Assessing Driving Styles in Commercial Motor Vehicle Drivers after Take-Over Conditions in Highly Automated Vehicles (August 2021)

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Abstract—**Assessing drivers' behavior after transition from automated to manual driving (referred as to take-over condition) in highly automated vehicles (SAE Level 4) is a widely studied area. However, analyzing Commercial Motor Vehicle (CMV) drivers' post-take-over behavior has received less attention, whereas it is forecasted that CMVs will be the first to vastly adopt highly automated vehicle technology. This study aims to analyze and compare CMV drivers' driving styles in take-over conditions with continuous manual driving. Assessing driving style, which is a function of various variables and actions, provides a comprehensive understanding of the changes in post-take-over behavior. Hence, the driving behaviors of 45 CMV drivers are collected using a driving simulator, and we investigated whether the driving style is subject to driving mode (take-over or manual), automation duration, repeated take-overs, and driver's factors. Here, drivers' driving behavior is classified into three driving styles, normal, conservative, and risky by using Multivariate Dynamic Time Warping approach followed by *k*-means clustering. Comparing driving styles in take-over and manual driving conditions showed that conservative and risky driving styles (as in more speed reduction, harder brakes, and unsafe turns) are more common in take-over conditions. Furthermore, to gain behavioral insight into the detected driving styles, Generalized Linear Models are applied to model the driving behavior indices in each driving style. Modeling results showed that long-phase automation, traffic/environmental conditions, and bad driving history deteriorate post-take-over behavior. The findings of this paper provide valuable information to automotive companies and transportation planners on the nature of take-over conditions.**

Index Terms— **Take-Over, Commercial Motor Vehicles, Highly Automated Vehicles, Driving Style, Multivariate Dynamic Time Warping**

I. Introduction

In recent years, investigating different aspects of automated driving from a human factors point of view has gained much attention due to its importance and potential risks. Recently, we witnessed the introduction of conditional automation (SAE Level 3 [1]) in passenger cars, and it is expected that level 4 of automation, Highly Automated Vehicles (HAV), will be introduced in the next few years. Due to the ever-increasing trend of surface freight transportation in the US as well as the significant investment of several companies in automated Commercial Motor Vehicle (CMV) technologies, it is forecasted that CMVs will be the first to vastly adopt highly automated vehicle technology compared to passenger vehicles [2], as organizational adoptions historically occur first compared to individual adoption[3]. Current studies focused more on passenger car drivers, and limited studies have addressed the behavior of CMV drivers in HAVs, which necessitates further research on this important group of drivers[4].

A critical issue in HAVs is the transition from Automated Driving (AD) to Manual Driving (MD), which is referred as to the take-over condition. Even though in HAVs, the driving system is responsible for the entire driving tasks and even intervenes in some cases of critical events or system failure, the transition from automated to manual driving is still needed to complete the trip especially if the system reaches its operational limits due to road conditions or unexpected system failure. Previous studies showed that take-over conditions and the associated changes in driving workload will impact drivers' driving behavior consequently [5]. Although the background of take-over studies is very rich, investigating the effect of take-over conditions on CMV drivers' driving styles and its associated parameters has received less attention. Only recently, two studies assessed truck drivers' behavior in HAVs: Zhang et al. [6] evaluated truck drivers' reaction time during the take-over by measuring eye-movement and considering three different levels of automated operation monitoring under platooning scenarios. In addition, Heikoop et al. [7] reviewed the effects of mental demand tasks on situation awareness in connected platoon scenarios; situation awareness, self-reported workload, and physiological state were measured at different levels of task demand.

In addition, to assess drivers' takeover behaviors, most researchers evaluated the changes in drivers' driving behavior indices (e.g., acceleration, speed, brake pressure) individually and compared them to continuous MD. To the best of our knowledge, assessing driving style after take-over condition, and comparing it to MD are not addressed directly in the literature. Driving style is a broad concept that can be a function of a considerable number of variables and factors including driving performance, situation and environmental awareness,

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willingness to take risks, and reasoning abilities [8]. In comparison to analyzing a single driving behavior index, analyzing driving style as a combination of driving performance and behavior reveals more comprehensive insights into driving behavior. The current study aims to address CMV drivers' post-takeover driving behavior in HAVs by assessing changes in driving style after the transition from AD to MD and evaluating effective parameters.

A. Related Literature

In this sub-section, the most recent studies in fields of take-over condition and driving style classification are provided.

1) Take-Over Condition

The take-over condition is a well-addressed area in HAV's literature. Valuable efforts have been dedicated to addressing questions such as "what aspects of drivers' behavior will be affected by take-over" and "what are the effective parameters?". In an early study, Merat and Jamson [9] showed that, generally, drivers' behavior after take-over would change compared to MD. Later, De Winter et al. [10] showed that these changes are more significant in HAVs compared to conditionally automated vehicles. Studies showed that transition from AD to MD increases drivers' reaction time [11]–[13], and deteriorates drivers driving behavior indices (e.g., acceleration, braking, and speed) [13], [14]. In addition, drivers' decision-making will be affected by this transition. Gold et al. [5] stated that in a conditional automation condition, decisions to steer or break in response to a take-over are impacted by surrounding traffic, secondary task, fatigue, and age. Naujoks et al. [15] found that in take-over conditions drivers tend to perform a lane change when they have larger time budgets, and the surrounding traffic allows. With shorter time budgets, drivers revert to braking responses but may include emergency steering as a last resort to avoid a crash.

To assess the effective variables on post-take-over driving behavior, a variety of parameters has been reviewed. An important parameter is the duration of AD. Only a few studies have been conducted to assess the effect of AD's duration on drivers' behavior and the results are varied. Some studies found significant effects of long AD on post-take-over behavior of drivers [11], [16]–[18], and some studies did not observe large aftereffects [19], [20].

Evaluating the effect of repeated exposure to take-overs is another source of interest because it can reveal whether drivers can transfer their experiences over repeated take-overs [21]. Studies in this area mostly showed that drivers' behavior will be improved after a sequence of take-overs [22]. Repeated exposures mediate the effect of factors such as fatigue, and the learning effect of additional iterations leads to improving take-over performance [23]. Moreover, Forster et al. [24] state that drivers' decision-making would be improved in repeated exposure to take-over due to an enhanced understanding of the way how to execute the control transitions.

In addition, researchers explored the effects of driver factors on post-take-over behavior. The interaction between driver's age and driving behavior has received more attention. Li et al. [25] showed that older drivers will have slower reaction times and poorer post-take-over behavior. Gold et al. [5] found that younger drivers would have faster take-over times while they did not find a significant impact of age on crash probability. Clark and Feng [26] showed that older drivers applied more pressure on the brake pedal and deviated less from the road centerline.

2) Driving Style Classification

Driving style classification is widely incorporated to improve traffic efficiency and safety [27]. Various methods have been proposed to classify driving behavior. Ma et al. [28] explored the relationship between driving style and driving behavior and applied SVM followed by multiple decision trees to estimate driving styles. Liang and Lee [29] developed a layered algorithm that integrated Dynamic Bayesian Network and supervised clustering to detect cognitive distraction using eye movement and driving performance measures. Wang et al. [30] used a semi-supervised approach for driving style classification integrating the *k*-means method with the SVM method. Drivers driving styles were classified into aggressive and normal styles. Results showed that integrated *k*-means and SVM could improve the accuracy of classification. Bejani and Ghatee [31] applied a combination of SVM, *k*-nearest Neighbors, and Multi-Layer Perception for driving style recognition using smartphone data. Mohammadnazar et al. [32] applied *k*-medoids and *k*-means to classify travelers' driving styles into three classes (aggressive, normal, and calm) using basic safety messages generated by connected vehicles. Classification approaches applied in previous studies mostly did not consider the time-series structure of driving behavior data sets and only analyzed some extracted features (maximum or minimum of data set) [33]; whereas a driving style consists of several responses and sub-actions, and one extracted feature cannot represent the entire driving behavior. Therefore, this study applies a classification method that considers the entire temporal sequence of driving.

B. Literature Gaps

Even though it is forecasted that CMVs will be the first generation of vast HAV-technology adoption[34], assessing CMV drivers' driving behavior transition from AD to MD and detecting effective parameters are not addressed in the literature. In addition, assessing driving behavior in this group of drivers is essential since CMV drivers usually must drive under time pressure, which increases the risk of crashes. They should drive to predefined destinations and are restricted to predefined roads. Their job is conditional to their driving behavior and driving records, and they can easily lose their job in case of unsafe driving behavior.

In addition, due to the huge capital investment needed for infrastructure improvement, it is expected that higher functional classes of highways (e.g., interstate highways and expressways) will be ready for HAVs first, and gradually other functional classes of highways (e.g., US highways, state highways, and city/county roads) will be upgraded for AD. Thus, drivers of the first generation of highly automated CMVs must take over vehicle control often in consecutive autonomous driving episodes followed by non-autonomous driving episodes (local highways) frequently. Hence, evaluating the effect of repeated exposure to take-over becomes important for CMV drives, although valuable efforts have been devoted to assessing this condition in literature for passenger cars.

Furthermore, since higher functional classes of highways will be the first host of the HAV technology, and they usually are used for long-distance trips, the effect of the long-automated operation on take-over conditions becomes an important issue. However, the literature failed to provide a consistent answer for the effects of long-duration automated operations that necessitates more research in this area.

Among studies on the effect of driver's factors on take-over conditions, assessing the effect of drivers' age is widely studied, however, other drivers' factors (e.g., driving history, years of experience) are not addressed. Besides, researchers believe that assessing the interaction between driver's factors and their driving style can reveal hidden aspects of take-over in HAVs and always is an important subject [25].

Finally, the literature is deficient in showing a comprehensive driving behavior model in terms of drivers driving style and decision making after the transition from AD to MD [35]. Previous studies evaluated the post-take-over behavior by analyzing driving behavior indices individually and assessing driving style in take-over conditions is not addressed.

C. *Objectives and Contributions*

Considering gaps in the literature, the present study aims to detect and compare CMV drivers' driving styles in bypassing critical events (e.g., car crashes, a sudden end of a lane, and road construction) in continuous MD and after take-over conditions (transition from AD to MD). The effect of automated operation duration, repeated take-overs, and driver's factors on driving styles will be evaluated in this study. This point should be mentioned that since drivers' behavior is assessed when they are bypassing critical events, this condition makes a Lane Changing (LC) scenario, which is a hot spot in the field of transportation safety research [15], [36].

To sum up, the contributions of this paper over previous research on the field of take-over conditions are fourfold. First, this study targets CMV drivers, an important group of drivers who have received less attention in the literature. Second, this study assesses the effect of take-over conditions on driving styles, instead of individual driving behavior indices. Third, the effect of duration of AD, repeated take-overs, and driver factors (i.e., age, gender, driving experience, and driving background) are evaluated on driving styles. Finally, the current study acquires behavioral insight into the detected driving styles by developing Generalized Linear Models (GLM) on driving behavior indices (i.e., max acceleration, max speed).

The rest of this paper is organized as follows: the next section discusses data collection and modeling approaches. Then, the results of driving style classification and modeling results are presented and discussed. The conclusion section provides the summary of the paper and avenues for future research.

II. Data and Method

To accomplish the goals of this research, an experiment is designed on a driving simulator, and the driving behaviors of 45 certified CMV drivers are collected in two driving modes, continuous MD and after the transition from AD to MD. An unsupervised classification approach is implemented to detect driving styles, and GLM is applied to model the driving behavior indices to gain a better behavioral insight into the detected driving styles.

A. *Data Collection*

45 verified CMV drivers (40 males and 5 females) aged between 22 and 59 years (mean=34.93, SD=9.60) with a minimum of one year of CMV driving experience and 15,000 kilometers driving per year were recruited to take part in this study. They were compensated $40 for taking the experiment. No additional criteria were used for recruiting participants. Participants' demographic information and driving background were collected through a questionnaire in which participants were asked to indicate their gender, age, education, the number of car crashes they had, the number of tickets received in the last two years, and the annual driven mileage; no identifiable information was collected. Drivers' longitudinal and lateral speed and acceleration, following distance (the minimum distance between the vehicle and the front vehicle), heading error (the maximum angle between the road center and vehicle's heading, indicating the smoothness of turns), headway, and Standard Deviation of Lateral Positioning (SDLP) are collected 60 times/sec using the driving simulator.

B. *Apparatus*

This research is conducted at the University of Memphis Driving Simulator lab, using RDS-500, a research driving simulator (developed by Real-time Technologies LLC.). RDS-500 uses three robust software, SimCreator 3.8 (a graphical and real-time simulation and modeling system), SimCreator DX (scenario developer), and SimVista (scenarios' environment developer), developed for high-fidelity research simulators. RDS-500 has an operator station laptop and a high-end simulation computer with one 55-inch HD monitor and a USB-based steering wheel and pedal set along with a 5.1 surround sound audio system.

C. *Experiment*

A 40-minute experiment was designed in the driving simulator. The environment of the experiment was a separated two-way freeway with 2 lanes in each direction containing gentle curves and speed limits of 110 km/hr. Before starting the experiment, participants had a 10-minute test drive to become familiar with the driving simulator and get used to the driving condition. The experiment was divided into two sections: the first section was 10 minutes of MD (the driver is responsible for vehicle control) in which two critical events happened in this section with a 5-minute interval. The second section contained 30 minutes of highly automated operation, where the system was responsible for longitudinal and lateral control of the vehicle and asked the driver to regain the vehicle control in case of critical events by sending an auditory alert, 10 seconds before the critical events in the highly automated section. Three scenarios are designed in the second section (scenarios A, B, and C). Six take-over conditions with a fixed time interval of 5 minutes were designed in scenario A, two take-over conditions with 15 minutes time intervals were considered in scenario B, and one take-over was planned after 30 minutes in scenario C. 45 Participants were randomly divided into three groups of 15 (Group A, B, and C), and each group took the corresponding scenario. Fig. 1 demonstrates the designed experiment's sections and scenarios.

After each take-over, participants must drive for 60 seconds and then turn on the AD again. In this experiment, designed critical events caused a capacity reduction and occurred in the same lane that the vehicle is, to force the drivers to perform an LC maneuver. Two general critical events were defined in this study: (i) a car crash with two cars and (ii) a sudden end of a lane due to road construction or a stationary vehicle. To avoid participants' prediction of the condition, the feature of the events was different, whereas the geometry of critical events (i.e., length, width, and effective area) was the same. The analysis interval starts from 10 seconds before the critical event in the MD section and from the take-over moment in AD and lasts until the LC is completed (driver bypasses the critical event) in both MD and AD.

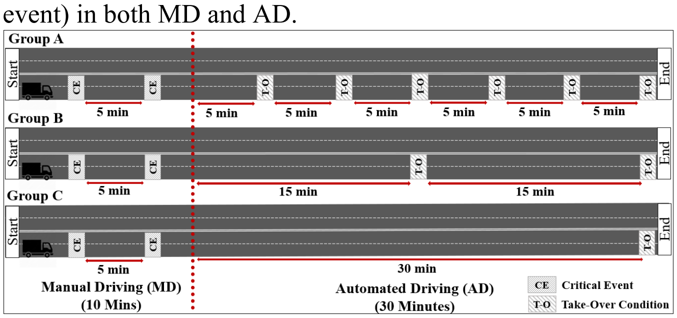


Fig. 1. The illustration of the designed experiment's sections.

D. Detecting Driving Styles

When dealing with driving data, single time series are logged in parallel with other variables, leading to multivariate time series, and the clustering of one variable does not lead to sufficient results. Hence, a multivariate time series clustering approach is required. In this study, a Multivariate Dynamic Time Warping (MDTW) followed by k-means clustering is applied to classify driving style before LC to bypass a critical event in continuous MD or after take-over.

Generally, three major approaches are applied to classify time series data, feature-based, model-based, and raw-data-based [33]. Dynamic Time Warping (DTW) drops between raw-data-based approaches, and unlike feature-based and model-based methods, it does not dependent on experts' influences and assumptions. DTW can directly deal with time series of different lengths and is not sensitive to distortion along the time axis. DTW compares the i^{th} point of time series A with the j^{th} point of time series B, resulting in a distance matrix from which the optimal warping path can be calculated. In the following sections, Univariate DTW followed by the extended formulation for Multivariate DTW will be discussed briefly.

1) Univariate DTW

Considering two time-series X and Y of length n and m ($X = x_1, x_2, \dots, x_n$) and $Y = (y_1, y_2, \dots, y_m)$). A matrix grid of n by m is constructed, where the matrix element (i, j) denotes the distance $d(x_i, y_j)$ between two points x_i and y_j. In this matrix, every element (i, j) corresponds to the alignment between the points x_i and y_j. To obtain the optimal alignment of the two univariate time series (UTS), a warping path W as a set of k matrix elements $w_k = (i, j)_k$ is created as:

$$W = w_1, w_2, \dots, w_k \; (\max(\mathrm{m}, \mathrm{n}) \leq \mathrm{K} < \mathrm{m} + \mathrm{n} - 1) \tag{1}$$

To achieve the optimal alignment, the warping costs must be minimized in terms of number and magnitude of elements w_k:

$$DTW(X, Y) = min\{\textstyle\sum_{k=1}^{K} w_k\} \tag{2}$$

This warping path can be found using a dynamic programming approach in which the cumulative distance $r(i, j)$ is defined as the sum of the distance $d(x_i, y_j)$ of the current cell and the minimum of the cumulative distances in adjacent cells:

$$r(i, j) = d(x_i, y_j) + \min\{r(i-1, j-1), r(i-1, j), r(i, j-1)\} \tag{3}$$

2) Multivariate DTW

Considering two Multivariate Time Series (MTS) X (with v variables and n discrete time steps) and Y (wit v variables and m discrete time steps) as follow,

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1l} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ x_{i1} & \cdots & x_{il} & \cdots & x_{in} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ x_{v1} & \cdots & x_{vl} & \cdots & x_{vn} \end{pmatrix} \text{and } Y = \begin{pmatrix} y_{11} & \cdots & y_{1l} & \cdots & y_{1m} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ y_{j1} & \cdots & y_{jl} & \cdots & y_{jm} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ y_{v1} & \cdots & y_{vl} & \cdots & y_{vm} \end{pmatrix} \tag{4}$$

The distance measure $D(X, Y)$ calculates the accumulated distance between the two MTS over $x_{il}$and y_{jl} and therefore, quantifies the (dis-)similarity. Different approaches are introduced in the literature to calculate $D(X, Y)$. Based on the method of calculating $D(X, Y)$, MDTW can be divided into two categories, Independent DTW and Dependent DTW.

Independent DTW (IDTW): the model assumes that variables are not correlated. Hence, each dimension l is warped independently using a univariate distance measure $d(x_{il}, y_{jl})$ and the warping costs on all dimensions are summed. The different dimensions can be weighted using the factor c_j [37].

$$IDTW(X, Y) = \textstyle\sum_{l=1}^{v} c_j \, DTW(x_l, y_l), with \; d(x_{il}, y_{jl}) \tag{5}$$

Dependent DTW (DDTW): MTS are treated as single series with v-dimensional vectors. In this case, only a single warping is conducted. This warping requires a cost function, $\delta(x_i, y_j)$, that can compare vectors of values. Therefore:

$$DDTW(X, Y) = DTW(x_l, y_l), with \; \delta(x_i, y_j) \tag{6}$$

$$\delta(x_i, y_j) = \left(\textstyle\sum_{l=1}^{v} c_l \left|x_{il} - y_{jl}\right|^p\right)^{\frac{1}{p}} \tag{7}$$

In (7), the cost function $\delta(x_i, y_j)$ is extended by a weighting factor c_l to adjust the interrelations of the variables. For $p = 2$

and $c_l = 1$, (7) becomes the Euclidean distance, which is incorporated in this study.

3) K-means clustering

After calculating the (dis)similarity between each pair of driving behavior collected after critical events/take-overs, *k*-means clustering is applied to divide the driver behavior into different clusters. The *k*-means clustering is a type of unsupervised learning method, which classifies the samples into several patterns and aims to partition the samples into k clusters in which each sample belongs to the clusters with the nearest mean. MDTW with *k*-means clustering is a novel method for partitional time-series clustering [38]. This method uses MDTW distance to measure the distance between temporal sequences to generate *k* clusters with homogeneous sequence profiles in each cluster [39]. From the perspective of driving style classification, each cluster represents a driving style. In *k*-means clustering, the number of clusters (k) is usually selected based on either the subjective judgment of the researcher or clustering quality measures [32]. In this study, the number of clusters is calculated based on clustering performance which is measured by the Silhouette score [40]. Silhouette score indicates the number of clusters by minimizing intra-cluster distance and maximizing within-cluster distance to achieve a trade-off. Silhouette score (SS) can be obtained as:

$$SS = \frac{D_w - D_i}{\max(D_w, D_i)} \quad (8)$$

Where D_i is the average distance between a sample and the host cluster center it belongs to, and D_w refers to the average distance between a sample and the nearest neighboring cluster center. The best value of the Silhouette score is 1 and values near 0 indicate overlapping clusters.

E. Modeling Driving Styles

To gain a better understanding of the driving classes detected by the MDTW, predictor models are developed to indicate the effectiveness of different parameters on the driving behavior indices of drivers in each class. Hence, max speed, mean speed, min speed, max heading error, max deceleration, mean acceleration, following distance at LC moment are considered as the response variables, to be predicted by the duration of automated operation, drivers' characteristics, and traffic/environmental condition. All independent variables are coded as categorical variables and are presented in Table I. In this study, GLM is incorporated to develop predictor models. GLMs can tackle a wider range of data with different types of response variables. A GLM is defined by specifying two components, the response, and the link function. The response should be a member of the exponential family distribution and the link function describes how the mean of the response and a linear combination of the predictors are related [41]. GLMs have a common algorithm for the estimation of parameters by maximum likelihood, which uses weighted least squares with an adjusted dependent variate and does not require preliminary guesses to be made of the parameters' values [42].

TABLE I
THE LIST OF INDEPENDENT VARIABLES FOR MODELING DRIVING STYLES

Independent variables	Categories	Description
Duration of AD	4	0=MD, 1= 5 minutes, 2= 10 minutes, and 3=30 minutes
Gender	2	0=female and 1= male
Age	4	1=less than 30, 2= between 30 to 40, 3= between 30 to 50, and 4= more than 50
Education	3	high school diploma or less, 2= college degree or associate degree, 3= bachelor's or higher professional degree
Driving experience	5	1= less than 5 years, 2= between 5 to 10, 3= between 10 to 15, 4= between 15 to 20, and 5= more than 20.
Number of crashes	2	0= no crash and 1= having car crashes in driving history
Number of tickets	2	0= no ticket and 1= receiving tickets in the past two years in driving history
Annual mileage	4	1= 15,000 to 20,000 km, 2=20,000 to 25,000 km, 3= 25,000 to 30,000 km, and 4= > 30,000 km.
Lane[1]	2	0=right and 1=Left
Headway[1]	3	1= less than 5 seconds, 2= less than 10 seconds, and 3= more than 10 seconds
Speed[1]	3	1=less than 30 m/s, less than 35 m/s, and 3= more than 35 m/s

[1] At the transition moment in AD and 10 seconds before critical events in MD

III. RESULTS

For each participant, driving behavior before LC in both MD and take-over conditions is collected, creating a data set of 225 time-series observations. Before running the MDTW, some data preparation is needed. First, since working with a large number of features is computationally expensive and the data generally has a small intrinsic dimension, dimensionality reduction is needed. Dimensionality reduction techniques can tremendously reduce the time complexity of machine learning techniques and make the interpretation of the results easier [33]. Principal Component Analysis (PCA) is adopted to select the best feature for clustering. PCA is a statistical method to reduce the dimensionality of the data by assuming that data with large variation is important, and it tries to identify a unit vector (first principal component) that minimizes the average squared distance from the points to the line. Among driving behavior indices, three indices with the largest variation are selected to be the input component of MDTW. The result of applying PCA showed that longitudinal acceleration, longitudinal speed, and heading error had the largest variation. After selecting appropriate features, each dimension is normalized to zero mean and unit variance, using the z-score normalization method, to render all dimensions comparable. Then the warping distance between each pair of data sets was calculated by using (7). After that, *k*-means clustering is applied to assign labels to the driving behavior while the appropriate number of clusters is selected using the Silhouette score. The results showed that clustering the driving style into three classes represents the drivers driving style classes better. The result of evaluating the appropriate number of clusters is presented in Fig. 2.

A. Analyzing Detected Driving Styles

Driving behavior before LC in both MD and AD is clustered into three categories. Three clusters are named "conservative", "normal", and "risky", due to the driving behavior indices, driving profiles, and inspired by [43]. To provide a better view

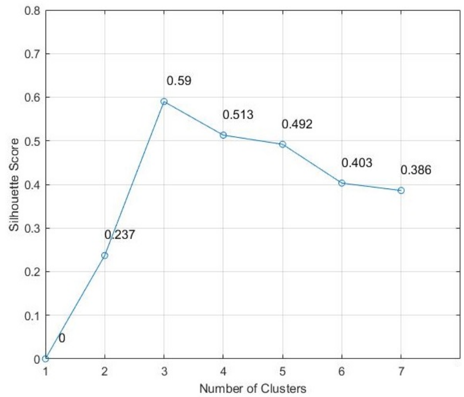


Fig. 2. Evaluating the number of clusters using the Silhouette Score.

of detected clusters, the mean of driving behavior indices of each driving style is tabulated in Table II, and drivers' acceleration, heading error, and speed profiles are presented for each driving style in Fig. 3. Where the average of driving indices at each moment is indicated by a red line.

Drivers with a normal driving style completed the LC quickly and preferred to encounter the critical event by performing an LC instead of applying hard brakes and reducing the speed. They all completed the LC in less than 13 seconds, and the average time needed was 10.06 seconds. This group showed max deceleration of -3.568 (m/s^2), and mean deceleration in this group was -0.713 (m/s^2). The speed reduction mostly happened in the first 5 seconds, and the variation of speed in this cluster was small. This driving style showed max speed of 31.18 (m/s), min speed of 26.97 (m/s), and an average speed of 29.20 (m/s). As Fig. 3 shows, drivers with a normal driving style had a small variation in their heading error which shows that the LC is performed smoothly. The max heading error on average in this group was 0.054 (rad), and the mean heading error was 0.0093 (rad) in their driving behavior before the LC.

TABLE II
THE AVERAGE OF DRIVING BEHAVIOR INDICES FOR EACH DRIVING STYLES

Driving behavior indices	Normal driving	Conservative driving	Risky driving
Time needed for LC (s)	10.06	12.10	23.52
Mean speed (m/s)	29.20	28.55	19.46
Min speed (m/s)	26.97	20.03	7.26
Max speed (m/s)	31.18	32.28	31.15
Min following distance (m)	61.24	58.2	42.30
Mean heading error (rad)	0.0093	0.0105	0.0146
Max heading error (rad)	0.0541	0.0695	0.1421
Max deceleration (m/s^2)	-3.568	-4.899	-7.029
Mean deceleration (m/s^2)	-0.713	-1.202	-2.177
Mean acceleration (m/s^2)	0.3514	0.4921	0.8895

Drivers with a conservative driving style needed more time to complete the LC compared to the normal driving style. On average, the LC is completed in 12.10 seconds in this style. Drivers tend to press the brake paddle more, and they preferred to change their lane with a lower speed. On average, drivers with conservative driving styles showed 28.55 (m/s) speed in their LC behavior. The average max and min speed in this class were 32.28 (m/s) and 20.03 (m/s) respectively. As Fig. 3 shows, the speed in this group is higher, and drivers applied more brakes (sudden changes in deceleration). The average of max deceleration in groups shows that harder brakes are taken, where on average the max deceleration was -4.899 (m/s^2). The variation of the heading error is larger in this group compared to the normal driving style. The average heading error was 0.0105 (rad) and the average max heading error was 0.0695 (rad). The mean of acceleration and deceleration in this group are increased compared to the normal driving style. The mean of deceleration and acceleration were -1.202 (m/s^2) and 0.4921 (m/s^2) respectively.

Finally, in the risky driving style, the LC is completed in

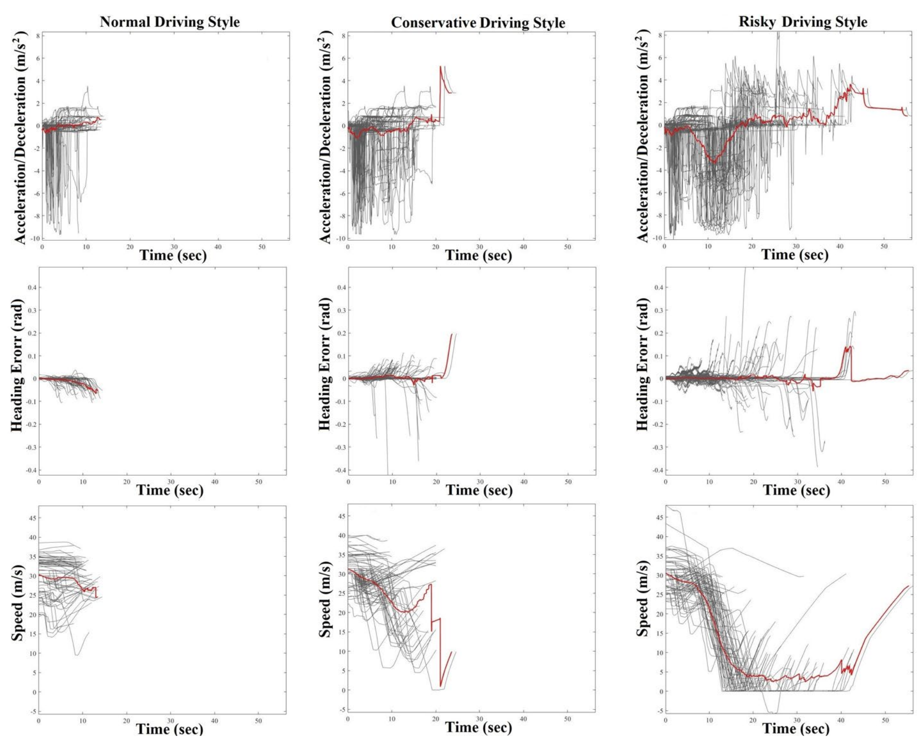


Fig. 3. The profile of Acceleration/deceleration, heading error, and speed for three detected driving styles.

23.52 seconds on average. Generally, most drivers in this group had a complete stop before the LC, harder brakes were taken, and drivers preferred to control the vehicle by taking the brake pedal and reducing the speed. The min speed and the max deceleration in this group are changed significantly compared with other classes. The min speed in this group was 7.26 (m/s) on average, and the max deceleration was -7.029 (m/s^2) on average. The variation of heading error is significantly larger than other driving styles. On average, the mean heading error was 0.0146 (rad), and the max heading error in this driving style was 0.1421 (rad). This driving style contains a higher acceleration rate since the mean acceleration on average was 0.8895 (m/s^2), which shows that drivers wanted to change their lane quickly after the complete stop.

Analyzing the detected styles showed that the frequency of conservative and conservation driving styles was more in AD (after take-over condition), whereas normal driving styles were observed more in MD. As presented in Fig. 4 with the distribution of three driving styles between MD and AD, the most observed driving style in take-over conditions is the conservative driving style.

The frequency of each driving style is provided in Fig. 5 for different AD duration and different numbers of take-overs. As Fig. 5 (a) shows, when the duration of AD increases, the drivers tend to follow the risky driving style. Fig. 5 (b) shows that in the repeated take-overs scenario, drivers tend to follow the conservative driving style more. Therefore, having the first experience of a take-over condition, drivers are likely to bypass the critical event cautiously and are more conservative about their driving behavior.

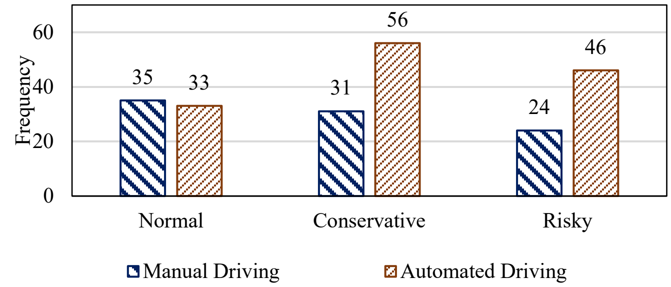
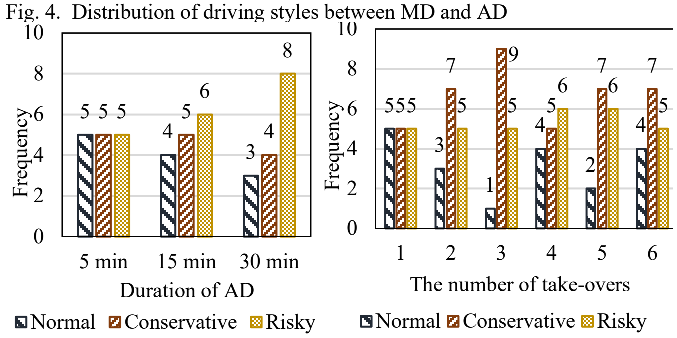


Fig. 4. Distribution of driving styles between MD and AD

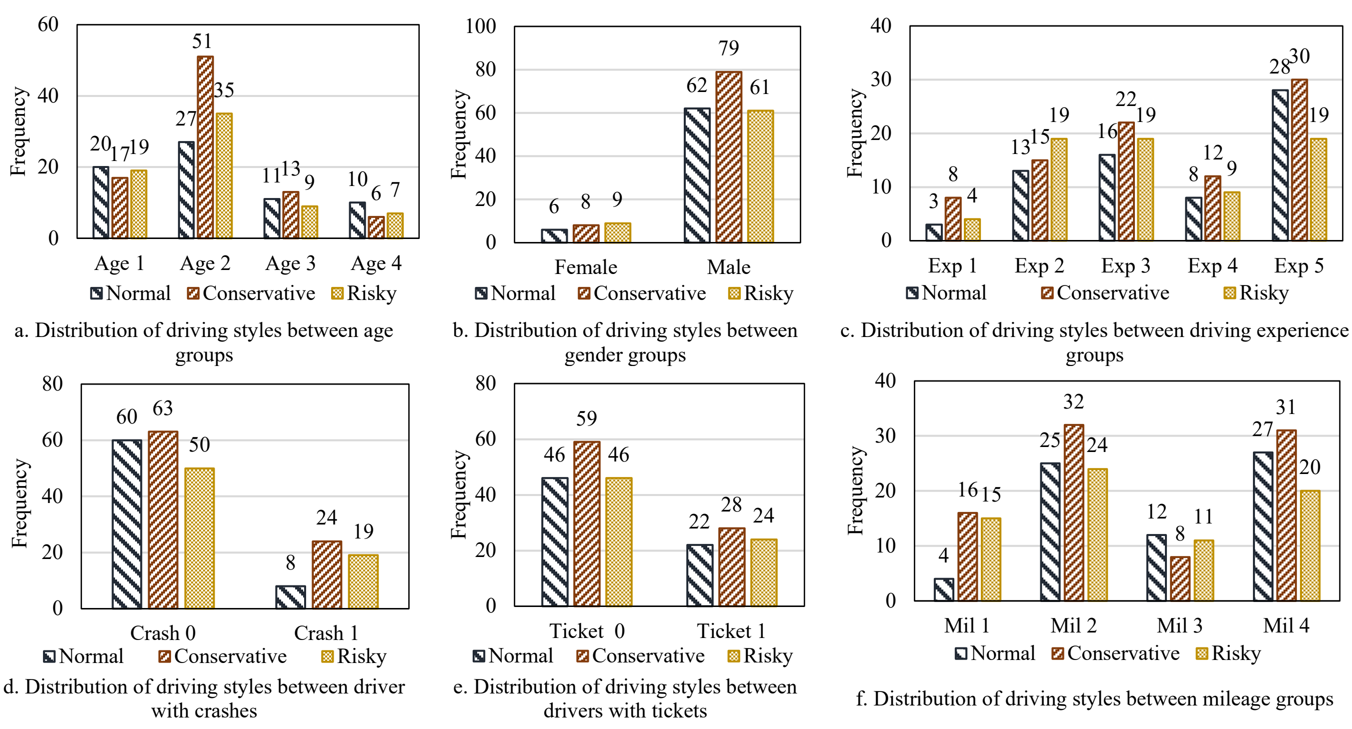


a. Distribution of driving styles between ADs with different durations

b. Distribution of driving styles between ADs with different numbers of take-overs

Fig. 5. Analyzing the effect of AD length and repeated take-over on the frequency of driving styles

In addition to analyzing the effect of AD conditions, the effect of drivers' characteristics is assessed. Fig. 6 shows the distribution of driving style based on drivers' (a) age, (b) gender, (c) driving experience, (d) tickets, (e) crashes, and (f) annual mileage. In a general view, the conservative driving style has the highest frequency in all categories.



a. Distribution of driving styles between age groups

b. Distribution of driving styles between gender groups

c. Distribution of driving styles between driving experience groups

d. Distribution of driving styles between driver with crashes

e. Distribution of driving styles between drivers with tickets

f. Distribution of driving styles between mileage groups

Fig. 6. Distribution of driving styles between driver's characteristics

B. *Modeling Driving Style Results*

The results of modeling driving behavior indices in each driving style are presented here to provide a better behavioral understanding of effective parameters in each driving style. GLM is incorporated to model the driving behavior indices based on the independent variables listed in Table I. Predictor models were developed for max, min, and mean speed, max and mean of heading error, max deceleration, max and mean acceleration, and following distance at LC moment (for brevity FD). Among these dependent variables, the modeling results are only provided for the models with the goodness of fit (R^2) of greater than 0.66. Since R^2 greater than 0.66 is defined as substantial fitting accuracy [44]. The modeling results for four driving behavior indices, mean speed, max speed, max deceleration, and FD are provided in Table III.

In the normal driving style, an increment in the duration of AD leads to a slower speed, higher max deceleration, and shorter FD. Generally, compared to MD, regaining vehicle control after an AD section would reduce the average speed and max speed in a normal driving style. Male drivers had more tendency to show lower speed and longer FD. Max speed, max deceleration, and FD are affected by the driver's age where older drivers had lower max speed and higher max deceleration, and shorter FD. Drivers with more driving experience had longer FD and lower average speed. Having crashes in driving history leads to higher max speed, higher max deceleration, and shorter FD. As Table III shows, the occurrence of the critical event in the left lane would increase the average speed and reduce the FD. In the normal driving style, an increment in the headway (at the take-over moment in AD or 10 seconds before critical events in MD) increases the mean speed, max speed, FD, and deceleration.

In the conservative driving style, the mean speed is affected by drivers' gender, driving experience, the lane the vehicle is

TABLE III
THE RESULTS OF GLM FOR DRIVING BEHAVIOR INDICES IN DETECTED DRIVING STYLES BEFORE LC, COEFFICIENT (T-VALUE)

	Log (mean speed)			Log (max speed)			Log (max deceleration)			Log (FD at LC moment)		
Driving style	Normal	Cons.*	Risky	Normal	Cons.*	Risky	Normal	Cons.*	Risky	Normal	Cons.*	Risky
5 minutes of AD			0.142			0.73			1.018	-0.565	-0.815	
			(1.16)			(1.161)			(1.25)	(-1.67)	(-1.45)	
15 minutes of AD					1.821			1.281	1.124	-0.419	-0.484	
					(1.594)			(1.25)	(1.43)	(-1.18)	(-1.08)	
30 minutes of AD				-1.868	1.334		6.420	4.623	1.749	-0.604	-1.057	-0.841
				(-1.49)	(1.464)		(6.79)	(4.63)	(2.01)	(-1.67)	(-1.79)	(-1.36)
Male	0.347	0.347			-2.745	-0.37		-2.921	2.068	-1.079		
	(1.62)	(1.62)			(-1.602)	(-1.306)		(-1.87)	(1.49)	(-2.37)		
Age 30-40				-2.656	-1.408			-2.161		-0.856		
				(-1.87)	(-1.182)			(-1.98)		(-1.26)		
Age 40-50				-6.627	-3.183		2.317	-1.975				
				(-2.26)	(-1.862)		(1.20)	(-1.26)				
Age >50				-6.849	-4.617		3.003					2.872
				(-2.01)	(-1.988)		(1.18)					(1.22)
Driving Exp.5-10 years					-2.762			2.432				
					(-1.65)			(1.58)				
Driving Exp. 10-15 years	-0.098	-0.098			-2.920				1.929	1.086		
	(-1.78)	(-1.78)			(-1.88)				(1.24)	(1.14)		
Driving Exp. 15-20 years								3.146	4.068	1.197		
								(2.18)	(2.79)	(1.13)		
Driving Exp. >20 years				2.215				1.858	4.729	1.293		
				(1.06)				(1.26)	(2.47)	(1.17)		
Crashes = 1				5.530			1.252	1.341		-0.509		
				(2.03)			(1.751)	(1.80)		(-1.11)		
Tickets = 1			0.224			0.140		2.221			-0.800	
			(1.91)			(2.49)		(2.45)			(-1.65)	
Annual mileage 20,000-25,000			-0.206					1.298				
			(-1.39)					(1.17)				
Annual mileage 25,000-30,000			-0.305	-4.661								
			(-1.55)	(-2.56)								
Annual mileage > 30,000			-0.211									
			(-1.19)									
Left lane	0.122	0.122	0.220		1.347	0.084		1.527		-1.415	-0.729	-0.715
	(2.02)	(2.02)	(2.05)		(1.48)	(2.58)		(1.74)		(-2.34)	(-1.55)	(-1.05)
Speed between 30-35 m/s				2.653	1.596	0.246		0.947	0.782		-0.661	
				(2.48)	(1.67)	(5.31)		(1.08)	(1.11)		(-1.48)	
Speed >35 m/s	0.285	0.285		8.357	6.950				-1.571	0.975	-0.841	
	(3.31)	(3.31)		(5.46)	(5.09)				(-1.57)	(2.04)	(-1.25)	
Headway 5-10 seconds	0.073	0.073		2.200	2.052	0.086	-1.470	-2.064	-2.012	1.182	1.431	
	(1.16)	(1.16)		(1.14)	(1.76)	(2.75)	(-1.526)	(-1.97)	(-1.36)	(4.36)	(3.86)	
Headway 10-15 seconds	0.154	0.154	0.560	1.886	1.400	0.069				2.834	2.695	1.411
	(1.88)	(1.88)	(3.94)	(1.81)	(1.39)	(2.31)				(3.79)	(2.58)	(2.15)
Headway >15 seconds			0.912					-1.01				1.52
			(2.18)					-(1.28)				(2.31)
R-squared	0.696	0.696	0.676	0.825	0.747	0.825	0.834	0.723	0.683	0.845	0.858	0.769

*Note: Cons. is the abbreviation for Conservative driving on, the vehicle's speed, and headway. The effects of the duration of AD, driver's age, gender, and driving experience are significant in modeling the max speed. The increment in the duration of AD increases the max speed. Male drivers as well as the older and more experienced ones will have lower max speed. Results showed that 30 minutes of AD would cause a lower max deceleration in a conservative driving style. Males and 30 to 50 years old drivers will have lower max deceleration. The coefficients of having crashes and receiving tickets cause higher max deceleration. In addition, driving in the left lane and having a speed of more than 35 (m/s) increase the max deceleration in this driving style. Finally, results of modeling FD in a conservative driving style showed that the following distance at the take-over moment and the duration of AD would reduce the FD. Also, receiving tickets, driving in the left lane, and having a speed between 30-35 (m/s) and more than 35 (m/s) before take-over reduces the FD, and the higher the headway at the transition moment the longer FD.

In a risky driving style, the lane, vehicle speed, and headway are more significant compared to drivers' characteristics. The duration of AD increases the mean speed, max speed, and max deceleration. This driving style shows higher max deceleration and shorter FD in AD. The coefficients of the driver's gender are significant in modeling max speed and max deceleration. The coefficients of the driver's driving experience are significant in modeling max deceleration. Drivers with traffic tickets in their driving history had lower max speed. Driving in the left lane before the critical event increases the mean and max speed and reduces the FD before LC. The coefficient of speed categories is significant in modeling max speed and max deceleration. Finally, headway greater than 10 seconds increases the mean speed, max speed, and the FD in this class of driving style.

IV. Discussion

The purpose of this research was to assess the effect of take-over conditions on CMV drivers' driving styles in an LC scenario in highly automated vehicles. Drivers driving behavior in the form of time series data were evaluated in two driving modes (MD and AD) using Multivariate Dynamic Time Warping (MDTW) followed by *k*-means clustering. MDTW is a time-series comparison method that measures the (dis)similarity between two temporal sequences with different lengths [38]. Furthermore, GLMs were developed for driving behavior indices (mean speed, max speed, max deceleration, and following distance) to investigate the effects of duration of AD, drivers' characteristics (i.e., gender, age, education, and driving history), and traffic/environmental conditions.

The transition from AD to MD inherently affects drivers' behavior and forcing drivers to change their lane would intensify the effect of this transition, as [45] showed that the complexity of the condition during the transition can directly reduce driving quality. Results showed that in an LC scenario, the driving style would change in take-over conditions compared to continuous MD such that conservative and risky driving styles, which contain more speed reduction, harder brakes (intensive deceleration), longer time needed for LC, and unsafe turns were observed more. A part of these changes can be attributed to drivers expecting a critical event to happen in take-over conditions. A sign of this effect was observed in the repeated take-over scenario, where the conservative driving style was observed more after the first take-over. Drivers' tendency to reduce speed after transition emphasizes the importance of braking systems in HAVs, and the presence of a brake assistance system can improve the safety of the HAVs in the transition from AD to MD.

In terms of assessing the effect of automated operation duration before take-over, the findings of this research are in line with the results of [17] who showed that a long AD phase significantly affects driving behavior. A source of these changes could be drivers' fatigue, drowsiness, and decrement in the level of consciousness [46]. Even though the sample size was small in this study, the increment in the observation of risky driving styles after 30 minutes of AD was notable.

Results of developing GLM showed that among all independent variables, 30 minutes of AD, crashes, tickets in the driving history, and occurrence of the critical event in the left lane deteriorate driving behavior in all detected driving styles. More importantly, headway with the lead vehicle at the transition moment in AD or corresponding moment in MD (10 seconds before critical events) showed significant effects on LC. Since it is envisioned that proper automated vehicle control could shorten the headway to a fraction of its current value, assessing the effect of different headway at transition moments on post-take-over driving behavior becomes crucial; however, limited studies addressed this problem. Recently, [47] showed that commercial vehicles with adaptive cruise control became more unstable as the headway was set to a smaller value, and the probability of risky driving behavior increases significantly in shorter headway. To provide a better insight into the effect of headway at take-over conditions, pseudo-elasticity is calculated for dependent variables. Results show that drivers' behavior before LC improves in all three driving styles when the headway at the transition moment increases. As Fig. 7 shows, headway 5-10 seconds reduces the max deceleration by 20% and increases FD by 60%. Results emphasize that drivers' post-take-over behavior will deteriorate significantly in small headway at the transition moment. The importance of headway is not neglected as the headway in the introduced automated vehicles (level 2 and level 3) are comparable to or even longer than human-driving vehicles, and automotive companies are aware of the risk involved in headway distance [47]. Hence, to deal with this factor in highly automated vehicles, more research and effective policies are needed in this field.

V. Conclusion

The current study addressed changes in the lane-changing driving styles of Commercial Motor Vehicle (CMV) drivers subject to the take-over condition compared to manual driving and assessed the effect of the long-automated operation, repeated take-overs, and driver characteristics. Three clusters of driving styles, normal, conservative, and risky, were detected using Multivariate Dynamic Time Warping followed by *k*-means clustering. In normal driving styles, drivers completed

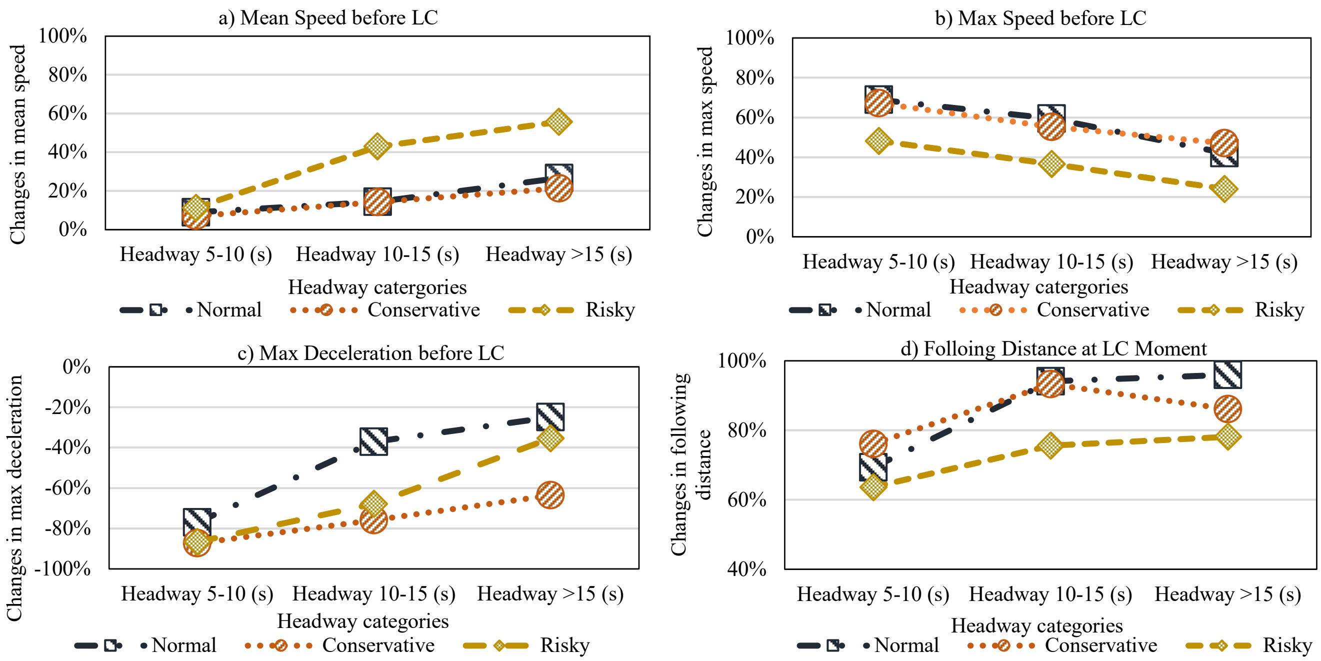


Fig. 7. Changes in mean speed, max speed, max deceleration, and FD based on changes in the headway

the lane changing quickly and the variation in speed and heading error were small. Fewer brakes were taken, and drivers preferred to change their lane first instead of controlling the vehicle by taking brakes. Normal driving style was more common in manual driving conditions. In the conservative driving style, the variation of speed and heading error was more than normal behavior. Drivers needed more time to complete the lane changing. This style was a combination of controlling the vehicle by the steering wheel and using the brake pedal. Conservative driving style was the most observed driving style in take-over conditions and was more frequent in repeated take-over scenarios. Finally, the r driving style contained intense speed reduction and hard brakes. A high deceleration rate was observed in this driving style and drivers mostly had complete stops before lane changing. The variation of heading error was significantly higher than other detected driving styles. This driving style was mostly observed in take-over conditions with long-automated operation duration. Moreover, developing GLM on driving behavior indices for each driving style showed that long-automated operation, the occurrence of critical events in the left lane, bad driving history (tickets and car crashes), and short headway at the transition moment will deteriorate the performance of drivers in all detected driving styles.

A. Limitation and Future Works

Some limitations of the present study should be acknowledged. First, because the experiment was conducted using a driving simulator, it is difficult to determine if the same results would be shown in a real vehicle. Moreover, the simulator used in this study is a low fidelity driving simulator with limitations in simulating the real world. For instance, although RDS-500 uses robust software, users cannot sense the speed at higher speeds. To overcome this problem, we asked our participants to constantly check their speed with the speedometer, but this problem might have affected the results.

Second, in the designed scenario for the repeated take-overs, the high frequency and the short interval between take-over conditions might have affected the results in this section. It is suggested that future studies consider longer time intervals.

Third, the present study tried to rule out the effect of non-driving related tasks or any distraction. However, since the experiment was not conducted in an isolated environment, participants may have been distracted in some cases and this could have affected the results and the data. This study did not consider the effect of engaging in non-driving related tasks during the automated operation.

In addition, the driver's gender was considered an effective parameter in this study and showed significant coefficients in some behavioral models. However, since only five females participated in this study, concluding from the results of this paper on the effect of gender on driving styles might involve errors. Hence, we suggest conducting more research on the effect of driver's gender on driving styles in take-over conditions.

This study only considered drivers driving styles in a lane-changing scenario, which is one of the hot spots in transportation safety studies. However, to achieve a comprehensive understanding of the effect of take-over conditions on driving styles, future studies can assess other scenarios, like, platooning, lead vehicles, collision hazards, and different traffic and weather conditions.

The current study did not consider the effect of engaging in non-driving-related tasks on driving styles after the take-over condition. Future studies can consider the effect of this important variable, especially in long automated operation conditions. Evaluating the effect of driving under time pressure on post-take-over driving behavior and driving styles is another avenue for future studies.

REFERENCES

[1] O.-R. A. V. S. SAE., "Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles," *SAE*, 2018.

[2] J. R. Simpson, S. Mishra, A. Talebian, and M. M. Golias, "An estimation of the future adoption rate of autonomous trucks by freight organizations," *Research in Transportation Economics*, vol. 76, p. 100737, 2019.

[3] D. Thapa, V. Gabrhel, and S. Mishra, "What are the factors determining user intentions to use AV while impaired?," *Transportation research part F: traffic psychology and behaviour*, vol. 82, pp. 238–255, 2021.

[4] M. Osman, S. Mishra, and R. Paleti, "Injury severity analysis of commercially-licensed drivers in single-vehicle crashes: Accounting for unobserved heterogeneity and age group differences," *Accident Analysis & Prevention*, vol. 118, pp. 289–300, 2018.

[5] C. Gold, R. Happee, and K. Bengler, "Modeling take-over performance in level 3 conditionally automated vehicles," *Accident Analysis & Prevention*, vol. 116, pp. 3–13, 2018.

[6] B. Zhang, J. de Winter, S. Varotto, R. Happee, and M. Martens, "Determinants of take-over time from automated driving: A meta-analysis of 129 studies," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 64, pp. 285–307, Jul. 2019, doi: 10.1016/j.trf.2019.04.020.

[7] D. D. Heikoop, J. C. de Winter, B. van Arem, and N. A. Stanton, "Effects of mental demands on situation awareness during platooning: A driving simulator study," *Transportation research part F: traffic psychology and behaviour*, vol. 58, pp. 193–209, 2018.

[8] S. M. Mousavi, O. A. Osman, D. Lord, K. K. Dixon, and B. Dadashova, "Investigating the safety and operational benefits of mixed traffic environments with different automated vehicle market penetration rates in the proximity of a driveway on an urban arterial," *Accident Analysis & Prevention*, vol. 152, p. 105982, 2021.

[9] N. Merat and A. H. Jamson, "How do drivers behave in a highly automated car?," 2009.

[10] J. C. De Winter, R. Happee, M. H. Martens, and N. A. Stanton, "Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence," *Transportation research part F: traffic psychology and behaviour*, vol. 27, pp. 196–217, 2014.

[11] K. Funkhouser and F. Drews, "Reaction times when switching from autonomous to manual driving control: A pilot investigation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2016, vol. 60, no. 1, pp. 1854–1858.

[12] W. Payre, J. Cestac, and P. Delhomme, "Fully automated driving: Impact of trust and practice on manual control recovery," *Human factors*, vol. 58, no. 2, pp. 229–241, 2016.

[13] J. Kim, H.-S. Kim, W. Kim, and D. Yoon, "Take-over performance analysis depending on the drivers' non-driving secondary tasks in automated vehicles," 2018, pp. 1364–1366.

[14] K. Mahajan, D. R. Large, G. Burnett, and N. R. Velaga, "Exploring the benefits of conversing with a digital voice assistant during automated driving: A parametric duration model of takeover time," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 80, pp. 104–126, 2021.

[15] F. Naujoks, S. Höfling, C. Purucker, and K. Zeeb, "From partial and high automation to manual driving: relationship between non-driving related tasks, drowsiness and take-over performance," *Accident Analysis & Prevention*, vol. 121, pp. 28–42, 2018.

[16] O. Jarosch and K. Bengler, "Is It the Duration of the Ride or the Non-driving Related Task? What Affects Take-Over Performance in Conditional Automated Driving?," in *Congress of the International Ergonomics Association*, 2018, pp. 512–523.

[17] A. Bourrelly, C. J. de Naurois, A. Zran, F. Rampillon, J.-L. Vercher, and C. Bourdin, "Long automated driving phase affects take-over performance," *IET Intelligent Transport Systems*, vol. 13, no. 8, pp. 1249–1255, 2019.

[18] A. R. Samani, S. Mishra, and K. Dey, "Assessing the effect of long-automated driving operation, repeated take-over requests, and driver's characteristics on commercial motor vehicle drivers' driving behavior and reaction time in highly automated vehicles," *Transportation research part F: traffic psychology and behaviour*, vol. 84, pp. 239–261, 2022.

[19] A. Feldhütter, C. Gold, S. Schneider, and K. Bengler, "How the duration of automated driving influences take-over performance and gaze behavior," in *Advances in ergonomic design of systems, products and processes*, Springer, 2017, pp. 309–318.

[20] L. Pipkorn, T. Victor, M. Dozza, and E. Tivesten, "Automation Aftereffects: The Influence of Automation Duration, Test Track and Timings," *IEEE Transactions on Intelligent Transportation Systems*, 2021.

[21] S. Brandenburg and F. Roche, "Behavioral changes to repeated takeovers in automated driving: The drivers' ability to transfer knowledge and the effects of takeover request process," *Transportation research part F: traffic psychology and behaviour*, vol. 73, pp. 15–28, 2020.

[22] F. Roche, A. Somieski, and S. Brandenburg, "Behavioral changes to repeated takeovers in highly automated driving: effects of the takeover-request design and the nondriving-related task modality," *Human factors*, vol. 61, no. 5, pp. 839–849, 2019.

[23] C. Kreuzmair, C. Gold, and M.-L. Meyer, "The influence of driver fatigue on take-over performance in highly automated vehicles," in *25th International Technical Conference on the Enhanced Safety of Vehicles (ESV) National Highway Traffic Safety Administration*, 2017, pp. 1–7.

[24] Y. Forster, S. Hergeth, F. Naujoks, M. Beggiato, J. F. Krems, and A. Keinath, "Learning to use automation: Behavioral changes in interaction with automated driving systems," *Transportation research part F: traffic psychology and behaviour*, vol. 62, pp. 599–614, 2019.

[25] S. Li, P. Blythe, W. Guo, and A. Namdeo, "Investigation of older driver's takeover performance in highly automated vehicles in adverse weather conditions," *IET*

Intelligent Transport Systems, vol. 12, no. 9, pp. 1157–1165, 2018.
[26] H. Clark and J. Feng, “Age differences in the takeover of vehicle control and engagement in non-driving-related activities in simulated driving with conditional automation,” *Accident Analysis & Prevention*, vol. 106, pp. 468–479, 2017.
[27] L. Yang, R. Ma, H. M. Zhang, W. Guan, and S. Jiang, “Driving behavior recognition using EEG data from a simulated car-following experiment,” *Accident Analysis & Prevention*, vol. 116, pp. 30–40, 2018.
[28] Y. Ma, Z. Li, Y. Li, H. Li, and R. Malekian, “Driving style estimation by fusing multiple driving behaviors: a case study of freeway in China,” *Cluster Computing*, vol. 22, no. 4, pp. 8259–8269, 2019.
[29] Y. Liang and J. D. Lee, “A hybrid Bayesian Network approach to detect driver cognitive distraction,” *Transportation research part C: emerging technologies*, vol. 38, pp. 146–155, 2014.
[30] W. Wang, J. Xi, A. Chong, and L. Li, “Driving style classification using a semisupervised support vector machine,” *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 5, pp. 650–660, 2017.
[31] M. M. Bejani and M. Ghatee, “A context aware system for driving style evaluation by an ensemble learning on smartphone sensors data,” *Transportation Research Part C: Emerging Technologies*, vol. 89, pp. 303–320, 2018.
[32] A. Mohammadnazar, R. Arvin, and A. J. Khattak, “Classifying travelers’ driving style using basic safety messages generated by connected vehicles: application of unsupervised machine learning,” *Transportation research part C: emerging technologies*, vol. 122, p. 102917, 2021.
[33] U. Moser and D. Schramm, “Multivariate dynamic time warping in automotive applications: A review,” *Intelligent Data Analysis*, vol. 23, no. 3, pp. 535–553, 2019.
[34] A. Talebian and S. Mishra, “Unfolding the state of the adoption of connected autonomous trucks by the commercial fleet owner industry,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 158, p. 102616, 2022.
[35] A. D. McDonald *et al.*, “Toward computational simulations of behavior during automated driving takeovers: a review of the empirical and modeling literatures,” *Human factors*, vol. 61, no. 4, pp. 642–688, 2019.
[36] D. Thapa, R. Paleti, and S. Mishra, “Overcoming challenges in crash prediction modeling using discretized duration approach: An investigation of sampling approaches,” *Accident Analysis & Prevention*, vol. 169, p. 106639, 2022.
[37] M. Shokoohi-Yekta, J. Wang, and E. Keogh, “On the non-trivial generalization of dynamic time warping to the multi-dimensional case,” in *Proceedings of the 2015 SIAM international conference on data mining*, 2015, pp. 289–297.
[38] T. Chen, X. Shi, and Y. D. Wong, “A lane-changing risk profile analysis method based on time-series clustering,” *Physica A: Statistical Mechanics and its Applications*, vol. 565, p. 125567, 2021.
[39] J. Paparrizos and L. Gravano, “k-shape: Efficient and accurate clustering of time series,” in *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, 2015, pp. 1855–1870.
[40] P. J. Rousseeuw, “Silhouettes: a graphical aid to the interpretation and validation of cluster analysis,” *Journal of computational and applied mathematics*, vol. 20, pp. 53–65, 1987.
[41] J. J. Faraway, *Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models*. CRC press, 2016.
[42] P. McCullagh and J. A. Nelder, *Generalized linear models*. Routledge, 2019.
[43] Y. Yao, X. Zhao, Y. Wu, Y. Zhang, and J. Rong, “Clustering driver behavior using dynamic time warping and hidden Markov model,” *Journal of Intelligent Transportation Systems*, pp. 1–14, 2020.
[44] W. W. Chin, “The partial least squares approach to structural equation modeling,” *Modern methods for business research*, vol. 295, no. 2, pp. 295–336, 1998.
[45] C. Gold, M. Körber, D. Lechner, and K. Bengler, “Taking over control from highly automated vehicles in complex traffic situations: the role of traffic density,” *Human factors*, vol. 58, no. 4, pp. 642–652, 2016.
[46] P. Graw, K. Kräuchi, V. Knoblauch, A. Wirz-Justice, and C. Cajochen, “Circadian and wake-dependent modulation of fastest and slowest reaction times during the psychomotor vigilance task,” *Physiology & behavior*, vol. 80, no. 5, pp. 695–701, 2004.
[47] X. Shi and X. Li, “Empirical study on car-following characteristics of commercial automated vehicles with different headway settings,” *Transportation Research Part C: Emerging Technologies*, vol. 128, p. 103134, 2021.

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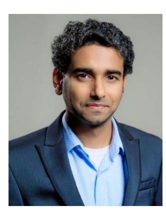

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