_{k=1}^{N} X(k)}$
16	Frequency centroid	fc	$T_{fc} = \frac{1}{m}\sum_{k=1}^{m} f_k X(k)$	18	Spectral entropy	se	$T_{se} = -\sum_{k=1}^{m} P(k)\log_2 P(k)$

have been used for bearing defect detection (Yiakopoulos et al., 2011; Caesarendra and Tjahjowidodo, 2017).

Frequency-based methods rely on the discrete Fourier transform of time series, $X(k)$, $k = 1, 2, \ldots, m$. m is the number of spectrum lines. f_k is the frequency value of the k-th spectrum line. Average amplitude measures the mean of discrete Fourier coefficients. Frequency centroid, or spectral centroid, can describe the center of 'gravity' of the frequency spectrum and reflects the distribution of the frequency spectrum. Frequency variance, or spectral spread, is the second central moment of the spectrum. The spectral entropy calculates the Shannon entropy of the time series' normalized power distribution in the frequency domain. The spectral entropy has been used for feature extraction in fault detection and diagnosis (Pan et al., 2009; Sharma and Parey, 2016), speech recognition (Shen et al., 1998), and biomedical signal processing (Vakkuri et al., 2004). $P(k)$ is the probability distribution of $S(k)$:

$$P(k) = \frac{S(k)}{\sum_{k=1}^{m} S(k)} \tag{1}$$

where $S(k) = |X(k)|^2$, is the power spectrum of time series T.

4.3. Feature ranking

Applying 18 feature extraction methods to the four driving parameters, we generate 72 features in total. We rely on machine learning modeling and feature importance to quantify and rank features to find the best feature extraction methods that can efficiently describe driving behavior characteristics. Features with the highest importance are considered the key features.

Many tools are available to measure feature importance. For example, Mean Decrease in Impurity (MDI) has been developed for feature importance measurement in tree-based models. However, MDI inflates the importance of numerical or categorical features with many categories (Strobl et al., 2007; Altmann et al., 2010). This paper applies a model-agnostic method, permutation importance, to calculate the importance. Permutation importance shows the drop in the score if the target feature is replaced with randomly permuted values and is widely used to interpret machine learning models. One weakness of permutation importance is to handle multicollinearity.

Multicollinearity describes a high correlation or strong linear dependence between two or more features. Features with multicollinearity may still provide unique information but are not large enough to give a notable impact for efficient data analysis and modeling (Senawi et al., 2017). Therefore, eliminating multicollinearity is crucial before measuring features' permutation importance. We identify collinear features by performing hierarchical clustering on the Spearman rank-order correlations. Features clustered into one group are highly correlated. We pick one feature from each group and generate a new set of features free of multicollinearity issues.

Using the new set of features as input, we train the driver identification model with an XGBoost classifier. The driving data of each driver is divided into data clips. Each sample contains 1 km of driving data. The label to predict is the driver's ID. The data is divided into train/test data using a stratified split. The permutation importance of each feature is calculated using a Python library, ELI5. The training process of XGBoost classifiers is repeated five times, and the average importance weights of features are used for feature ranking. Features with the highest weights are considered the key features.

The advantage of this feature selection method is that we create a supervised machine learning task to select key features, even if the original data has no labels on driving style or skill level. Driving behavior data, including naturalistic driving experiment data, driving simulator data, and vehicle trajectory data collected by the aerial camera, always contains the driver's ID. Using this method, we select features that capture significant differences in driving behavior between individuals. Supervised models are not directly trained to predict a driver's driving style or skill, which can be obtained from the self-assessment questionnaire results. This is because we try to keep the questionnaire data out of feature selection. In this study, the questionnaire data is used for feature evaluation only.

4.4. Feature evaluation

We evaluate the key features' ability to characterize the driving style and driving skill with the help of DBQ. First, all drivers are divided into groups using hierarchical clustering based on the key features. Driver's clustering result should be stable over multiple experiments. Second, the reliability of the DBQ result is measured by Cronbach's alpha score, and key questions are derived from the DBQ by Analysis of variance (ANOVA). Third, drivers' performance in each cluster on key questions related to driving style and driving skill is analyzed. Each cluster is named based on its driving style and driving skill level. Last, the distribution of key features in each cluster is analyzed. The effect of driving style and driving skill on key features is discussed. Through the analysis processes above, we can conclude whether the key features we find to characterize the driving style and driving skill are stable, reliable, and reasonable.

5. Result analysis

5.1. Key features

We identify groups of collinear features by hierarchical clustering in Table 2. The nomenclature of feature names is shown in Fig. 4. We consider four driving parameters: longitudinal (y-axis) acceleration, lateral (x-axis) acceleration, yaw rate (z-axis angular velocity), and speed. The abbreviations of these driving parameters are ay, ax, wz, and spd, respectively, and the abbreviation of feature extraction methods are shown in Table 1. The most widely accepted feature in each group is reserved, while the rest are removed. For example, the maximum, crest factor, impulse factor, and margin factor of the time series of longitudinal acceleration are highly correlated. The maximum of the time series of longitudinal acceleration is reserved since it has been used as a feature in literature, while the other three features are new to the field of study. There are 34 features removed, and the new set has 38 features free of multicollinearity issues.

Next, the driver identification model is well-trained using an XGBoost classifier with 38 features. Feature's permutation importance is calculated and averaged over multiple training. We select five key features with the highest permutation importance: ay_{max}, ay_{fc}, ax_{rms}, ax_{sf}, and spd_{std}. Three driving parameters are involved: longitudinal acceleration, lateral acceleration, and speed. The yaw rate is shown to have no significant contribution to driver identification. Five feature extraction methods are involved: maximum, standard deviation, root mean square, shape factor, and frequency centroid.

5.2. Driver clustering

Based on the five key features, 42 loops of driving data from 19 drivers are assigned into 3 clusters by hierarchical clustering. The dendrogram is shown in Fig. 5. The loop ID is composed of a letter representing driver ID and a number representing the loop number for that specific driver. For example, R-5 is the fifth loop of the experiment taken by driver "R".

Table 3 shows the clustering result of each loop. Twelve drivers have multiple loops of driving data, and ten of them have consistent clustering results over different loops. For example, driver "R" took the driving experiment 7 times on different days, and all loops, from R-1 to R-7, are in cluster 1. The only two exceptions are drivers "L" and "Q". L-1 and Q-2 are in cluster 1, while L-2 and Q-1 are in cluster 3. Therefore, we believe that drivers in the same cluster have similar driving behaviors, and the key features can be used to present drivers' driving characteristics that are stable over time.

Table 2
Correlated features in groups.

Correlated features reserved	Correlated features removed
ay_{max}	ay_{cf}, ay_{if}, ay_{mf}
ay_{min}	ay_{pk}
ay_{mean}	ay_{arv}, ay_{rms}
ay_{std}	ay_{va}, ay_{sf}, ay_{aa}
ay_{fc}	ay_{fv}
ay_{pe}	spd_{pe}
ax_{max}	ax_{pk}
ax_{rms}	ax_{arv}
ax_{std}	ax_{va}, ax_{aa}, ax_{fc}, ax_{fv}
ax_{cf}	ax_{if}, ax_{mf}
wz_{max}	wz_{pk}
wz_{std}	wz_{av}, wz_{va}, wz_{rms}, wz_{aa}
wz_{fv}	wz_{fc}
spd_{max}	spd_{pk}
spd_{mean}	spd_{arv}, spd_{rms}, spd_{aa}
spd_{std}	spd_{va}
spd_{sk}	spd_{sf}
spd_{cf}	spd_{if}, spd_{mf}
spd_{f_c}	spd_{f_v}

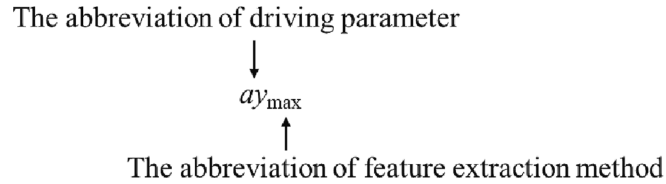

Fig. 4. Nomenclature of feature names.

5.3. Key driving behaviors

Reliability analysis of the DBQ is measured by Cronbach's alpha score. Cronbach's alpha measures the internal consistency of drivers' responses to Likert questions in DBQ. The Cronbach's alpha of our questionnaire is 0.80 indicating the survey data is reliable. Next, driver's responses to Likert questions in the DBQ are used for ANOVA analysis to test whether there are differences between driver clusters, and the results are shown in Appendix B. The level of significance is set at 0.05. The results show significant differences across clusters on seven questions, which are Q9, Q12, Q13, Q16, Q21, Q31, and Q32. These questions measure the key behaviors to be discussed in the rest of this paper, including "override lane markings when driving", "be nervous of driving on the highway or in peak hours", "look away from the road while driving, such as glance at outside, look at billboards", "use a mobile phone, drink, eat or dress up while driving", "cannot drive alone, need assistance from others", "be impatient while driving", and "swear, honk, use high beams or do quick and forced lane-change to show anger". Being unable to drive alone and being nervous reflect a low level of driving skills. Being distracted, impatient, and rude during driving reflects a reckless and irresponsible driving style. Based on these behaviors, we can determine the driver's driving style and skill level.

5.4. Cluster labeling

We label driver clusters based on their demographics and performance on key behaviors. Drivers in cluster 1 are novices and lack driving experience, while drivers in clusters 2 and 3 have more than five years of driving experience and drive more than 20,000 km per year. Drivers in cluster 1 also feel nervous when driving on highways or during peak hours and cannot drive alone without assistance. Drivers in cluster 2 never override lane markings when driving and never be distracted or impatient while driving. Drivers in cluster 3 often swear, honk, use high beams or do quick and forced lane-change to show their anger. Therefore, cluster 1 is labeled as novice driver, cluster 2 is labeled as experienced and cautious driver, and cluster 3 is labeled as experienced and reckless driver.

Next, we discuss the performance of drivers on each key behavior in detail. In the DBQ, drivers respond to questions related to the seven key behaviors on a 5-point scale (1 = never, 2 = seldom, 3 = occasionally, 4 = usually, 5 = always). Five behaviors are related to driving style: "override lane markings when driving", "look away from the road while driving, such as glace at outside, look at billboards", "use a mobile phone, drink, eat or dress up while driving", "swear, honk, use high beams or do quick and forced lane-change to show anger", and "be impatient while driving". The other two behaviors are related to driving skill level: "cannot drive alone, need assistance from others", "be nervous of driving on the highway or in peak hours". We discuss behaviors related to driving style and driving skill separately.

5.4.1. Driving style analysis

(1) Behavior: override lane markings when driving

Driving override lane markings is legal but discouraged. Fig. 6 shows that cluster 2 drivers never have this behavior, while in cluster 3, 66% of drivers answered "seldom" and 33% of drivers answered "usually". Cluster 1 drivers' response is between cluster 2 and cluster 3. 42% of

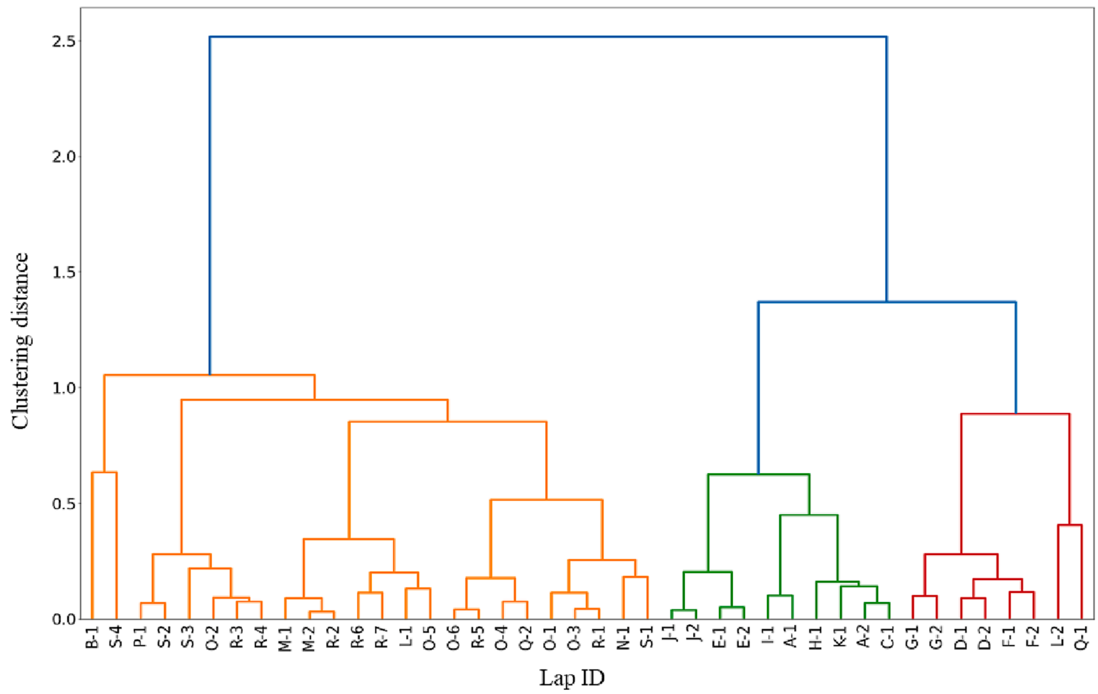

Fig. 5. Hierarchical clustering of selected driving features.

Table 3
The clustering result of each loop of driving data.

ID	Cluster	ID	Cluster	ID	Cluster
A-1	2	J-1	2	P-1	1
A-2	2	J-2	2	Q-1	3
B-1	1	K-1	2	Q-2	1
C-1	2	L-1	1	R-1	1
D-1	3	L-2	3	R-2	1
D-2	3	M-1	1	R-3	1
E-1	2	M-2	1	R-4	1
E-2	2	N-1	1	R-5	1
F-1	3	O-1	1	R-6	1
F-2	3	O-2	1	R-7	1
G-1	3	O-3	1	S-1	1
G-2	3	O-4	1	S-2	1
H-1	2	O-5	1	S-3	1
I-1	2	O-6	1	S-4	1

drivers in cluster 1 never override lane markings when driving.

(2) Behavior: look away from the road while driving

Looking away from the road while driving implies an impatient and distracted driving style. Cautious drivers should keep attention to road conditions. Fig. 7 shows that Cluster 2 drivers claim that this behavior never occurs. Cluster 3 drivers have this behavior, seldomly or more often. Again, cluster 1 drivers' response is between clusters 2 and 3. In cluster 1, 14% of drivers claim they always look away from the road while driving. Studies have shown that young novice drivers are more likely to be distracted than adults (Chan et al., 2008; Miller and Taubman, 2010).

(3) Behavior: use a mobile phone, drink, eat or dress up while driving.

This behavior is a clear signal of distracted and unsafe driving style. Fig. 8 shows that only 28% of drivers in cluster 1 and 14% of drivers in cluster 2 seldomly have this behavior, while all cluster 3 drivers have this behavior seldomly or more often. Studies found that most drivers admitted to eating or drinking at least some of the time (NHTSA, 2003;

-
-

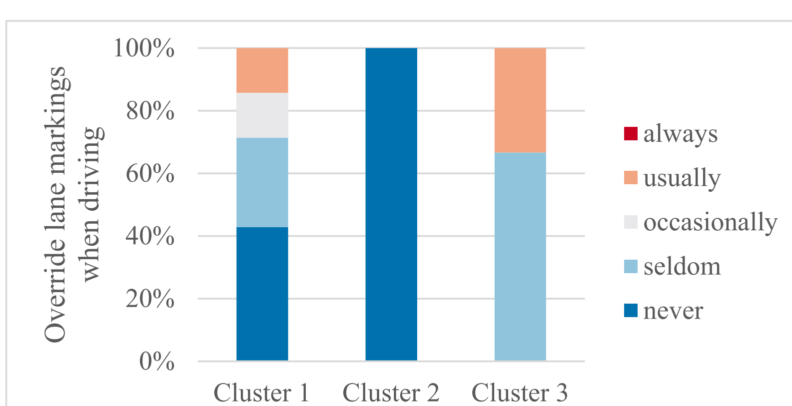

Fig. 6. Drivers' frequency of behavior: override lane markings when driving.

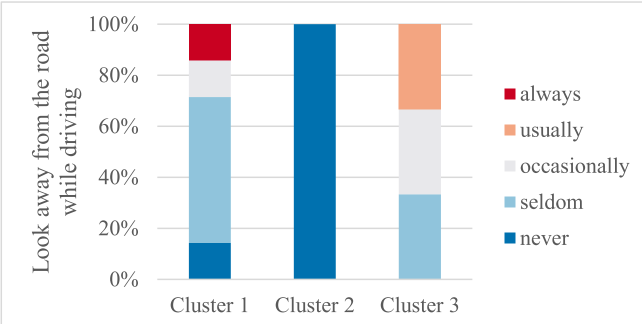

Fig. 7. Drivers' frequency of behavior: look away from the road while driving.

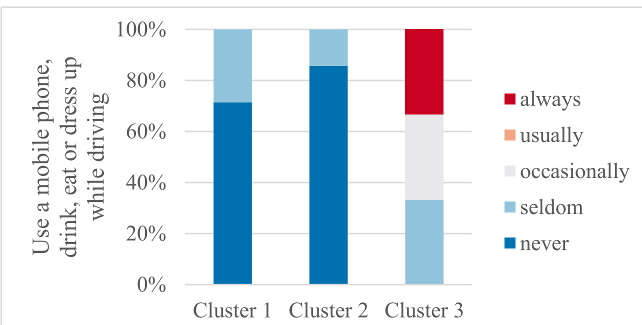

Fig. 8. Drivers' frequency of behavior: use a mobile phone, drink, eat or dress up while driving.

Stutts et al., 2005), and using mobile phones seems to be prevalent activity while driving (Young et al., 2008). There is no specific offense for taking hands off the wheel or eyes off the road. Drivers may perceive eating or drinking as a safe or low-risk activity (White et al., 2004). However, using a hand-held phone call is one of the worst factors in driver distraction and risky driving (Young et al., 2008). Using a mobile phone while driving can reduce driving performance, increasing the risk of road accidents (Phuksuksakul et al., 2021). Therefore, novices are less prone to engage in these activities because they lack self-confidence and driving skills. Due to the cautious attitude, drivers in cluster 2 tend to avoid these behaviors. Reckless drivers in cluster 3 are more likely to involve these behaviors and commit violations.

(4) Behavior: be impatient when driving

The behavior is related to impatient driving. In Fig. 9, no drivers in cluster 2 have impatient driving, and being patient is an assurance of careful driving. Conversely, impatience is a manifestation of reckless driving, so 66% of drivers in cluster 3 usually or always feel impatient. Drivers in cluster 1 also feel impatient, although less often than in cluster 3, which may be caused by excessive tension during driving.

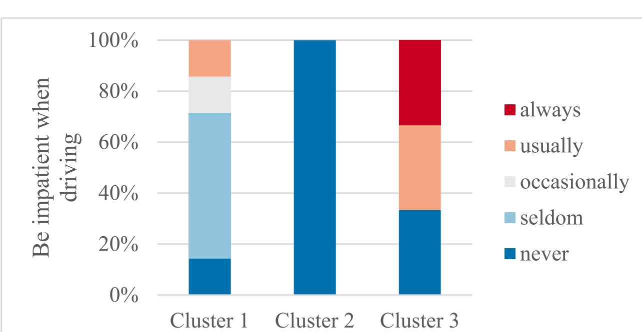

Fig. 9. Drivers' frequency of behavior: be impatient when driving.

(5) Behavior: swear, honk, use high beams or do quick and forced lane-change to show anger.

The behavior is related to impatient driving and hostile driving. Shown in Fig. 10, drivers in cluster 2 claim they never do these behaviors, while 66% of drivers in cluster 3 claim "usually" or "occasionally". Swearing and honking are common expressions of verbal aggression by drivers in response to anger or fear generated by another road user (Popuşoi et al., 2018). These behaviors could be seen as subtypes of hostile aggression, a strong negative affective state that can make drivers unload tension (Shinar, 1998). Therefore, these behaviors can be observed between novice and experienced drivers.

5.4.2. Driving skill analysis

(1) Behavior: be nervous of driving on the highway or in peak hours.

The interpretation of this behavior could be mixed. How a driver feels when driving in a challenging environment may reflect their driving style and driving skills. Fig. 11 shows that cluster 2 drivers agree that they would never feel nervous when driving on the highway or in peak hours. However, only 14% of cluster 1 drivers are not nervous on the highway or during peak hours. Experienced drivers, as their skills improve, eliminate their nervousness. Novice drivers often feel stressed and are scared of driving in given traffic situations due to the lack of driving skills, confidence, and fear of making mistakes (Miller and Taubman, 2010). There are also 33% of drivers in cluster 3 who feel nervous. Research indicates a correlation between anxiety and aggressive behavior (Clapp et al., 2011).

(2) Behavior: cannot drive alone, need assistance from others

Shown in Fig. 12, both cluster 2 and cluster 3 are experienced drivers, so they all choose the option of "never". 86% of drivers in cluster 1 appear to need assistance for driving to a certain degree.

The driving style and driving skill analysis in this section verifies the clustering labeling result. The definition of each cluster can find corresponding and reasonable explanations from the driver's responses to key behaviors. In summary, cluster 1 is novices with less experience and driving skills. Both clusters 2 and 3 are skilled drivers. Cluster 2 drivers have a more careful and defensive driving style. Cluster 3 drivers are impatient and reckless and tend to engage in risk-related behaviors. The driving style of drivers in cluster 1 is mixed. They may drive in a risky manner, such as crossing solid lane markings, looking away from the road while driving, etc. One assumption is that cluster 1 drivers commit risky behaviors due to a lack of driving skills, while cluster 3 drivers intentionally choose a reckless driving style.

5.5. Key features analysis

The distribution of five key features is compared by groups in boxplots (Figs. 13–15), and the results indicate that the differences among groups are significant. In this section, we try to explain the differences in feature distributions representing different driving styles and driving skill levels.

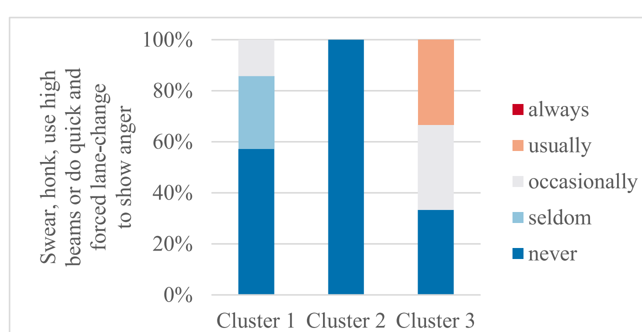

Fig. 10. Drivers' frequency of behavior: swear, honk, use high beams or do quick and forced lane-change to show anger.

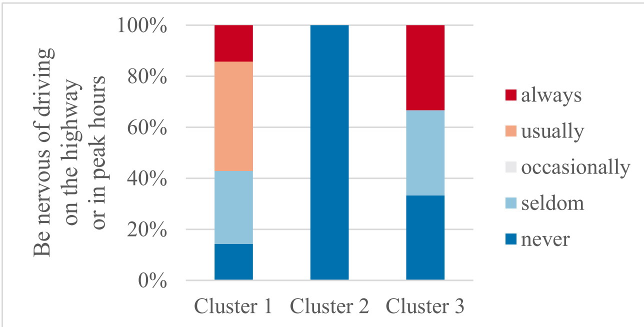

Fig. 11. Drivers' frequency of behavior: be nervous of driving on the highway or in peak hours.

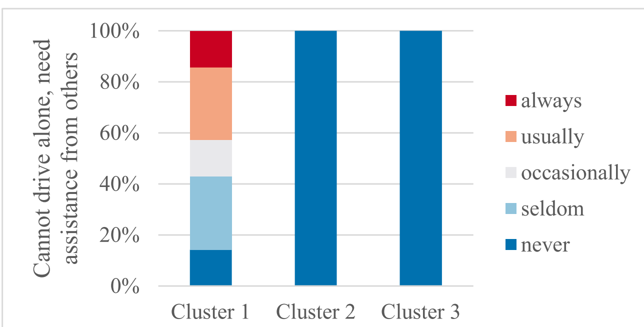

Fig. 12. Drivers' frequency of behavior: cannot drive alone, need assistance from others.

For longitudinal acceleration, the key features are ay_{fc} and ay_{max}. The frequency centroid can reflect the signal power spectral density distribution and characterize high-frequency components. Fig. 13(a) shows that cluster 2 drivers have a higher frequency centroid of longitudinal acceleration than others because they are cautious of changes in driving conditions and adjust the accelerator frequently, resulting in a higher frequency centroid of longitudinal acceleration. Cluster 3 drivers are reckless, and cluster 1 are novices lacking driving experience. They change longitudinal acceleration occasionally, and their ay_{fc} values are relatively lower. It is not surprising that the maximum longitudinal acceleration of cluster 3 is higher than the others, as reckless driving often comes with extremely high acceleration, as shown in Fig. 13(b).

For lateral acceleration, there are two key features: ax_{sf} and ax_{rms}.

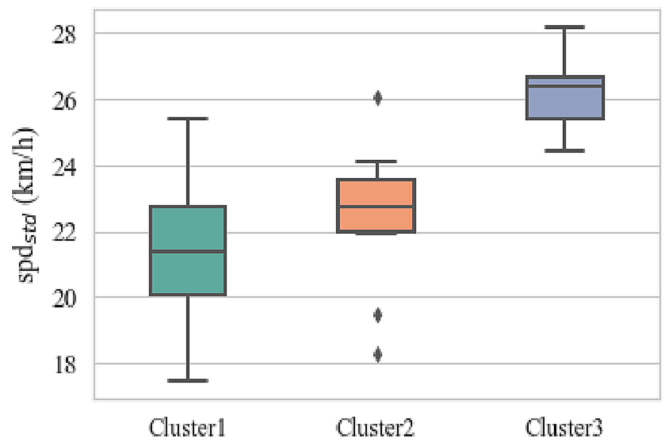

Fig. 15. Distribution of speed features in 3 clusters.

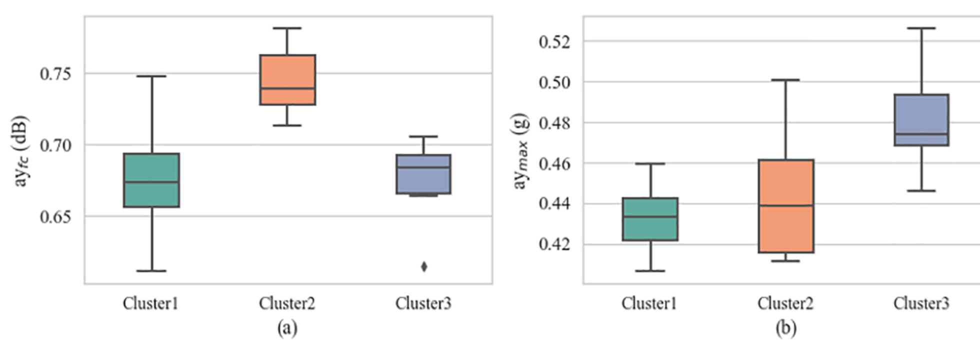

Fig. 13. Distribution of longitudinal acceleration in 3 clusters.

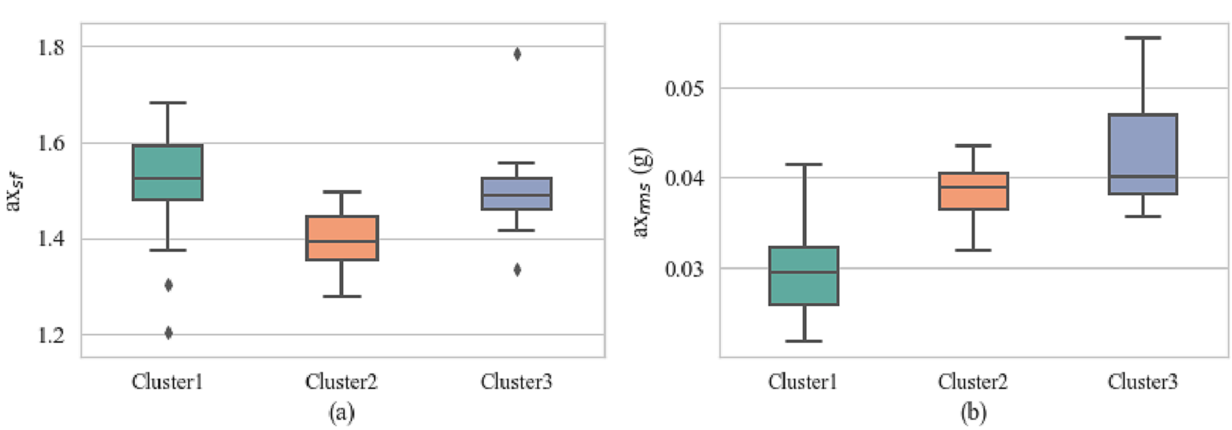

Fig. 14. Distribution of lateral acceleration in 3 clusters.

The shape factor was observed empirically as being lower for regular signals and generally higher for abnormal signals (Shidore et al., 2021). Fig. 14(a) shows that drivers in cluster 1 are unstable in lateral control due to larger shape factors. Lack of driving skills, novices are prone to apply a sudden change in lateral acceleration. Similarly, the shape factor of cluster 3 is greater than cluster 2 due to reckless driving style.

Lateral acceleration involves both positive and negative values, and the root mean square is suitable for measuring the absolute size of the lateral acceleration time series. Fig. 14(b) shows that cluster 1 has the lowest ax_{rms}, cluster 3 has the highest ax_{rms}, and cluster 2 is in-between. Drivers in cluster 3 have more volatile lateral accelerations due to frequent and aggressive lane changes. The novice has fewer number of lane-changes than experienced drivers in other clusters.

The key feature related to speed is spd_{std}. Cluster 3 drivers have higher spd_{std}, indicating that their speed deviates from the average, which is consistent with an aggressive driving style related to high speed and speed instability. Cluster 2 has a medium standard deviation, which means its speed changes smoothly. The novice's standard deviation of speed will not exceed the other two groups.

5.6. *Post hoc power analysis*

Due to the limited sample size, we conducted post hoc power analysis to detect confidence in the inferences drawn from the results. Statistical power is the probability that a statistical test will correctly reject a null hypothesis, meaning the probability of not committing a Type II error or making a false negative decision (Murphy and Myors, 2003). The post hoc power analysis results for the five key features are shown in Table 4. We made pairwise comparisons of feature differences between clusters, and the significance level is set at 0.05, which is the most commonly used criterion. Table 4 shows that all five features have a 90% or higher probability of concluding that differences exist between at least one pair of clusters. While there are a few lower power values between clusters, indicating that the difference between these two clusters is insignificant or a larger sample size is needed to make a conclusion with statistical significance. The results are consistent with the box plots discussed in Section 5.5.

5.7. *Limitations*

The analysis of 19 drivers' driving data is a demonstration that the proposed feature selection method can generate a subset of features for driving style and skill clustering effectively. However, it is necessary to clarify the limitations of what we found in the section of result analysis due to the study scope and small sample size.

First, there are only two female participants in the study. Both are classified as cluster 1 novice drivers. Gender has an important but mixed impact on driving behavior. Some studies found that males tend to drive more aggressively and have higher engaging in traffic violations than females (Rhodes and Pivik, 2011; Morgan and Mannering, 2011), while others found that female drivers commit more errors and reported more incidences compared to male drivers (Arnett et al., 1997; Williams, 2003; De Winter and Dodou, 2010). Female drivers' performance on key features in each cluster may be different from male drivers. However, without enough samples from female drivers, we are not able to discuss the gender differences in driving behavior in this paper.

Table 4
Post hoc power analysis of key features.

Feature	Cluster 1 vs Cluster 2	Cluster 1 vs Cluster 3	Cluster 2 vs Cluster 3
ay_{max}	0.169	1.000	0.820
ay_{fc}	1.000	0.053	0.999
ax_{rms}	0.999	0.999	0.372
ax_{sf}	0.921	0.052	0.580
spd_{std}	0.246	1.000	0.984

Second, the small statistical power of certain key features implies that a small sample size may lead to inadequate results in key feature analysis over clusters. Recruiting more participates in each cluster can help us generate a more robust conclusion on key feature distribution of drivers with different driving styles and skills.

Third, a specific road stretch of 14 km on the premises of Tongji University was selected for the experiment, which means the findings of key features may not be directly applied to different circumstances, such as highways located in the city center with heavy commute traffic. Moreover, the characteristics of the vehicle may impact driving behavior and the determination of driving style and skill. The test vehicle is a plug-in hybrid sedan without an advanced driver-assistance system or any active safety equipment. Since the growing penetration of electric vehicles with advanced driver-assistance and artificial intelligence, especially in China and European countries, it is a future direction to study the driving style and driving skill determination under the influence of cutting-edge technology in the vehicle industry.

6. Conclusions

Since the ground truth labels of driving behavior, such as driving style or driving skill, are unavailable in many driving behavior datasets, the literature has applied unsupervised clustering methods to analyze driving behavior characteristics. To overcome the drawback of existing feature selection algorithms, we propose a feature selection method for clustering driving characteristics by creating a new supervised machine learning task. The driving data of each driver is divided into data clips, and we establish a supervised machine learning model using the driver's ID as the label to predict. The key features for clustering are selected from the driver identification model with the highest permutation importance.

We introduce 18 feature extraction methods and compare their ability to characterize the individual driving style and driving skill levels from naturalistic driving data. After removing correlated features, we build a driver identification model using the XGBoost classifier. The key driving parameters and key features are selected based on the feature's permutation importance in the driver identification model. We find that longitudinal acceleration, lateral acceleration, and speed are the key driving parameters, and there are five important feature extraction methods: mean, maximum, standard deviation, root mean square, shape factor, and frequency centroid.

Based on the five key features selected, we cluster 42 naturalistic driving data samples into three groups. Verified by the self-assessment driving behavior questionnaire results, we name cluster 1, 2, 3 as novice, experienced, and cautious drivers, respectively. We show that the selected key features can effectively distinguish different driving styles and driving skill levels. Three rarely used features, root mean square, shape factor, and frequency centroid, have their advantages in the characterization of driving style and driving skill: (1) the frequency centroid of longitudinal acceleration can measure how often the driver adjusts longitudinal acceleration; (2) the shape factor of lateral acceleration can measure the level of instability of lateral control; (3) the root mean square of lateral acceleration can represent the degree of aggressiveness in speed control.

While the distributions of all five key features in clusters 2 and 3 are distinct, the performance of novice drivers is complex. For the frequency centroid of longitudinal acceleration and the shape factor of lateral acceleration, the novice driver's value is close to a reckless driver, indicating there are similarities in some aspects. Regarding the maximum longitudinal acceleration, the root mean square of lateral acceleration, and the standard deviation of speed, novice drivers behave more like cautious drivers rather than reckless drivers.

The work done in this paper can be extended in the future. First, the robustness of our proposed feature selection method can be further tested on an extended dataset that covers more traffic conditions, road types, and more diverse drivers. Second, the performance of other feature selection algorithms for clustering can be compared using benchmarks. Third, the permutation importance can be replaced by other feature importance measurement that is not affected by feature multicollinearity.

CRediT authorship contribution statement

Yao Chen: Conceptualization, Data curation, Formal analysis, Validation, Visualization, Methodology, Writing – original draft, Writing – review & editing. **Ke Wang:** Conceptualization, Methodology, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing. **Jian John Lu:** Resources, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The data that has been used is confidential.

Acknowledgement

This research was funded by the National Natural Science Foundation of China (No. 52102417) and Jiangsu Technology Innovation&C-V2X Academy Open Topics (KC-V2X2021002).

Appendix A

Driving behavior questionnaire

I. Basic information.

1. Age _______

A. under 20   B. 21–40   C. 41–60   D. over 60

2. Gender _______

A. male   B. female

3. The time elapsed since getting the driving license ________

A. under a year   B. 1–3 years   C. 3–5 years   D. over five years

4. Yearly driving (kilometers) _______

A. under 5000 km   B.5000–10000 km   C.10000–20000 km   D. over 20000 km

5. Incomes (per month) _______

A. < 5000 yuan   B. 5000–10000 yuan   C. 10000–20000 yuan   D. greater than 20000 yuan

6. Education level _______

A. junior and under.   B. high school   C. Bachelor   D. Master and above

7. Marriage status ________

A. married   B. single

II. Respond to driving questions on a 5-point scale (1 = never, 2 = seldom, 3 = occasionally, 4 = usually, 5 = always).

8. Misoperation, such as intend to use the windscreen wipers, but turn on the lights.	1	2	3	4	5
9. Override lane markings when driving.	1	2	3	4	5
10. Parking do not need any assistance.	1	2	3	4	5
11. Distracted driving with no attention to pedestrians.	1	2	3	4	5
12. Be nervous of driving on the highway or in peak hours.	1	2	3	4	5
13. Look away from the road while driving, such as glance at outside, look at billboards, etc.	1	2	3	4	5
14. Honk the slow-moving vehicles.	1	2	3	4	5
15. High level driving skills recognized by others.	1	2	3	4	5
16. Use a mobile phone, drink, eat or dress up while driving.	1	2	3	4	5
17. Without use turn signals before the lane change or turn.	1	2	3	4	5
18. Enjoy driving and feel relaxed.	1	2	3	4	5
19. Close to the front car to prevent others cutting in.	1	2	3	4	5
20. Curse other drivers while driving.	1	2	3	4	5
21. Cannot drive alone, need assistance from others.	1	2	3	4	5
22. Even if a car is ahead, still use high beams.	1	2	3	4	5
23. Miss exits or make mistakes due to distraction.	1	2	3	4	5
24. Speed up to prevent others overtaking.	1	2	3	4	5
25. Indulge in driving fast.	1	2	3	4	5
26. Temporary parking without position lamps turning on.	1	2	3	4	5
27. Accelerate through a yellow light.	1	2	3	4	5
28. Not to exceed speed limits on highways.	1	2	3	4	5

(*continued on next page*)

(*continued*)

29. Be nervous when driving around pedestrians, cyclists, or barriers.	1	2	3	4	5
30. In a traffic jam, insert the adjacent lane as soon as the traffic begins to move.	1	2	3	4	5
31. Be impatient while driving.	1	2	3	4	5
32. Swear, honk, use high beams or do quick and forced lane-change to show anger.	1	2	3	4	5
33. Throw trash out of the window.	1	2	3	4	5

Appendix B

ANOVA of driving behavior questionnaire

Questions		Sum of Squares	df	Mean Square	F	Sig.
Q8	Between Groups	3.703	2	1.852	1.504	0.256
	Within Groups	17.238	14	1.231		
	Total	20.941	16			
Q9	Between Groups	6.863	2	3.431	4.504	0.031
	Within Groups	10.667	14	0.762		
	Total	17.529	16			
Q10	Between Groups	12.185	2	6.092	3.245	0.070
	Within Groups	26.286	14	1.878		
	Total	38.471	16			
Q11	Between Groups	3.384	2	1.692	1.289	0.306
	Within Groups	18.381	14	1.313		
	Total	21.765	16			
Q12	Between Groups	16.947	2	8.473	5.511	0.017
	Within Groups	21.524	14	1.537		
	Total	38.471	16			
Q13	Between Groups	11.227	2	5.613	6.709	0.009
	Within Groups	11.714	14	0.837		
	Total	22.941	16			
Q14	Between Groups	4.880	2	2.440	3.039	0.080
	Within Groups	11.238	14	0.803		
	Total	16.118	16			
Q15	Between Groups	2.022	2	1.011	0.543	0.593
	Within Groups	26.095	14	1.864		
	Total	28.118	16			
Q16	Between Groups	11.165	2	5.583	11.242	0.001
	Within Groups	6.952	14	0.497		
	Total	18.118	16			
Q17	Between Groups	0.336	2	0.168	1.647	0.228
	Within Groups	1.429	14	0.102		
	Total	1.765	16			
Q18	Between Groups	9.384	2	4.692	2.935	0.086
	Within Groups	22.381	14	1.599		
	Total	31.765	16			
Q19	Between Groups	5.630	2	2.815	1.682	0.221
	Within Groups	23.429	14	1.673		
	Total	29.059	16			
Q20	Between Groups	5.899	2	2.950	3.285	0.068
	Within Groups	12.571	14	0.898		
	Total	18.471	16			
Q21	Between Groups	16.471	2	8.235	9.608	0.002
	Within Groups	12.000	14	0.857		
	Total	28.471	16			
Q22	Between Groups	0.577	2	0.289	0.213	0.811
	Within Groups	18.952	14	1.354		
	Total	19.529	16			
Q23	Between Groups	3.854	2	1.927	1.206	0.329
	Within Groups	22.381	14	1.599		
	Total	26.235	16			
Q24	Between Groups	2.403	2	1.202	0.853	0.447
	Within Groups	19.714	14	1.408		
	Total	22.118	16			
Q25	Between Groups	1.787	2	0.894	1.545	0.248
	Within Groups	8.095	14	0.578		
	Total	9.882	16			
Q26	Between Groups	1.905	2	0.952	0.443	0.651
	Within Groups	30.095	14	2.150		
	Total	32.000	16			
Q27	Between Groups	0.756	2	0.378	0.337	0.720
	Within Groups	15.714	14	1.122		
	Total	16.471	16			
Q28	Between Groups	4.106	2	2.053	0.639	0.542
	Within Groups	44.952	14	3.211		
	Total	49.059	16			

(*continued on next page*)

(*continued*)

Questions		Sum of Squares	df	Mean Square	F	Sig.
Q29	Between Groups	11.384	2	5.692	2.808	0.094
	Within Groups	28.381	14	2.027		
	Total	39.765	16			
Q30	Between Groups	0.644	2	0.322	0.262	0.773
	Within Groups	17.238	14	1.231		
	Total	17.882	16			
Q31	Between Groups	12.846	2	6.423	6.380	0.011
	Within Groups	14.095	14	1.007		
	Total	26.941	16			
Q32	Between Groups	5.854	2	2.927	4.890	0.025
	Within Groups	8.381	14	0.599		
	Total	14.235	16			
Q33	Between Groups	0.756	2	0.378	1.425	0.273
	Within Groups	3.714	14	0.265		
	Total	4.471	16			

References

Ahmad, N., Wali, B., Khattak, A.J., Dumbaugh, E., 2021. Built environment, driving errors and violations, and crashes in naturalistic driving environment. Accid. Anal. Prev. 157, 106158 https://doi.org/10.1016/j.aap.2021.106158.

Ahmad, N., Arvin, R., Khattak, A.J., 2023. Exploring pathways from driving errors and violations to crashes: The role of instability in driving. Accid. Anal. Prev. 179, 106876 https://doi.org/10.1016/j.aap.2022.106876.

Altmann, A., Toloşi, L., Sander, O., Lengauer, T., 2010. Permutation importance: a corrected feature importance measure. Bioinformatics, 26, 1340–1347. doi: 10.1093/bioinformatics/btq134.

Amata, H., Miyajima, C., Nishino, T., Kitaoka, N., Takeda, K., 2009. Prediction model of driving behavior based on traffic conditions and driver types. In: 2009 12th International IEEE Conference on Intelligent Transportation Systems, pp. 1–6. https://doi.org/10.1109/ITSC.2009.5309718.

Arnett, J.J., Offer, D., Fine, M.A., 1997. Reckless driving in adolescence: 'state' and 'trait' factors. Accid. Anal. Prev. 29 (1), 57–63. https://doi.org/10.1016/S0001-4575(97)87007-8.

Bagdadi, O., 2013. Assessing safety critical braking events in naturalistic driving studies. Transport. Res. F: Traffic Psychol. Behav. 16, 117–126. https://doi.org/10.1016/j.trf.2012.08.006.

Caesarendra, W., Tjahjowidodo, T., 2017. A review of feature extraction methods in vibration-based condition monitoring and its application for degradation trend estimation of low-speed slew bearing. Machines 5 (4), 21. https://doi.org/10.3390/machines5040021.

Cai, J., Luo, J., Wang, S., Yang, S., 2018. Feature selection in machine learning: a new perspective. Neurocomputing 300, 70–79. https://doi.org/10.1016/j.neucom.2017.11.077.

Chan, T.K., Chin, C.S., Chen, H., Zhong, X., 2019. A comprehensive review of driver behavior analysis utilizing smartphones. IEEE Trans. Intell. Transp. Syst. 21 (10), 4444–4475. https://doi.org/10.1109/TITS.2019.2940481.

Chan, E., Pradhan, A.K., Knodler, M.A., Pollatsek, A., Fisher, D.L., 2008. Empirical evaluation on driving simulator of effect of distractions inside and outside the vehicle on drivers' eye behavior. Transportation Research Board 87th Annual Meeting.

Chen, J., Wu, Z., Zhang, J., 2019b. Driver identification based on hidden feature extraction by using adaptive nonnegativity-constrained autoencoder. Appl. Soft Comput. 74, 1–9. https://doi.org/10.1016/j.asoc.2018.09.030.

Chen, C., Zhao, X., Zhang, Y., Rong, J., Liu, X., 2019a. A graphical modeling method for individual driving behavior and its application in driving safety an. Transport. Res. F: Traffic Psychol. Behav. 63, 118–134. https://doi.org/10.1016/j.trf.2019.03.017.

Clapp, J.D., Olsen, S.A., Danoff-Burg, S., Hagewood, J.H., Hickling, E.J., Hwang, V.S., Beck, J.G., 2011. Factors contributing to anxious driving behavior: the role of stress history and accident severity. J. Anxiety Disord. 25 (4), 592–598. https://doi.org/10.1016/j.janxdis.2011.01.008.

Cutler, B.L., Kravitz, D.A., Cohen, M., Schinas, W., 1993. The driving appraisal inventory: psychometric characteristics and construct validity1. J. Appl. Soc. Psychol. 23, 1196–1213. https://doi.org/10.1111/j.1559-1816.1993.tb01028.x.

Dash, M., Liu, H., 1999. Handling large unsupervised data via dimensionality reduction, in: Proceedings of SIGMOD Research Issues in Data Mining and Knowledge Discovery Workshop (DMDK). Philadelphia, USA, May.

de Winter, J.C.F., Dodou, D., 2010. The Driver Behaviour Questionnaire as a predictor of accidents: a meta-analysis. J. Saf. Res. 41 (6), 463–470. https://doi.org/10.1016/j.jsr.2010.10.007.

de Winter, J.C.F., de Groot, S., Mulder, M., Wieringa, P.A., Dankelman, J., Mulder, J.A., 2009. Relationships between driving simulator performance and driving test results. Ergonomics 52, 137–153. https://doi.org/10.1080/00140130802277521.

de Zepeda, M.V.N., Meng, F., Su, J., Zeng, X.-J., Wang, Q., 2021. Dynamic clustering analysis for driving styles identification. Eng. Appl. Artif. Intel. 97, 104096 https://doi.org/10.1016/j.engappai.2020.104096.

Deepthi, P., Thampi, S.M., 2015. Unsupervised gene selection using particle swarm optimization and k-means, in. In: Proceedings of the Second ACM IKDD Conference on Data Sciences, pp. 134–135. https://doi.org/10.1145/2732587.2732615.

del Campo, I., Asua, E., Martínez, V., Mata-Carballeira, Ó., Echanobe, J., 2018. Driving style recognition based on ride comfort using a hybrid machine learning algorithm. In: 2018 21st International Conference on Intelligent Transportation Systems (ITSC), pp. 3251–3258. https://doi.org/10.1109/ITSC.2018.8569722.

Deng, Z., Chu, D., Wu, C., Liu, S., Sun, C., Liu, T., Cao, D., 2022. A probabilistic model for driving-style-recognition-enabled driver steering behaviors. IEEE Transactions on Systems, Man, and Cybernetics: Systems 52, 1838–1851. https://doi.org/10.1109/TSMC.2020.3037229.

Dörr, D., Grabengiesser, D., Gauterin, F., 2014. Online driving style recognition using fuzzy logic. In: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 1021–1026. https://doi.org/10.1109/ITSC.2014.6957822.

Eboli, L., Guido, G., Mazzulla, G., Pungillo, G., Pungillo, R., 2017. Investigating car users' driving behaviour through speed analysis. PROMET-Traffic & Transportation 29 (2), 193–202. https://doi.org/10.7307/ptt.v29i2.2117.

Eftekhari, H.R., Ghatee, M., 2018. Hybrid of discrete wavelet transform and adaptive neuro fuzzy inference system for overall driving behavior recognition. Transport. Res. F: Traffic Psychol. Behav. 58, 782–796. https://doi.org/10.1016/j.trf.2018.06.044.

Elander, J., West, R., French, D., 1993. Behavioral correlates of individual differences in road-traffic crash risk: an examination of methods and findings. Psychol. Bull. 113 (2), 279–294. https://doi.org/10.1037/0033-2909.113.2.279.

Feng, Y., Pickering, S., Chappell, E., Iravani, P., Brace, C., 2018. Driving style analysis by classifying real-world data with support vector clustering. In: In 2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE), pp. 264–268. https://doi.org/10.1109/ICITE.2018.8492700.

Figueredo, G.P., Agrawal, U., Mase, J.M.M., Mesgarpour, M., Wagner, C., Soria, D., Garibaldi, J.M., Siebers, P.-O., John, R.I., 2019. Identifying heavy goods vehicle driving styles in the United Kingdom. IEEE Trans. Intell. Transp. Syst. 20 (9), 3324–3336.

French, D.J., West, R.J., Elander, J., Wilding, J.M., 1993. Decision-making style, driving style, and self-reported involvement in road traffic accidents. Ergonomics 36 (6), 627–644. https://doi.org/10.1080/00140139308967925.

Groeger, J.A., Murphy, G., 2020. Driver performance under simulated and actual driving conditions: Validity and orthogonality. Accid. Anal. Prev. 143, 105593 https://doi.org/10.1016/j.aap.2020.105593.

Gulian, E., Matthews, G., Glendon, A.I., Davies, D.R., Debney, L.M., 1989. Dimensions of driver stress. Ergonomics 32 (6), 585–602. https://doi.org/10.1080/00140138908966134.

Habibifar, N., Salmanzadeh, H., 2022. Relationship between driving styles and biological behavior of drivers in negative emotional state. Transport. Res. F: Traffic Psychol. Behav. 85, 245–258. https://doi.org/10.1016/j.trf.2022.01.010.

Hamdar, S.H., Qin, L., Talebpour, A., 2016. Weather and road geometry impact on longitudinal driving behavior: Exploratory analysis using an empirically supported acceleration modeling framework. Transp. Res. Part C: Emerging Technol. 67, 193–213. https://doi.org/10.1016/j.trc.2016.01.017.

Hess, S., Choudhury, C.F., Bliemer, M.C.J., Hibberd, D., 2020. Modelling lane changing behaviour in approaches to roadworks: Contrasting and combining driving simulator data with stated choice data. Transp. Res. Part C: Emerging Technol., 112, 282–294. .

Hong, J.-H., Margines, B., Dey, A.K., 2014. A smartphone-based sensing platform to model aggressive driving behaviors. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 4047–4056. https://doi.org/10.1145/2556288.2557321.

Johnson, D.A., Trivedi, M.M., 2011. Driving style recognition using a smartphone as a sensor platform. In: 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 1609–1615. https://doi.org/10.1109/ITSC.2011.6083078.

Kalsoom, R., Halim, Z., 2013. Clustering the driving features based on data streams. In Inmic.IEEE, pp. 89–94. .

Khattak, A.J., Ahmad, N., Wali, B., Dumbaugh, E., 2021. A taxonomy of driving errors and violations: evidence from the naturalistic driving study. Accid. Anal. Prev. 151, 105873 https://doi.org/10.1016/j.aap.2020.105873.

Kosuge, R., Okamura, K., Nakano, Y., Fujita, G., 2021. Characteristics of driving self-assessments and factors related to inaccurate self-assessment in Japanese older adults. Accid. Anal. Prev. 159, 106235 https://doi.org/10.1016/j.aap.2021.106235.

Kwak, B., Han, M., Kim, H.K., 2020. Driver identification based on wavelet transform using driving patterns. IEEE Trans. Ind. Inf. 17 (4), 2400–2410. https://doi.org/10.1109/TII.2020.2999911.

Lajunen, T., Summala, H., 1995. Driving experience, personality, and skill and safety-motive dimensions in drivers' self-assessments. Pers. Individ. Differ. 19, 307–318. https://doi.org/10.1016/0191-8869(95)00068-H.

Li, G., Zhu, F., Qu, X., Cheng, B., Li, S., Green, P., 2019. Driving style classification based on driving operational pictures. IEEE Access 7, 90180–90189. https://doi.org/10.1109/ACCESS.2019.2926494.

Lin, N.a., Zong, C., Tomizuka, M., Song, P., Zhang, Z., Li, G., 2014. An overview on study of identification of driver behavior characteristics for automotive control. Math. Probl. Eng. 2014, 1–15.

Liu, H., Zhao, H., Jia, L., 2000. A study on the control algorithm for automatic train operation. China Academy of Railway Sciences 04, 40–45.

Lombardi, D.A., Horrey, W.J., Courtney, T.K., 2017. Age-related differences in fatal intersection crashes in the United States. Accid. Anal. Prev. 99, 20–29. https://doi.org/10.1016/j.aap.2016.10.030.

Lyu, N., Wang, Y., Wu, C., Peng, L., Thomas, A.F., 2021. Using naturalistic driving data to identify driving style based on longitudinal driving operation conditions. J. Intelligent Connected Vehicles 5, 17–35. https://doi.org/10.1108/JICV-07-2021-0008.

Ma, Y., Li, W., Tang, K., Zhang, Z., Chen, S., 2021. Driving style recognition and comparisons among driving tasks based on driver behavior in the online car-hailing industry. Accid. Anal. Prev. 154, 106096 https://doi.org/10.1016/j.aap.2021.106096.

Ma, Z., Zhang, Y., 2021. Drivers trust, acceptance, and takeover behaviors in fully automated vehicles: Effects of automated driving styles and driver's driving styles. Accid. Anal. Prev. 159, 106238 https://doi.org/10.1016/j.aap.2021.106238.

Mahmud, S.M.S., Ferreira, L., Hoque, M.S., Tavassoli, A., 2022. Overtaking risk modeling in two-lane two-way highway with heterogeneous traffic environment of a low-income country using naturalistic driving dataset. J. Saf. Res. 80, 380–390. https://doi.org/10.1016/j.jsr.2021.12.019.

Martinez, C.M., Heucke, M., Wang, F.Y., Gao, B., Cao, D., 2018. Driving style recognition for intelligent vehicle control and advanced driver assistance: a survey. IEEE Trans. Intell. Transp. Syst. 19, 666–676. https://doi.org/10.1109/TITS.2017.2706978.

Martinussen, L.M., Hakamies-Blomqvist, L., Møller, M., Özkan, T., Lajunen, T., 2013. Age, gender, mileage and the DBQ: The validity of the Driver Behavior Questionnaire in different driver groups. Accid. Anal. Prev. 52, 228–236. https://doi.org/10.1016/j.aap.2012.12.036.

Martinussen, L.M., Møller, M., Prato, C.G., 2014. Assessing the relationship between the Driver Behavior Questionnaire and the Driver Skill Inventory: Revealing sub-groups of drivers. Transport. Res. F: Traffic Psychol. Behav. 26, 82–91. https://doi.org/10.1016/j.trf.2014.06.008.

Martinussen, L.M., Møller, M., Prato, C.G., 2017. Accuracy of young male drivers' self-assessments of driving skill. Transport. Res. F: Traffic Psychol. Behav. 46, 228–235. https://doi.org/10.1016/j.trf.2017.03.001.

Meseguer, J.E., Calafate, C.T., Cano, J.C., 2018. On the correlation between heart rate and driving style in real driving scenarios. Mobile Networks and Applications 23, 128–135. https://doi.org/10.1007/s11036-017-0833-x.

Miller, G., Taubman - Ben-Ari, O., 2010. Driving styles among young novice drivers—the contribution of parental driving styles and personal characteristics. Accid. Anal. Prev. 42, 558–570. https://doi.org/10.1016/j.aap.2009.09.024.

Miyajima, C., Nishiwaki, Y., Ozawa, K., Wakita, T., Itou, K., Takeda, K., Itakura, F., 2007. Driver modeling based on driving behavior and its evaluation in driver identification. Proc. IEEE 95 (2), 427–437. https://doi.org/10.1109/JPROC.2006.888405.

Mohammadnazar, A., Arvin, R., Khattak, A.J., 2021. Classifying travelers' driving style using basic safety messages generated by connected vehicles: application of unsupervised machine learning. Transp. Res. Part C: Emerging Technol. 122, 102917 https://doi.org/10.1016/j.trc.2020.102917.

Morgan, A., Mannering, F.L., 2011. The effects of road-surface conditions, age, and gender on driver-injury severities. Accid. Anal. Prev. 43 (5), 1852–1863. https://doi.org/10.1016/j.aap.2011.04.024.

Murphy, K.R., Myors, B., 2003. Statistical Power Analysis: A Simple and General Model for Traditional and Modern Hypothesis Tests. Lawrence Erlbaum Associates.

NHTSA, 2003. National survey of distracted and drowsy driving attitudes and behavior 2002: Vol. 1 – Findings. Report no.: DOT HS 809 566.

Paddan, G.S., Griffin, M.J., 2002. Evaluation of whole-body vibration in vehicles. J. Sound Vib. 253, 195–213. https://doi.org/10.1006/jsvi.2001.4256.

Pan, Y.N., Chen, J., Li, X.L., 2009. Spectral entropy: A complementary index for rolling element bearing performance degradation assessment. Proc. Inst. Mech. Eng. C J. Mech. Eng. Sci. 223, 1223–1231. https://doi.org/10.1243/09544062JMES1224.

Phuksuksakul, N., Kanitpong, K., Chantranuwathana, S., 2021. Factors affecting behavior of mobile phone use while driving and effect of mobile phone use on driving performance. Accid. Anal. Prev. 151, 105945 https://doi.org/10.1016/j.aap.2020.105945.

Popuşoi, S.A., Havârneanu, G.M., Havârneanu, C.E., 2018. "Get the f#*k out of my way!" Exploring the cathartic effect of swear words in coping with driving anger. Transport. Res. F: Traffic Psychol. Behav. 56, 215–226. https://doi.org/10.1016/j.trf.2018.04.013.

Qu, T., Chen, H., Cao, D., Guo, H., Gao, B., 2015. Switching-based stochastic model predictive control approach for modeling driver steering skill. IEEE Trans. Intell. Transp. Syst. 16, 365–375. https://doi.org/10.1109/TITS.2014.2334623.

Reason, J., Manstead, A., Stradling, S., Baxter, J., Campbell, K., 1990. Errors and violations on the roads: a real distinction? Ergonomics 33 (10–11), 1315–1332. https://doi.org/10.1080/00140139008925335.

Rhodes, N., Pivik, K., 2011. Age and gender differences in risky driving: the roles of positive affect and risk perception. Accid. Anal. Prev. 43 (3), 923–931. https://doi.org/10.1016/j.aap.2010.11.015.

Sagberg, F., Selpi, Bianchi Piccinini, G.F., Engström, J., 2015. A review of research on driving styles and road safety. Hum. Factors 57 (7), 1248–1275.

Saxena, A., Pal, N.R., Vora, M., 2010. Evolutionary methods for unsupervised feature selection using Sammon's stress function. Fuzzy Inf. Eng. 2, 229–247. https://doi.org/10.1007/s12543-010-0047-4.

Senawi, A., Wei, H.-L., Billings, S.A., 2017. A new maximum relevance-minimum multicollinearity (MRmMC) method for feature selection and ranking. Pattern Recogn. 67, 47–61. https://doi.org/10.1016/j.patcog.2017.01.026.

Sharma, V., Parey, A., 2016. A review of gear fault diagnosis using various condition indicators. Procedia Eng. 144, 253–263. https://doi.org/10.1016/j.proeng.2016.05.131.

Shen, J.-L., Hung, J.-W., Lee, L.-S., 1998. Robust entropy-based endpoint detection for speech recognition in noisy environments. In: Proc. ICSLP98. Australasian Speech Science and Technology Association; 1998. pp. 1015–1018.

Shidore, M.M., Athreya, S.S., Deshpande, S., Jalnekar, R., 2021. Screening of knee-joint vibroarthrographic signals using time and spectral domain features. Biomed. Signal Process. Control 68, 102808. https://doi.org/10.1016/j.bspc.2021.102808.

Shinar, D., 1998. Aggressive driving: the contribution of the drivers and the situation. Transport. Res. F: Traffic Psychol. Behav. 1 (2), 137–160. https://doi.org/10.1016/S1369-8478(99)00002-9.

Shirmohammadi, H., Hadadi, F., Saeedian, M., 2019. Clustering analysis of drivers based on behavioral characteristics regarding road safety. Int. J. Civ. Eng. 17, 1327–1340. https://doi.org/10.1007/s40999-018-00390-2.

Song, X., Yin, Y., Cao, H., Zhao, S., Li, M., Yi, B., 2021. The mediating effect of driver characteristics on risky driving behaviors moderated by gender, and the classification model of driver's driving risk. Accid. Anal. Prev. 153, 106038 https://doi.org/10.1016/j.aap.2021.106038.

Strobl, C., Boulesteix, A.-L., Zeileis, A., Hothorn, T., 2007. Bias in random forest variable importance measures: Illustrations, sources and a solution. BMC Bioinf. 8, 25. https://doi.org/10.1186/1471-2105-8-25.

Stutts, J., Feaganes, J., Reinfurt, D., Rodgman, E., Hamlett, C., Gish, K., Staplin, L., 2005. Driver's exposure to distractions in their natural driving environment. Accid. Anal. Prev. 37, 1093–1101. https://doi.org/10.1016/j.aap.2005.06.007.

Sundström, A., 2008. Self-assessment of driving skill – a review from a measurement perspective. Transport. Res. F: Traffic Psychol. Behav. 11, 1–9. https://doi.org/10.1016/j.trf.2007.05.002.

Taubman-Ben-Ari, O., Mikulincer, M., Gillath, O., 2004. The multidimensional driving style inventory—scale construct and validation. Accid. Anal. Prev. 36, 323–332. https://doi.org/10.1016/S0001-4575(03)00010-1.

Vaiana, R., Iuele, T., Astarita, V., Caruso, M.V., Tassitani, A., Zaffino, C., Giofrè, V.P., 2014. Driving behavior and traffic safety: an acceleration-based safety evaluation procedure for smartphones. Mod. Appl. Sci. 8 (1), 88–96. https://doi.org/10.5539/mas.v8n1p88.

Vakkuri, A., Yli-Hankala, A., Talja, P., Mustola, S., Tolvanen-Laakso, H., Sampson, T., Viertiö-Oja, H., 2004. Time-frequency balanced spectral entropy as a measure of anesthetic drug effect in central nervous system during sevoflurane, propofol, and thiopental anesthesia. Acta Anaesthesiol. Scand. 48, 145–153. https://doi.org/10.1111/j.0001-5172.2004.00323.x.

Van Ly, M., Martin, S., Trivedi, M. M., 2013. Driver classification and driving style recognition using inertial sensors. In 2013 IEEE Intelligent Vehicles Symposium (IV). Presented at the 2013 IEEE Intelligent Vehicles Symposium (IV), pp. 1040–1045. doi: 10.1109/IVS.2013.6629603.

Wang, Z., Cheng, X., 2021. Adaptive optimization online IMU self-calibration method for visual-inertial navigation systems. Measurement 180, 109478. https://doi.org/10.1016/j.measurement.2021.109478.

Wang, Y., Qu, W., Ge, Y., Sun, X., Zhang, K., Zajenkowski, M., 2018. Effect of personality traits on driving style: Psychometric adaption of the multidimensional driving style inventory in a Chinese sample. PLoS One 13 (9), e0202126.

Wang, W., Xi, J., Chong, A., Li, L., 2017. Driving style classification using a semisupervised support vector machine. IEEE Trans. Hum.-Mach. Syst. 47, 650–660. https://doi.org/10.1109/THMS.2017.2736948.

Wang, W., Xi, J., Zhao, D., 2019. Driving style analysis using primitive driving patterns with bayesian nonparametric approaches. IEEE Trans. Intell. Transp. Syst. 20, 2986–2998. https://doi.org/10.1109/TITS.2018.2870525.

Wang, X., Xu, R., Zhang, S., Zhuang, Y., Wang, Y., 2022. Driver distraction detection based on vehicle dynamics using naturalistic driving data. Transp. Res. Part C: Emerg. Technol. 136, 103561 https://doi.org/10.1016/j.trc.2022.103561.

West, R., French, D., Kemp, R., Elander, J., 1993. Direct observation of driving, self reports of driver behaviour, and accident involvement. Ergonomics 36 (5), 557–567. https://doi.org/10.1080/00140139308967912.

White, M.P., Eiser, J.R., Harris, P.R., 2004. Risk perceptions of mobile phone use while driving. Risk Analysis: An International Journal 24 (2), 323–334. https://doi.org/10.1111/j.0272-4332.2004.00434.x.

Williams, A.F., 2003. Teenage drivers: patterns of risk. J. Saf. Res. 34 (1), 5–15. https://doi.org/10.1016/S0022-4375(02)00075-0.

Xue, Q., Wang, K., Lu, J.J., Liu, Y., 2019. Rapid driving style recognition in car-following using machine learning and vehicle trajectory data. J. Adv. Transp. 2019, 9085238. https://doi.org/10.1155/2019/9085238.

Yan, L., Wan, P., Qin, L., Zhu, D., 2018. The induction and detection method of angry driving: evidences from EEG and physiological signals. Discret. Dyn. Nat. Soc. 2018, 3702795. https://doi.org/10.1155/2018/3702795.

Yang, L., Ma, R., Zhang, H.M., Guan, W., Jiang, S., 2018. Driving behavior recognition using EEG data from a simulated car-following experiment. Accid. Anal. Prev. 116, 30–40. https://doi.org/10.1016/j.aap.2017.11.010.

Yang, L., Guan, W., Ma, R., Li, X., 2019. Comparison among driving state prediction models for car-following condition based on EEG and driving features. Accid. Anal. Prev. 133, 105296 https://doi.org/10.1016/j.aap.2019.105296.

Yiakopoulos, C.T., Gryllias, K.C., Antoniadis, I.A., 2011. Rolling element bearing fault detection in industrial environments based on a K-means clustering approach. Expert Syst. Appl. 38, 2888–2911. https://doi.org/10.1016/j.eswa.2010.08.083.

Young, M.S., Mahfoud, J.M., Walker, G.H., Jenkins, D.P., Stanton, N.A., 2008. Crash dieting: the effects of eating and drinking on driving performance. Accid. Anal. Prev. 40, 142–148. https://doi.org/10.1016/j.aap.2007.04.012.

Yu, J., 2011. Bearing performance degradation assessment using locality preserving projections and Gaussian mixture models. Mech. Syst. Sig. Process. 25, 2573–2588. https://doi.org/10.1016/j.ymssp.2011.02.006.

Zhang, X., Huang, Y., Guo, K., Li, W., 2019. Driving style classification for vehicle-following with unlabeled naturalistic driving data. In 2019 IEEE Vehicle Power and Propulsion Conference (VPPC), pp. 1–5. doi: 10.1109/VPPC46532.2019.8952462.

Zhao, X., Xu, W., Ma, J., Li, H., Chen, Y., 2019. An analysis of the relationship between driver characteristics and driving safety using structural equation models. Transport. Res. F: Traffic Psychol. Behav. 62, 529–545. https://doi.org/10.1016/j.trf.2019.02.004.