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A Novel Framework for Identifying Driving Heterogeneity Through Action Patterns

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***Abstract*— Identifying driving heterogeneity plays an important role in improving traffic safety and efficiency. This paper proposes a novel framework to identify driving heterogeneity from the underlying characteristics of driving behaviour. The framework includes three processes: *Action phase* extraction, *Action pattern* calibration, and *Action pattern* classification. The concepts of *Action phase* and *Action patterns* are proposed to decipher and interpret driving behaviours. *Action phases* are extracted by rule-based segmentation methods and *Action patterns* are calibrated based on an unsupervised learning approach. The extraction and calibration processes provide a rigorous labelling approach for the attention-based LSTM *Action pattern* classification process. Evaluation of the framework on a large-scale naturalistic driving dataset reveals six distinct *Action patterns*. The implementation of the attention mechanism to LSTM models significantly enhanced both the accuracy and time efficiency of *Action pattern* identification. The proposed framework offers benefits in detecting and reducing variability in driving behaviour through ITS applications such as user-based traffic management, personalised Advanced Driver Assistance Systems (ADAS), and advanced autonomous vehicles (AV) design, thereby enhancing road safety and traffic efficiency.**

***Index Terms*— Driving behaviour analysis, driving heterogeneity, driving pattern classification, attention-based LSTMs.**

I. Introduction

DRIVING behaviour varies from one driver to another, even the same driver can behave differently under identical traffic conditions depending on their current state [1]. This variability in driving behaviour is termed driving heterogeneity. There is strong evidence that driving heterogeneity leads to an increase in traffic accidents and exacerbation of traffic congestion [2], [3]. For instance, inconsistent acceleration and braking patterns of drivers are major contributors to rear-end collisions [4]. Additionally, aggressive drivers may adopt a more moderate driving style when constrained by less aggressive drivers in front of them, which can decrease overall traffic efficiency [5]. To enhance the stability of traffic flow and improve safety, future autonomous vehicle (AV) control systems must account for the diverse driving styles of surrounding human-driven vehicles [6], [7]. Thus, a thorough understanding and identification of driving heterogeneity are crucial for reducing its adverse effects and improving traffic safety and efficiency.

Driving heterogeneity has been studied in the literature from various perspectives, including inter- vs. intra-driver heterogeneity, long-term vs. short-term variability, and global vs. situational patterns [8]. Long-term individual tracking in naturalistic driving data is often unavailable due to privacy concerns and resource constraints. Consequently, much of the driving behaviour analysis has focused on short trajectory segments, which have proven effective in identifying variations in driving characteristics [9]. Key behavioural characteristics, such as acceleration profiles [10] and car-following patterns [11], can be observed within short time windows, and when analysed systematically across large datasets, they reveal stable trends in driving heterogeneity. These short-term driving variations reflect immediate and context-dependent driver responses and are widely used in driving heterogeneity identification such as driving style recognition [12], risk level evaluation [13], and driving skill characterisation [14].

Machine Learning (ML) methods can model complex numerical relationships with accurate results [13], making them widely used in (transportation) research. Recently, the increased availability of naturalistic driving data has boosted using Machine Learning (ML) methods to identify driving heterogeneity. Unsupervised learning techniques such as K-means and fuzzy C-means (FCM) are commonly used to cluster driver behaviours into distinct groups, with driving styles inferred from statistical analyses of the clusters [12]. While this approach allows for direct extraction of behavioural patterns from raw data, it often lacks interpretability, and the discovered clusters may not always correspond to realistic or meaningful driving behaviours. Conversely, supervised learning methods train models to learn the relationship between input features and output labels, enabling them to classify or predict driving behaviours in new, unlabelled data. Various supervised learning classifiers, such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Long Short-Term Memory Networks (LSTM) and Convolutional Neural Network(CNN)-based neural network models, have been employed to recognise driving styles, driving skills, and risk levels [12], [13], [14]. Supervised learning models typically require labelled training data, which is often obtained through expert knowledge or a combination of other techniques. For example, some studies use rule-based strategies, where physical driving variables, such as large

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brake or accelerator pedal inputs, are used to infer aggressive driving styles [11]. Other studies utilise unsupervised learning techniques alongside statistical analysis to categorise drivers for assigning labels. For example, Deng et al. [15] categorised 30 participants into cautious, moderate, and aggressive driving styles using principal component analysis (PCA) and K-means clustering, creating labelled datasets for subsequent classification model training. With properly labelled data, supervised learning models have demonstrated remarkable accuracy in driving heterogeneity identification. SVM models, for instance, have achieved up to 95% accuracy in distinguishing driving patterns and identifying risky drivers [13], [16]. Similarly, deep learning models, such as LSTMs and CNNs, have been developed for driver behaviour classification, achieving recognition accuracies as high as 99% [17].

Labelling approaches often assign fixed driving profiles to drivers by analysing the mean or distribution of variables in driving trajectories. This type of global trajectory analysis may overlook granular behaviour changes in time, such as specific acceleration changes at short time intervals, consequently missing the full spectrum of driving behaviour [18]. This highlights a necessity for a refined labelling process that uncovers the fundamental characteristics of driving behaviour. Moreover, omitting the temporal dynamics inherent in driving behaviour oversimplifies driving heterogeneity identification tasks, raising concerns about the performance of current supervised models. This underscores the need for advanced models that can handle complex driving data, improving both accuracy and computational efficiency. Attention mechanisms have been successfully used in neural networks to handle complicated classification tasks such as text classification [19] and network traffic classification [20]. This approach offers a promising solution to deal with driving heterogeneity tasks in complex time-series driving data, though its effectiveness in this context remains to be explored.

This paper proposes a novel framework to identify driving heterogeneity by analysing the underlying characteristics of driving behaviour. The paper's contributions are threefold: (i) Introduce the concepts of *Action phase* and *Action pattern* to decode and interpret driving behaviour, providing a new lens for understanding driving behaviour in a human-comprehensible manner; (ii) propose a novel framework to systematically identify driving heterogeneity, encompassing the processes of *Action phase* extraction, *Action pattern* calibration, and *Action pattern* classification; and (iii) implement an attention mechanism on LSTM models, which significantly improves the *Action pattern* classification accuracy and time efficiency.

The remainder of this paper is structured as follows. Section II outlines the methodology of the proposed framework and preliminary experimental settings. Section III and IV introduce the methodology and results of *Action phase* extraction and *Action pattern* calibration, respectively. V presents methodology and results of *Action pattern* classification. The main findings and limitations with future directions are discussed in Section VI, and conclusions are presented in Section VII.

II. Methodology

This section introduces the overall framework and briefly presents data and experimental setup. The flow diagram of the proposed framework (referred to as the action framework hereafter) is illustrated in Figure 1, and the definitions of the key concepts are summarised in Table I. In the proposed action framework, *Action phase* extraction initially deciphers driving trajectories into "primitives" with semantic meanings. Following this, *Action patterns* are calibrated by categorising *Action phases* and analysing driving characteristics. The outputs of *Action pattern* classification aid in the labelling process for the subsequent *Action pattern* classification, where several supervised learning algorithms equipped with attention mechanisms are utilised.

A. Action Phase Extraction

Action phases are defined as driving trajectory segments with distinct physical meanings, serving as "primitives" that capture underlying driving characteristics [21]. In literature, "action points" refer to specific moments of acceleration changes [10]. The proposed *Action phases* in this study offer a more comprehensive representation of driving characteristics by incorporating multiple variables, capturing the complexity of driving behaviours that single-variable analyses might overlook.

Action phases are extracted by identifying *action trends* of variables involved in driving behaviour analysis. An *action trend* refers to a distinct change within a driving variable (e.g., speed), characterised as "Increasing (I)", "Decreasing (D)", or "Stable in a high value (H)" or "Stable in a low value (L)". It should be noted that these action trends are chosen by choice and can also be selected in a different way. *Action phases* represent driving trajectory segments with multiple driving variables, where each univariate exhibits a single *action trend*. Driving variables considered in this study include velocity (v), acceleration (a), time headway (T), and speed difference (Δv). Both *action trends* and *Action phases* are identified and extracted using rule-based segmentation methods [21]. All *Action phases* extracted from a given dataset constitute the *Action phase* Library under that traffic condition. Detailed methodology and results of *Action phase* extraction are presented in Section III.

B. Action Pattern Calibration

When multiple driving variables are considered, the number of *Action phase* categories increases rapidly as more variables are included. This can lead to minor differences in observed driving behaviour among different *Action phases* and complicate the interpretation of driving behaviour. To address this, we propose the concept of *Action pattern* that represents group-specific driving characteristics. Therefore, the second step of the action framework consolidates similar *Action phases* into a small number of *Action patterns* using unsupervised learning techniques.

Two clustering techniques, agglomerative clustering dynamic tree cut (AC-DTC) and X-means, are employed in this step to facilitate optimal results. Each cluster represents a

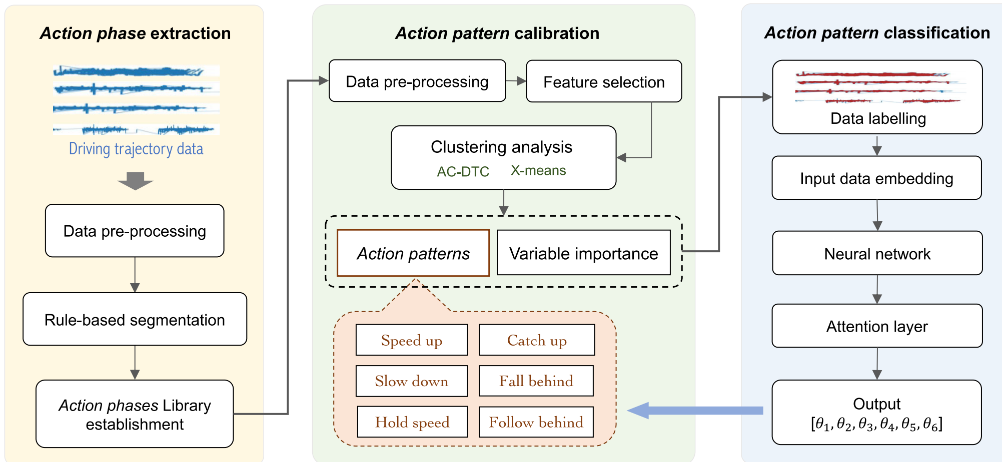

Fig. 1. The flow diagram of the proposed action framework.

TABLE I

BRIEF INTRODUCTION OF CONCEPTS

Name	Meaning
action point [10]	Specific moments of change in acceleration during driving
turning point	Points on the driving variable curve where the concavity changes
Action trend	A distinct change within a driving variable (e.g., speed)
Action phase	Multi-variable driving trajectory segments with each univariate having a single *action trend*.
Action phase Library	All *Action phases* extracted from a certain traffic flow condition
Action pattern	Driving behaviours with group-specific driving characteristics

distinct *Action pattern*, with the characteristics of each pattern obtained through statistical analysis of the *Action phase* data within the cluster. It is assumed that greater dissimilarity of a driving variable among clusters indicates higher importance in distinguishing *Action patterns*. Consequently, driving variable importance is determined. Detailed methodology and results of *Action pattern* calibration are presented in Section IV.

C. Action Pattern Classification

The third step of the action framework involves training models to classify *Action patterns* with high accuracy and time efficiency. Driving trajectories are first labelled as *Action patterns* using the rule-based method that considers driving variable importance. Then a bidirectional Long Short-Term Memory network integrated with an attention mechanism (ABi-LSTM) is applied for the *Action pattern* classification task, handling multi-variable varied-length data. Baseline models, including basic LSTM, bidirectional LSTM (Bi-LSTM), and attention LSTM (ALSTM), are also employed for the same classification task to evaluate the effectiveness of the ABi-LSTM model in training accuracy and time efficiency. Detailed methodology and results of *Action pattern* classification are presented in Section V.

D. Data and Experimental Set Up

The Lyft-5 open dataset contains large-scale real-world human driving data with detailed kinematic features, making it well-suited for identifying and analysing distinct characteristics in human driving behaviour. Thus, we utilise the Lyft level-5 as the primary dataset for evaluating the proposed framework in this study. This dataset includes 29k+ HV-following-AV (HV-AV) pairs and 42k+ HV-following-HV (HV-HV) pairs with a total driving distance of 150k+ km in similar environments [22]. We exclude driving trajectories with a speed of $v = 0$m/s to eliminate stopping and restarting behaviour. Additionally, only drivers with trajectories lasting more than 20 seconds were selected to ensure an adequate data volume for analysing longitudinal driving behaviours. A Kalman filter is employed to detect outliers and missing values of driving trajectory data. While larger sizes of data can improve robustness in capturing behavioural variability, they also introduce computational challenges. To balance behavioural detail and computational efficiency, we select 3000 HV-HV pairs for *Action phase* extraction and another set of 3000 HV-HV pairs for *Action pattern* classification. All the extracted *Action phases* are used as input for calibrating *Action patterns* and analysing driving variable importance. In the *Action pattern* classification task, car-following trajectories are first labelled as *Action patterns* according to driving variable importance. These labelled *Action patterns* serve as input for LSTM-based classification models. Detailed experiments are presented in the following sections.

III. ACTION PHASE EXTRACTION

This section details the methodology for *Action phase* extraction, followed by the presentation of experiments and results.

A. Definition Description

A driving trajectory has distinct states, as illustrated by the example of the velocity (v) of an arbitrary vehicle in

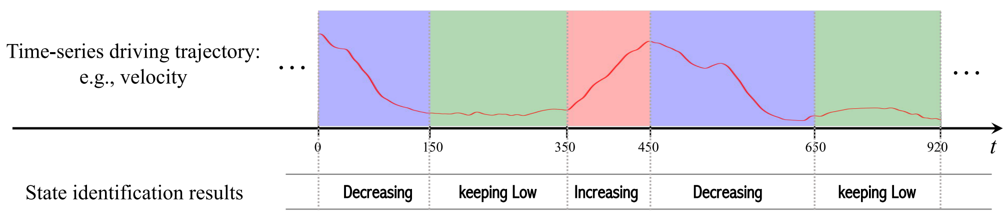

Fig. 2. Visualisation of *action trends*: An example of velocity.

Figure 2. Some periods exhibit upward trends, some display downward trends, and others fluctuate in a small range which can be considered a stable trend. In this study, we refer to these characteristics of a driving trajectory as *action trends*, distinguished by turning points. Specifically, we classify *action trends* into "Increasing (I)", "Decreasing (D)", or "Stable (S)". The "Stable" trend is further categorised as "Stable in a high value (H)" and "Stable in a lower value (L)". Thus, the *action trend* space can be represented as $S = \{I, D, H, L\}$. For example, the velocity trajectory shown in Figure 2 can be expressed as $S_v = \{D, L, I, D, L\}$. Any variables considered in driving behaviour analysis have a corresponding *action trend* space, thus extending the univariate analysis to multivariate analysis. Note that it is possible to define *action trends* differently, either based on other variables or other charactristics.

Driving variables often exhibit correlated changes. For instance, Makridis et al. [9] indicated a non-linear relationship between speed and longitudinal acceleration. *Action trends* can dissociate temporal changes of different variables. For example, an *action trend* of velocity with "Increasing" might coincide with various acceleration trends of "Increasing", "Decreasing", "Stable", or a combination of them. This desynchronisation enables *action trends* to address the correlation problem and capture the characteristics of individual variables independently. *Action phases* are extracted by identifying multi-variable driving trajectory segments where each univariate with a single *action trend*.

B. The Procedure of Action Phase Extraction

Driving trajectory data is represented as $x_1, x_2, \ldots, x_t$, where x_t denotes a driving variable at the t-th frame. The set of driving variables is denoted as $\Upsilon = \{\upsilon_1, \upsilon_2, \ldots, \upsilon_m\}$, which are velocity, acceleration, time headway, and speed difference in this study. For a given variable υ_m, set of turning points is represented as $P_m = (x_1^m, y_1^m), \ldots, (x_n^m, y_n^m)$. The procedure *Action phases* extraction is illustrated in Figure 3. After data preprocessing, driving trajectory data are fed into a univariate segmentation algorithm (**Algorithm 1**). This algorithm assigns an *action trend* l_n^m to each driving segment for variable υ_m in the n-th segment, where $n = 1, 2, \ldots, N$. Consequently, the *action trends* of multi-variable driving segments at time frame t are denoted as $S_t = \{l^1, l^2, \ldots, l^m\}$, highlighting the unique driving characteristics at that moment.

Next, trajectories with assigned *action trends* are fed into another rule-based segmentation algorithm (**Algorithm 2**) for multivariate segmentation. The outputs of this segmentation process are *Action phases*, represented as $S_{n'} = \{A^1, A^2, \ldots, A^m\}$, where n' signifies the n'- th *Action phase*, $n' \in N'$. Here, N' is the total number of *Action phases* identified from an individual driving trajectory. All the extracted *Action phases* collectively form the *Action phase* Library under a specific traffic flow. Details of the univariate and multivariate segmentation processes are provided in Algorithm 1 and 2, respectively. The parameters for both rule-based segmentation algorithms are determined based on uniform criteria that represent collective driving behaviour within the given traffic condition.

Algorithm 1 Univariate Segmentation

Data preparation:
for each variable υ in Υ **do**
  Identify turning points (TP) of Υ
  Calculate Δy and Δx between neighbouring TPs
end for
Threshold setting:
Define thresholds θ_1 and θ_2 for Δy
Set threshold γ for Δx
Initial categorisation:
for each segment between turning points in each variable **do**
  if $\Delta y > \theta_1$ **then**
    Label segment as Increasing (I)
  else if $\Delta y < \theta_2$ **then**
    Label segment as Decreasing (D)
  else
    Label segment as Stable (S)
  end if
end for
Merging segments:
for each segment labelled S **do**
  if Δx of segment $< \gamma$ and Δx of both neighbouring segments $> \gamma$ **then**
    Merge segment with its neighbouring segment
  end if
end for
Stable refinement:
for each segment labelled S **do**
  Calculate mean of variable values in segment
  if mean $> \delta$ **then**
    Refine label to High (H)
  else
    Refine label to Low (L)
  end if
end for
return *action trends* for each variable in Υ

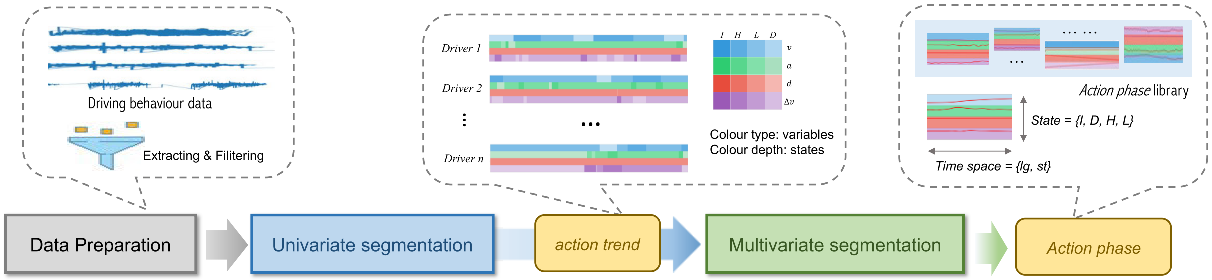

Fig. 3. The procedure of *Action phase* extraction.

Algorithm 2 Multivariate Segmentation

Identify turning points across all variables in Υ
Segment multivariate driving trajectories using these turning points
Discard short segments:
for each multivariate segment **do**
    if segment length $< \tau$ **then**
        Discard segment
    end if
end for
Extract Action phases:
for each driver **do**
    Extract *Action phases* based on the refined and segmented data
    Add *Action phases* to *Action phase* Library
end for
return *Action phase* Library

TABLE II
PARAMETER SETTINGS OF ALGORITHM 1

Δy **/(unit)**	θ_1	θ_2	δ	γ / 0.1s	τ / 0.1s
$v/(m/s)$	1.5	-1.5	13	10	10
$a/(m/s^2)$	0.25	-0.25	0.25	10	10
$T/(s)$	0.15	-0.15	1.5	10	10
$\Delta v/(m/s)$	0.8	-0.8	0.8	10	10

C. Parameter Settings

The parameters of rule-based segmentation algorithms are determined based on empirical knowledge from existing literature, as summarised in Table II. Specifically, the threshold γ in Algorithm 1 and τ in Algorithm 2 are both set to 1 second to ensure that the extracted driving trajectory segments exceed the typical human reaction time, effectively capturing meaningful driving phases while preventing excessive fragmentation. This selection is supported by studies indicating that driver reaction times typically range between 0.7 and 1.5 seconds under various driving conditions [23]. Additionally, the thresholds for "stable high/low" in key driving variables, such as speed, time headway, and speed difference, are set based on typical traffic flow conditions in non-congested environments. The acceleration thresholds are derived from driver perception studies [24], ensuring that the segmentation process reflects the acceleration forces that drivers commonly experience and respond to in real-world driving.

TABLE III
FREQUENCY OF *Action Name* IN EACH DRIVING VARIABLE

	I	D	H	L
v	3860	2501	7745	4649
a	5764	6226	3483	3327
T	4320	4123	4008	6343
Δv	3661	3729	3383	8027

D. Results of Action Phase Extraction

A total of 18800 *Action phases* with 255 different *action trend* combinations are extracted, constituting an *Action phase* Library of the selected 3000 drivers in Lyft-5 dataset. This *Action phase* Library serves as input data for the subsequent *Action pattern* calibration. Specifically, the extracted *Action phases* vary in duration, ranging from a minimum of 1.1 seconds to a maximum of 13.4 seconds, with an average length of 2.48 seconds. The most frequently observed *Action phases* are "(H, L, L, L)", (H, L, H, L)", and "(H, H, L, L)", reflecting common driving characteristics across the dataset.

The frequency of identified *action trends* for each driving variable is presented in Table III. Notably, the most dominant *action trends* are 'H' and 'L', suggesting that vehicles predominantly maintain steady car-following behaviour under the given traffic condition. To further demonstrate the variability in driver responses under similar stimuli, we illustrate *Action phases* of several drivers experiencing comparable driving conditions in Figure 4. Specifically, Figure 4(c) shows that these drivers have a time headway with a "Low" trend, indicating that they receive similar stimuli from their preceding vehicles. However, despite this commonality, their driving actions exhibit significant differences. As shown in Figure 4(a)-(b), some drivers accelerate (e.g., drivers represented in purple, blue, and grey), while others decelerate (e.g., the driver represented in red and green). These variations highlight the heterogeneity in driving behaviour, which may be influenced by factors such as individual driving styles, risk perception, and latent decision-making tendencies. This finding underscores the importance of considering multiple driving variables when understanding and identifying driving heterogeneity.

IV. ACTION PATTERN CALIBRATION

This section presents the methodology and results of *Action pattern* calibration.

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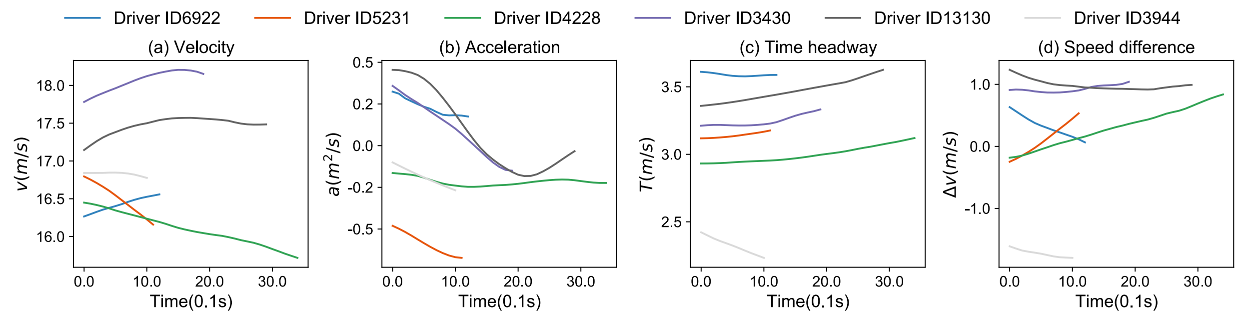

Fig. 4. The differences in *actions trends* with similar stimuli.

A. Clustering Techniques

Clustering approaches are generally divided into two distinct categories [25]: hierarchical clustering and partitioning clustering. We employ both techniques to cluster *Action phases*, aiming to achieve optimal results for *Action pattern* calibration.

Agglomerative clustering (AC) is a hierarchical clustering technique that initiates with individual data points as singleton clusters and recursively merges them based on similarity [26]. This method constructs a dendrogram to explore different granularity levels of clustering. Such flexibility in adjusting cluster boundaries is particularly beneficial for *Action phases* data, where the number of clusters is unknown. The dynamic tree cut (DTC) method further refines the hierarchical clustering process by analysing the dendrogram's structure to make context-sensitive decisions on cluster division. The hierarchical nature of AC-DTC effectively captures the temporal dependencies and variations within *Action phases* data, facilitating accurate clustering of similar *Action phases* while reflecting subtle differences. In agglomerative clustering with dynamic tree cut (AC-DTC), the distance among clusters is determined using linkage methods, which represent the hierarchical tree structure by specifying how distances between clusters are calculated [27].

X-means is a partitioning clustering technique that extends the K-means algorithm by introducing a mechanism to automatically determine the optimal number of clusters (k) [28]. It starts with a lower bound for k and iteratively adjusts it, aiming to find an optimal number of clusters by balancing model complexity and fit based on specific criteria. This method maintains a level of scalability and computational efficiency similar to K-means while eliminating the need for pre-defined cluster numbers.

Evaluation indicators provide quantitative measures to guide the clustering process and validate clustering results. Three commonly used indicators, including Silhouette Score (SS), Calinski-Harabasz Index (CHI), and Davies-Bouldin Index (DBI), are employed for both AC-DTC and X-means clustering in this study. Specifically, the best value of SS is 1 and the worst value is -1. A higher CHI score indicates that clusters are well-separated and dense within clusters. DBI values closer to 0 represent better clustering performance [29].

B. Experiments and Results of Calibration

1) Data Preparation: Action phases are composed of multiple driving variables, each with varying durations. The

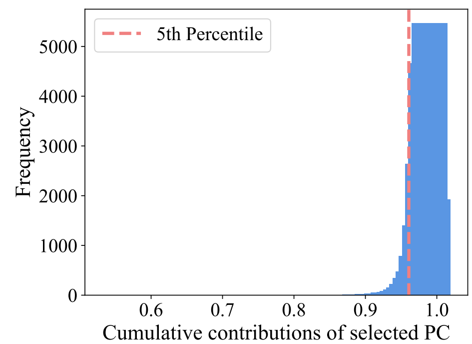

Fig. 5. Statistics of PC1's cumulative contributions.

Resampling and Downsampling Method (RDM) is employed to standardise the length of *Action phases* for clustering analysis. Specifically, *Action phases* with lengths shorter than a reference length (e.g., the median length of all *Action phases*) are resampled using Fast Fourier Transform (FFT) and Inverse Fourier Transform (IFFT) [30]. Conversely, *Action phases* exceeding the reference length are downsampled through isometric extraction. To mitigate issues such as the curse of dimensionality and computational burden, Principal Component Analysis (PCA) is utilised to reduce the complexity of *Action phase* data. It consolidates variables into principal components that capture the most significant features. Results in Figure 5 reveal that for 96.08% of *Action phases*, the first principal component (PC1) accounted for over 95% of cumulative contributions, as highlighted by the red dotted line. Consequently, PC1s are selected as input for clustering algorithms.

2) Clustering Analysis: Clustering analysis employs both AC-DTC and X-means, with each having ablation studies to facilitate optimal clustering results. Four linkage functions, including "Weighted", "Average", "Complete", and "Ward", are employed for AC-DTC clustering. The cluster number k for X-means ranged from 4 to 7. The results are presented in Table IV. For both clustering techniques, the best-performing settings for each evaluation indicator are highlighted in bold. Note that the "Ward" linkage function, which minimises the variance within clusters to create more homogeneous groups, demonstrated superior performance by identifying six distinct categories of *Action phases*. X-means clustering with $k = 6$ exhibits superior performance across all k values.

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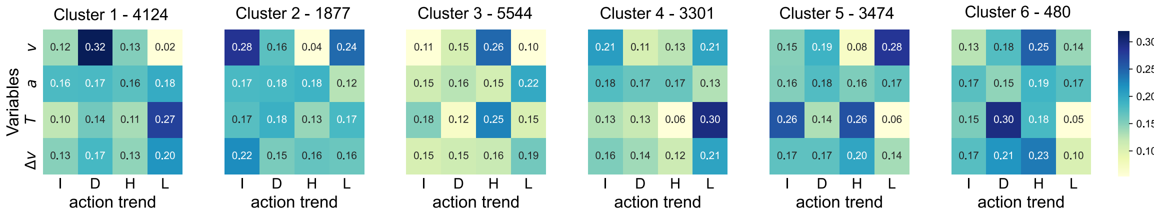
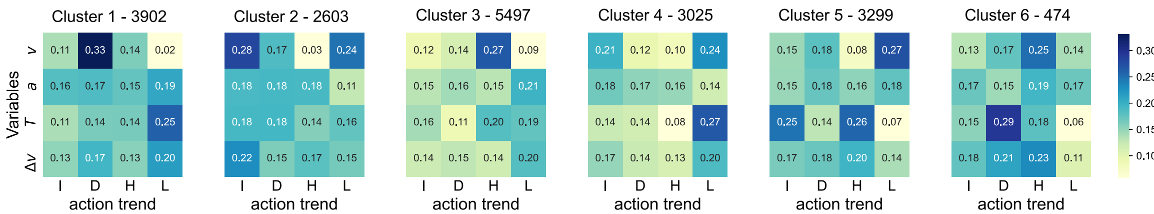


(a) Agglomerative clustering with dynamic tree cut



(b) X-means clustering

Fig. 6. Statistics of *action trends* in each cluster. (*After calibration, Clusters 1 to 6 are labelled with the following patterns: "Slow down", "Speed up", "Hold speed", "Follow behind", "Fall behind", and "Catch up".)

TABLE IV
RESULTS OF AGGLOMERATIVE AND X-MEANS CLUSTERING

	linkage	SS	CHS	DBS	Clusters
AC-DTC	Average	0.37	4229.43	**0.72**	8
	Complete	0.28	6286.08	0.90	8
	Weighted	0.31	5823.54	0.92	7
	Ward	**0.41**	**14673.48**	0.83	6
X-means	/	0.44	14115.50	0.81	4
	/	0.45	14638.43	**0.79**	5
	/	**0.46**	**15768.43**	0.80	6
	/	0.38	14740.08	0.00	7

Figure 6 provides statistics on *action trends* within each cluster. Each block represents a specific *action trend* of a variable, with numbers indicating the percentage of each *action trend* within the six clusters. Darker colours represent higher proportions. For instance, *action trend* "D" for variable v is prevalent in Cluster 3 and relatively rare in other clusters, see Figure 6a. Notably, clustering results of both techniques show a high degree of similarity in the distribution of *action trends* for each variable within each cluster, (see numbers in brackets in Figure 6. These consistencies justify the six identified categories of *Action phases*. Given the superior performance of X-means clustering over AC-DTC, subsequent analyses of cluster characteristics are based on X-means results.

3) Recognition of Action Patterns and Variable Importance: The six categories of *Action phases* correspond to six distinct *Action patterns*, recognised by characteristics of *action trends* within their respective clusters. Higher percentages of *action trends* indicate greater importance in reflecting driving characteristics and interpreting driving behaviours. As such, in Figure 6b, Cluster 1 is dominated by the *action trends* 'D' and 'L' for velocity (v) and time headway (T), respectively, indicating a "Slow down" pattern where velocity decreases and time headway remains low. Cluster 2 is characterised by increasing velocity and speed difference, suggesting a "Speed up" pattern. Cluster 3 shows a "Holding speed" pattern with velocity (v) maintaining a high value (H) and acceleration (a) remaining low (L). Clusters 4 and 5 both highlight the primary variables of velocity (v) and time headway (T), with Cluster 4 maintaining constant time headway (L) and Cluster 5 showing increasing time headway (I), indicating a "Follow behind" pattern and a "Fall behind" pattern, respectively. Cluster 6 is characterised by a decreasing time headway and consistently low velocity, indicating a "Catch up" pattern where the following vehicle is closing in their leading vehicle. These six *Action patterns* are detailed in Table V.

The importance of a driving variable in distinguishing *Action patterns* is indicated by its dissimilarity across the six clusters. This is quantified using Kullback–Leibler (KL) divergence, denoted as $D_{KL}(P||Q)$, which measures the deviation between two probability distributions P and Q [31]. In this study, *action trends* are quantified using the slope of a given variable: a positive slope indicates an increasing trend, while a negative slope implies a decreasing trend, and sequences of gentle slopes indicate a stable trend. Considering the diverse manifestations of identical *action trends* (e.g., linear increase, convex/concave progression, or slight fluctuations), a "sliding window" method to detect local trends within specific intervals. This approach ensures overall *action trend* representation by averaging trends across these windows.

Results of the KL divergence analyses are illustrated in Figure 7. Significant variance is observed for time headway (T) and velocity (v) across clusters, underscoring their greater variable importance compared to acceleration (a) and speed difference (Δv). This aligns with real-world driving observations, where time headway and velocity are more perceptible and influential in driving behaviour. Recognised *Action patterns* and variable importance provide robust references for labelling driving trajectories in supervised learning driving behaviour analyses, which is then utilised for subsequent *Action pattern* classification.

V. ACTION PATTERN CLASSIFICATION

In this section, we first introduce the methodology for *Action pattern* classification, followed by a presentation of

TABLE V

RESULTS OF *Action Pattern* RECOGNITION (ACCORDING TO X-MEANS CLUSTERING)

Clusters	**Variables**	***action trend***	**Observations**	***Action pattern***
1	v, T	D, L	Speed decreasing, time headway stable	Slow down
2	v, Δv	I, I	Speed increasing, speed difference increasing	Speed up
3	v, a	H, L	Speed stable, small acceleration	Hold speed
4	T, v	L, L	Time headway stable, speed stable	Follow behind
5	T, v	I, L	Time headway increasing, speed stable	Fall behind
6	T, v	D, H	Time headway decreasing, speed stable	Catch up

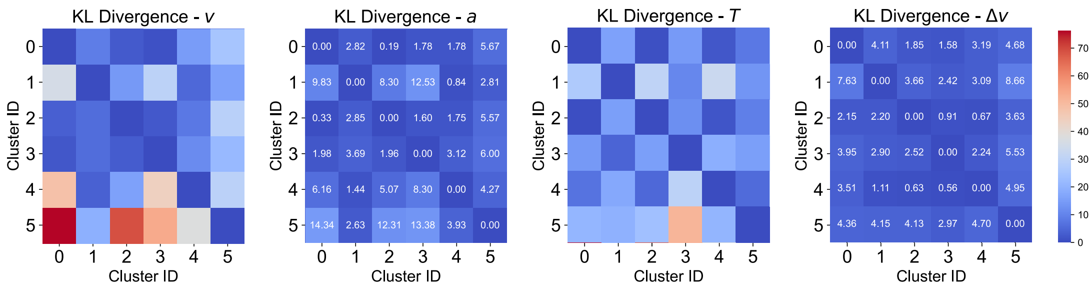


Fig. 7. KL divergence of four driving variables.

the experiments and results, which include driving trajectory labelling, experimental settings, and results.

A. Attention-Based Bidirectional LSTM Model

In this paper, we apply a bidirectional Long Short-Term Memory network integrated with an attention mechanism (ABi-LSTM) for *Action pattern* classification. The architecture of this model, illustrated in Figure 8, comprises the following four layers:

- Embedding Layer: This initial layer transforms each *Action phase* from the input sequence into a compact vector form, facilitating the capture of relationships between different *Action phases*.
- Bi-LSTM Layer: The vectorised sequence is then processed by a Bi-LSTM layer which captures contextual information from the entire sequence by analysing embedding data in both forward and backward directions.
- Attention Layer: An attention layer then computes context vectors by assigning attention weights to Bi-LSTM's hidden states. This mechanism allows the model to focus on the most relevant parts of the input sequence when classifying *Action phases*, particularly beneficial for handling highly complex sequences.
- Dense Classification Layer: The resulting context vectors are finally processed through one or more dense layers, culminating in a softmax output layer to classify *Action patterns* into multiple categories.

B. Experimental Settings

1) Driving Trajectory Labelling: As mentioned in Section II-D, 3000 HV-HV pairs are selected from the Lyft-5 dataset for the *Action pattern* classification task. Car-following trajectories are labelled as various *Action pattern* sequences according to the criteria presented in Table VI. The labelling criteria are based on the importance of driving variables and

TABLE VI

RULE-BASED *Action Pattern* LABELLING

Variable	*action trend*					
T	I	D	S	S	S	S
v			I	D	S	S
a					I&D	S
Action pattern	Fall behind	Catch up	Speed up	Slow down	Follow behind	Hold speed

action trends. Specifically, time headway (T) is the most critical variable, thus prioritised in the labelling process. Driving segments with an increasing trend in T increasing (I) indicates the ego vehicle is distancing from its leading vehicle, labelled as a "Fall behind" pattern. Conversely, a decreasing trend in T is labelled as a "Catch up" pattern. When T is constant, the focus shifts to velocity (v). An increasing trend in v is labelled as a "Speed up" pattern, while a decreasing trend in (v) is labelled as a "Slow down" pattern. Driving segments where both velocity and acceleration show minimal changes are labelled as a "Hold speed" pattern. Otherwise, they are labelled as a "Follow behind" pattern. Examples of the labelling results are shown in Figure 9. This labelling approach ensures that all drivers' trajectories are categorised into distinct *Action patterns*, prepared for the subsequent classification task.

2) Model Training Experimental Settings: To address the variability in *Action pattern* data lengths, *Action pattern* sequences are reshaped to a consistent length for neural network batch processing. Traditional length reshaping methods such as truncation or padding can distort the original *Action pattern* data, either by omitting critical data or introducing irrelevant zeroes. Therefore, we employ the PackedSequence technique in PyTorch to manage variable-length sequences effectively [32]. This technique sorts sequences by length and converts them into a PackedSequence object while retaining metadata that indicates each sequence's boundaries, allowing

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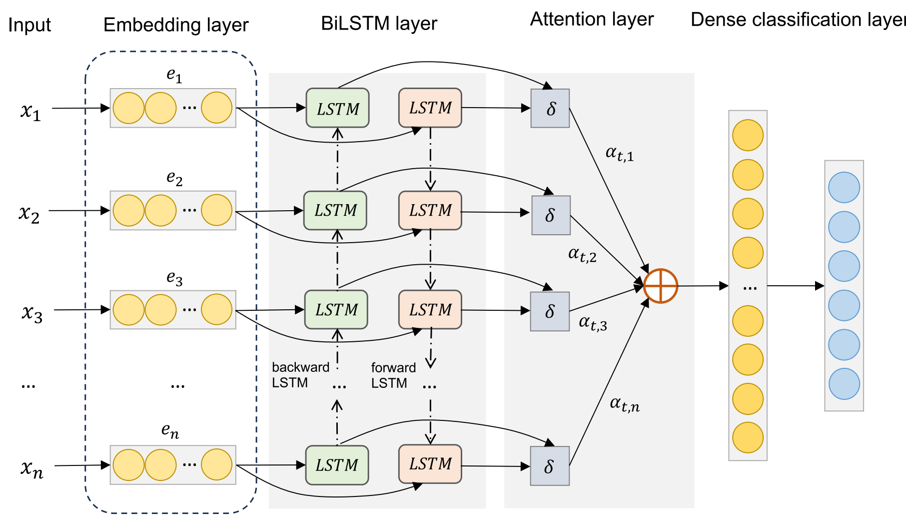
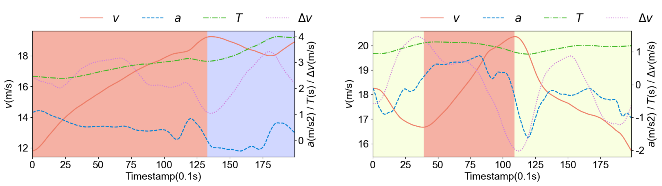


Fig. 8. ABi-LSTM model architecture.



(a) Driver ID218 (b) Driver ID409

Fig. 9. Examples of labelled driving trajectories.

the ABi-LSTM model to process sequences according to their actual lengths without data distortion.

Each variable in *Action pattern* data is independently normalised within a [0, 1] range before being fed to the ABi-LSTM model. The input dimension of the ABi-LSTM model is set as 4, corresponding to the four driving variables considered in this study. Both the batch size and the model's hidden size are set to 64, and the dropout rate is 0.6. Additionally, we use k-fold cross-validation with the k set to 10 to ensure consistent model performance across different subsets of driving trajectory data. The Adam optimizer, known for its efficiency in handling sparse gradients and noisy data, is employed for model training, enhancing the ABi-LSTM model's adaptability to diverse data distributions. Ablation studies are conducted to optimise model performance in *Action pattern* classification, exploring LSTM hidden layers of 64, 128, and 256, and neural network layers ranging from 2 to 5. Learning rates vary from 0.00001 to 0.0001, increasing incrementally by 0.00002.

Benchmark models are utilised to assess the effectiveness of the bi-directional technique and the attention mechanism in *Action pattern* classification, including simple LSTM, bi-directional LSTM (Bi-LSTM), and attention-based LSTM (ALSTM). All hyperparameters are maintained consistent across the models to ensure a fair evaluation.

3) Performance Evaluation Metrics: The models for *Action pattern* classification in the experiment are evaluated using four evaluation metrics: accuracy, F1-score, precision, and recall. These parameters are defined as follows.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \tag{4}$$

where True Positives (TP) represent the number of correctly classified positive instances, and True Negatives (TN) denote the number of correctly classified negative instances. False Negatives (FN) refer to the number of positive instances incorrectly classified as negative, and False Positives (FP) signify the number of negative instances incorrectly classified as positive.

C. Results and Discussions

Results of ablation studies on the ABi-LSTM model are illustrated in Figure 10. The highest accuracy for both training and testing is achieved at a learning rate of 0.00006 and with three layers, as depicted in Figure 10a and Figure 10b, respectively. The training and testing process with a learning rate of 0.00006 and three layers is illustrated in Figure 11a, with corresponding numerical results shown in Table VII. The training accuracy (see solid red line in Figure 11a) increases rapidly during the first 30 epochs, reaching an accuracy around 89%, then stabilises with small increases and finally converges at 200 epochs with an accuracy of 95.68%. This indicates effective learning of the training data by the model. The testing accuracy (see dashed pink line) follows a similar trend as the training process and converges with an accuracy of 94.33%, suggesting the model's good generalisation to unseen data. Both the training loss (solid blue line) and testing loss (dashed cyan line) decrease sharply in the initial 30 epochs and then stabilise at a low value of around 0.3, demonstrating effective error minimisation on both training and testing data. The

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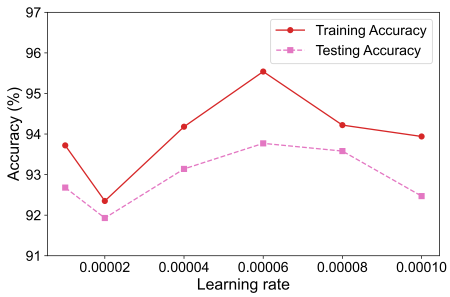
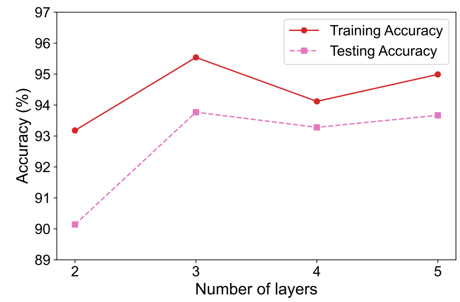
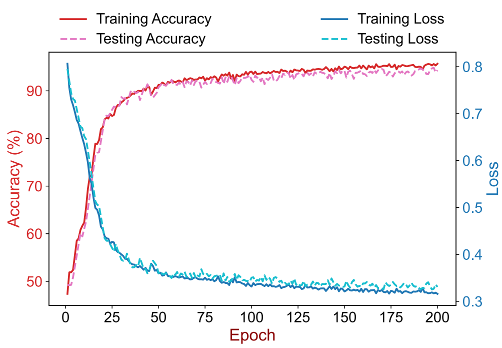


(a) Training accuracy with different learning rates (Layer = 3).

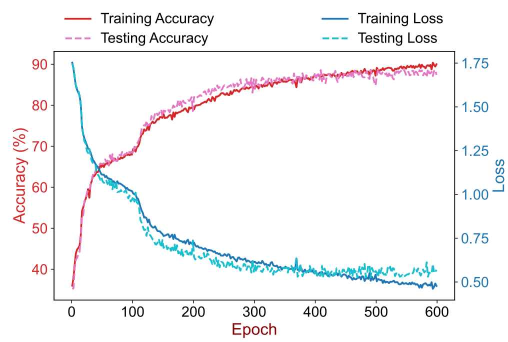


(b) Training accuracy with a different number of layers (Learning rate = 0.00006).

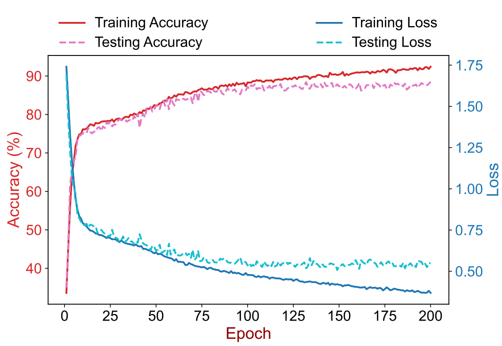
Fig. 10. Parameter tuning with various learning rates and number of layers.



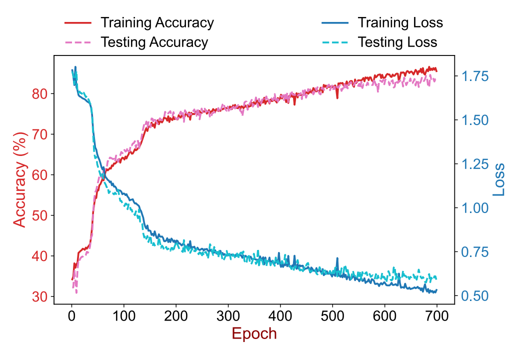
(a) ABi-LSTM model (Layer=3).



(b) Bi-LSTM model (Layer=3).



(c) ALSTM model (Layer=3).



(d) LSTM model (Layer=3).

Fig. 11. Performance of LSTM models and Attention-LSTM methods.

TABLE VII
PERFORMANCE COMPARISON OF DIFFERENT MODELS FOR *Action Pattern* CLASSIFICATION

Models	Num layers	Epoch	Training accuracy (%)	Training loss	Testing accuracy (%)	Testing loss	Testing Precision (%)	Testing Recall (%)	Testing F1- score
ABi-LSTM	3	200	95.68	0.31	94.33	0.33	93.89	91.83	92.85
BiLSTM	4	600	89.88	0.47	88.97	0.52	88.27	89.44	88.85
ALSTM	3	200	92.41	0.36	88.51	0.51	91.94	87.10	89.45
LSTM	4	700	86.45	0.52	83.23	0.60	83.41	85.71	84.55

difference in training and testing loss is around 0.02, indicating that the ABi-LSTM model learns the characteristics of *Action pattern* data without overfitting.

The training and testing results of baseline models are shown in Figure 11 and Table VII. In Figure 11b, the training and testing accuracies of the Bi-LSTM model steadily increase at the first 50 epochs with an accuracy of around 65%, then increase more slowly, finally converging at 600 epochs with accuracies of 89.88% and 88.97%, respectively. The training loss and testing loss decrease and converge at 0.47 and 0.52, respectively, which are higher than the ABi-LSTM model. The ALSTM model shows rapid increases in training and testing accuracy during the first 15 epochs, reaching around an accuracy of 77%, see Figure 11c. Then the accuracies increase slowly and the ALSTM model finally converges at around 200 epochs with training and testing accuracies of 92.41% and 88.51%, respectively. However, the noticeable gap between the training and testing process suggests overfitting, indicating Bi-LSTM models' inferior performance in the *Action pattern* classification task. The LSTM model shown in Figure 11d gradually improves training and testing accuracy and finally converges at 700 epochs with accuracies of 86.45% and 83.23%, respectively.

Overall, the ABi-LSTM model achieves the highest accuracy in fewer epochs compared to baseline models, with optimal results of precision (89.39%), recall (87.83%), and F1-score (88.60%), illustrating its remarkable effectiveness in classifying *Action patterns*. Additionally, models incorporating the attention mechanism (ABi-LSTM and ALSTM) consistently outperform their non-attention counterparts (Bi-LSTM and LSTM). These findings demonstrate the advantages of the attention mechanism in better generalisation by focusing on highly relevant features, thus enhancing classification precision and computational efficiency. The robust performance of *Action pattern* classification highlights the effectiveness of the proposed action framework in analysing complex driving behaviours and identifying driving heterogeneity in a comprehensive way.

VI. Discussion

In this section, we summarise the main findings of this study and discuss the limitations along with directions for future research.

A. Main Findings

1) Action Phase: The concept of *Action phase* offers a new perspective to decode and interpret the intrinsic characteristics of driving behaviours. The established *Action phase* Library serves as a comprehensive database that encompasses a wide range of driving characteristics within a traffic flow, allowing for more detailed and structured analyses of driving behaviour.

2) Action Pattern: Distinct *Action patterns* can be identified from *Action phases* data, representing various group-specific driving characteristics. Six *Action patterns* are delineated in this study, interpreted as "Speed up", "Slow down", "Hold speed", "Catch up", "Fall behind", and "Follow behind". Each pattern represents a unique aspect of driver stimuli-response during driving, highlighting the heterogeneous nature of driving behaviour. This categorisation provides a granular view of driving trajectories, facilitating a more nuanced understanding and interpretation of driving heterogeneity, which can be beneficial for real-world applications such as traffic management and personalised ADAS.

3) Driving Variable Importance: Time headway (T) and velocity (v) exhibit higher importance than acceleration (a) and speed difference (Δv) in distinguishing *Action patterns*, underscoring their critical roles in reflecting driving characteristics. This aligns with realistic driving observations where time headway and velocity are more perceptible and influential in driving behaviour. Understanding the importance of driving variables can enhance driving behaviour analysis, such as improving the labelling process in supervised learning tasks by prioritising more influential variables.

4) Attention-Based LSTMs: Incorporating the attention mechanism significantly enhances the performance of LSTM models in handling the complex *Action pattern* classification task with varied-length, multi-variable time-series data. The ABi-LSTM model improves classification accuracy by 1.39%-8.53% and reduces computational complexity by 66.67%-71.43% compared to baseline counterparts. This finding underscores the effectiveness of advanced techniques in improving accuracy, generalisation, and time efficiency for deep learning models, making them increasingly applicable for real-time driving behaviour analysis.

Overall, these findings highlight the advantages of the proposed action framework in identifying driving heterogeneity: i) the action framework offers a more precise, interpretable, and efficient approach to analyse complex driving behaviours and ii) provides actionable insights for its practical applications, such as enhancing traffic flow analysis, improving vehicle automation systems, and advancing driving behaviour modelling.

B. Limitations and Future Work

While the proposed action framework offers promising advantages in understanding and identifying driving heterogeneity, it also has certain limitations that provide valuable directions for future research. These are outlined below.

1) Threshold Sensitivity and Environmental Dependency: Threshold settings are crucial for rule-based *Action phase* extraction, as they influence how driving trajectory data is segmented into meaningful pieces that accurately reflect driving characteristics. This makes the action framework sensitive to threshold selection, where slight adjustments could significantly impact the resulting *Action phases* and the subsequent *Action pattern* calibration. These thresholds are currently derived from expert insights within the literature. However, their effectiveness may vary depending on road characteristics, such as speed limits, roadway design, and traffic infrastructure, which can influence speed and acceleration distributions.

To improve the framework's adaptability across diverse driving environments, future research could explore adaptive thresholding techniques, where threshold values are dynamically optimised based on dataset characteristics rather than predefined fixed values. Additionally, conducting sensitivity analyses across different roadway settings could help refine threshold selection and ensure greater robustness in real-world applications.

2) Selection and Interdependence of Driving Features: Driving variables play an important role in the action framework, as they influence the feature selection process and, consequently, impact the overall identification results. In this study, we utilise four variables (v, a, T, and Δv), which are empirically known to be highly relevant to driving behaviour. The proposed *action trends* treat these variables independently by dissociating variable changes.

Given the correlations among driving variables, future research should explore multivariate feature selection techniques or dimensionality reduction methods to better capture the relationships between variables. Such improvements could further refine the *Action phase* extraction and *Action pattern* calibration processes, improving the framework's ability to distinguish nuanced variations in driving behaviour.

3) Generalisability Across Different Driving Contexts: Driving behaviour is inherently influenced by both internal (e.g., driver cognition, risk perception) and external (e.g., road conditions, traffic flow, infrastructure) factors. This study evaluates the proposed action framework based on observed driving variables, and its generalisability across different traffic environments remains further consideration. One potential factor to be considered is the presence of autonomous vehicles (AVs) in the dataset. Interactions between human-driven vehicles (HVs) and AVs may introduce behavioural adaptations that differ from conventional HVs-only environments.

Future studies could investigate how HV-AV interactions influence driving heterogeneity and whether the extracted *Action patterns* remain consistent in AV-integrated traffic. Additionally, testing the framework across datasets from different geographical regions, where variations in driving culture, regulations, and infrastructure exist, can further validate its robustness and applicability.

4) Practical Implications for Real-World Applications: The proposed action framework systematically interprets driving behaviour and can promote implications for various real-world applications. For instance, Advanced Driver Assistance Systems (ADAS) and Adaptive Cruise Control (ACC) could leverage the extracted driving patterns to predict driver behaviour, leading to more adaptive and personalised automation features. Traffic management and control systems could benefit from the framework's ability to classify heterogeneous driving behaviours, helping optimise traffic signal timing, lane management, or speed harmonisation strategies. Safety assessment models could incorporate *Action patterns* to analyse driving risks, helping improve proactive measures for accident prevention. Future research could further explore how the action framework can be integrated into simulation environments, vehicle automation algorithms, or traffic control systems, ensuring its practical applicability in transportation engineering and intelligent mobility solutions.

VII. Conclusion

Understanding the heterogeneous nature of driving behaviour is crucial for traffic flow analysis and the design of better road safety measures. Existing methods often lack the granularity and precision required to capture subtle heterogeneity in driving behaviour. This study proposes a novel framework to systematically identify driving heterogeneity by analysing underlying characteristics of driving behaviour. The concept of *Action phase* is introduced to decompose driving trajectories into "primitives" with physical meanings. Then *Action patterns* are calibrated by clustering *Action phases* based on group-specific characteristics. The *Action pattern* calibration process provides a rigorous labelling method for *Action pattern* classification. Evaluation using a large-scale naturalistic driving dataset demonstrates the framework's effectiveness in capturing driving characteristics and identifying driving heterogeneity. The incorporation of an attention mechanism enhances LSTM models' performance in terms of both accuracy and time efficiency. This framework improves capturing subtle behavioural differences within and amongst individual drivers, supporting advancements in personalised driving assistance systems and user-based traffic management.

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