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A Driving-Primitive-Based Framework for Modeling the Evolution of Unprotected Left-Turn Interactions Using UAV Trajectory Data

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Abstract

Unprotected left turns at urban intersections require drivers to continually regulate their driving behavior while negotiating conflicts with opposing through traffic. Existing studies have mostly examined such maneuvers through gap-acceptance decisions and surrogate conflict indicators, which cannot reflect how driving behavior changes for unprotected left-turn interaction events. To explore the evolution of unprotected left-turn interactions, this study develops a data-driven framework to decompose continuous left-turn trajectories into interpretable, variable-length driving primitives. Using high-resolution unmanned aerial vehicle trajectory data, 2490 valid left-turning and opposing-through vehicle interaction events were extracted. A Non-Homogeneous Hidden Markov Model was adopted to segment each interaction event into driving primitives. These primitives are then clustered using Time-Series K-Means with Dynamic Time Warping. The clustering results yielded six behavior patterns: cautious turning, low-speed waiting, accelerating departure, deceleration observation, intensive turning, and steady driving. These patterns were then mapped back to the temporal sequence of each interaction event to construct behavioral transition chains. The results demonstrate that an unprotected left turn typically evolves as an ordered combination of the identified behavior patterns, from waiting and observation to turning and departure, and that transitions among these patterns are associated with changing opposing-traffic conditions.

Keywords: unprotected left turn; driving primitive; Non-Homogeneous Hidden Markov Model; Dynamic Time Warping; vehicular interaction; behavior evolution



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1. Introduction

Understanding and predicting vehicle behavior in complex urban traffic environments is essential for traffic safety analysis and automated driving applications [1]. Existing research has increasingly employed scenario understanding [2] and trajectory-based methods [3] to describe vehicle motion and anticipate future actions. However, driving behavior is not determined solely by the motion state of an individual vehicle. It also evolves through continuous interactions with surrounding road users [4], making behavioral intention difficult to identify from isolated observations [5]. Incorporating behavioral and interaction knowledge into trajectory analysis is therefore important for obtaining interpretable descriptions of how driving decisions develop over time [6]. This issue is particularly relevant to unprotected left turns, during which a turning driver must continuously coordinate with opposing through traffic without the separation provided by a protected signal phase.

Previous studies on unprotected left turns have primarily examined path variation, trajectory preference, gap acceptance, and decision prediction. Zhao et al. modeled variations in left-turn paths and demonstrated that turning trajectories are influenced by surrounding traffic conditions [7]. Han et al. further investigated driver trajectory preferences and their implications for traffic safety [8]. Gap-acceptance studies generally describe the maneuver as a discrete decision in which a driver accepts or rejects an available temporal gap, with the decision affected by factors such as waiting time, traffic pressure, and opposing-vehicle motion [9]. More recently, interpretable machine-learning approaches have been developed to predict left-turn decisions and quantify their uncertainty using detailed trajectory and interaction information [10]. These studies have substantially improved the understanding of left-turn decisions and associated safety outcomes. Nevertheless, they mainly focus on the selected path, the acceptance of a gap, or the final interaction outcome, providing limited insight into the internal behavioral evolution of the complete maneuver.

The increasing availability of high-resolution unmanned aerial vehicle (UAV) trajectory data provides an opportunity to examine this process in greater detail. Datasets such as CitySim contain vehicle trajectories and spatial information suitable for interaction-oriented traffic safety analysis [11]. Beyond visual sensing accuracy, the reliability of UAV-based data systems is also related to secure data aggregation and communication mechanisms. Recent studies have investigated cross-domain heterogeneous data aggregation with dynamic group key agreement in hybrid satellite networks [12] and authentication mechanisms for securing UAV flying ad hoc wireless networks [13]. These studies indicate that robust UAV-based observation depends not only on sensing capability, but also on reliable and secure data transmission. In other interactive driving scenarios, process-oriented analysis has shown that a complete maneuver can be decomposed into local behavior patterns and represented through their temporal combinations. For example, driving primitives have been used to identify merging behavior patterns and reveal their evolution during freeway on-ramp interactions [14]. Additional UAV datasets collected at intersections and under diverse traffic conditions have further improved the availability of detailed vehicle kinematic and interaction information [15,16]. Multiagent modeling has also demonstrated the importance of accounting for the responses of interacting road users when analyzing conflict behavior [17]. However, the availability of detailed trajectories does not by itself provide an interpretable representation of how local driving behaviors are organized within a complete unprotected left turn.

Driving-behavior segmentation offers a potential means of identifying such local behavioral units. Hidden Markov models have been employed to recognize latent driving states and distinguish driving styles from observed kinematic variables [18]. Bayesian methods have similarly been used to update assessments of driving style as vehicle interactions develop [19]. Unsupervised data-mining approaches have identified recurring behavior patterns in lane-change trajectories and examined their associations with traffic risk [20]. Meanwhile, trajectory-prediction research has emphasized the importance of representing temporal dependencies and heterogeneous motion patterns [21], and risk-based driver models have linked behavioral adjustments to changing interaction conditions [22]. Despite these advances, directly applying a common state model to all unprotected left-turn events remains problematic. Individual maneuvers may contain different numbers of behavioral adjustments and may unfold over substantially different durations. Moreover, hidden states estimated separately from different events do not necessarily possess consistent behavioral meanings, even when they share the same numerical label.

Consequently, an important research gap concerns the process-level organization of unprotected left-turn behavior. Existing approaches generally explain whether a driver accepts a gap, predicts the final decision, or evaluates the resulting conflict risk, but do not

explicitly identify the local behavior patterns embedded within the complete maneuver or the transitions connecting them. It therefore remains unclear which recurring behavior patterns constitute an unprotected left turn, how these patterns are combined in temporal order, and how transitions among them are associated with changing opposing-traffic conditions. Addressing these questions requires a framework that can accommodate event-specific temporal complexity while establishing a common behavioral representation across different interaction events.

To address this gap, this study develops a data-driven framework that represents complete unprotected left-turn interactions as ordered sequences of variable-length driving primitives. Valid interaction events are first extracted from high-resolution UAV trajectories using a conflict-zone-centered definition. An event-specific Non-Homogeneous Hidden Markov Model (NHMM) is then used to segment each trajectory according to the kinematic state of the left-turning vehicle and its interaction with the opposing vehicle. Because the resulting hidden states are specific to individual events, the extracted primitives are subsequently pooled and clustered using Time-Series K-Means (TSKM) with Dynamic Time Warping (DTW). This procedure converts event-specific primitives into behavior patterns that are comparable across events. Finally, the identified patterns are mapped back to their original temporal sequences to examine the behavioral composition and transition characteristics of complete left-turn maneuvers.

The main contributions of this study are summarized as follows:

- (1) An event-specific NHMM-based framework is established to decompose complete unprotected left-turn interactions into variable-length driving primitives while accounting for changing opposing-traffic conditions.
- (2) A two-level segmentation and clustering procedure is developed to transform event-specific hidden states into behavior patterns that are semantically comparable across interaction events.
- (3) The identified behavior patterns are reconstructed as event-level transition sequences, revealing how unprotected left turns evolve through ordered combinations of local behaviors and how pattern transitions are associated with opposing traffic.

The remainder of this paper is organized as follows. Section 2 presents the proposed framework and methods. Section 3 describes the trajectory data and parameter settings. Section 4 reports and discusses the empirical results. Section 5 concludes the study and outlines directions for future research.

2. Methods

This study proposes a primitive-based framework for analyzing unprotected left-turn behavior patterns and their evolution mechanism. As shown in Figure 1, the framework includes four modules: event and feature extraction, NHMM-based primitive segmentation, DTW-based behavior pattern clustering, and pattern evolution analysis. First, valid left-turn interaction events are extracted from UAV trajectories based on the conflict zone, and both endogenous feature variables and exogenous interaction covariates are constructed. Then, NHMM is used to segment complete left-turn processes into driving primitives. The extracted primitives are further clustered using DTW-based time-series K-means to identify representative behavior patterns. Finally, the evolution chains of these patterns are analyzed to reveal how drivers adjust their behavior in response to opposing traffic.

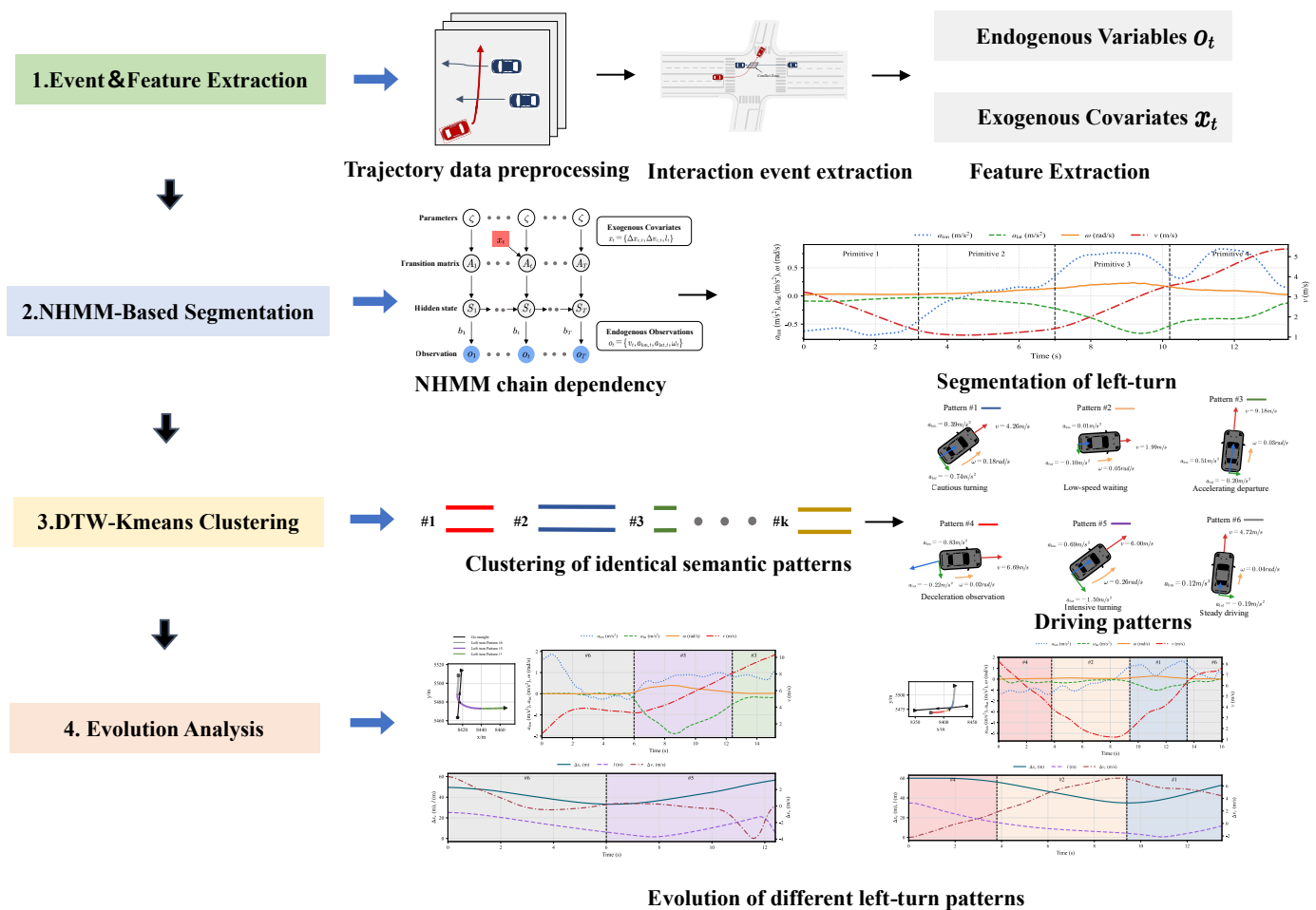


Figure 1. Overall framework of the proposed primitive-based analysis method.

2.1. Unprotected Left-Turn Interaction Event Extraction

Unprotected left-turn scenarios can be broadly divided into two cases: the left-turning vehicle yields to the opposing through vehicle, or the left-turning vehicle proceeds before the opposing through vehicle [23]. In both cases, the core interaction takes place around the spatial crossing area of the two trajectories. However, accurately determining the moments when vehicles enter or leave this area is difficult because the physical conflict area of a left-turn maneuver is irregular. To obtain a computable geometric representation of the interaction area, this study approximates the conflict area as a parallelogram and represents each vehicle by its rectangular outline. Compared with point-based vehicle representation, rectangular vehicle outlines can better preserve the spatial occupation characteristics of vehicles in aerial trajectory data [24].

As illustrated in Figure 2, P denotes the intersection of the left-turning and opposing-through trajectories and is taken as the center of the conflict zone. The parameters θ_L and θ_s represent the yaw angles of the left-turning and opposing-through vehicles at P , respectively. Both angles are measured counterclockwise from the positive x -axis. The included angle between the two local trajectory directions is denoted by φ . The parameters W_L and W_s denote the widths of the left-turning and opposing-through vehicles, respectively. The projected extent of the left-turning vehicle width along the opposing-through direction is denoted by H , which is calculated as $H = \frac{W_L}{\sin \varphi}$.

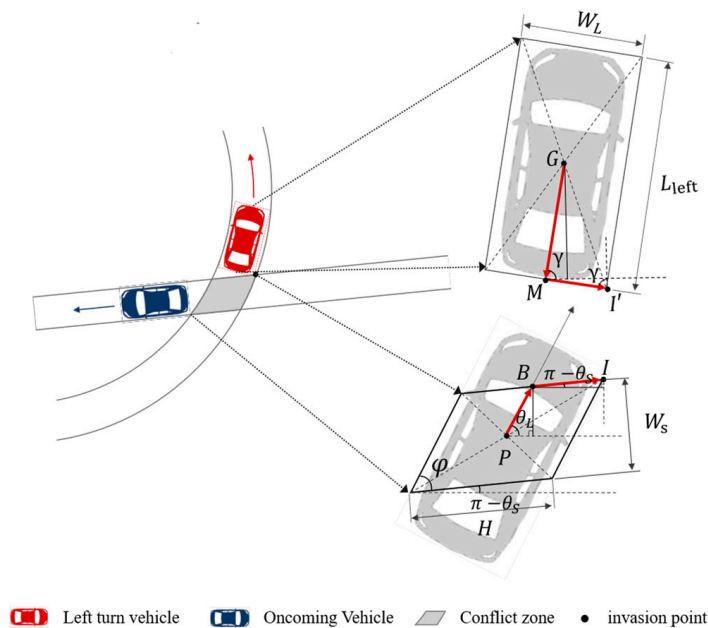


Figure 2. Geometric construction of the conflict zone and determination of vehicle invasion.

These quantities are event-specific geometric variables. For each interaction event, W_L and W_s are obtained from the vehicle-dimension attributes provided in the trajectory dataset. The yaw angles θ_L and θ_s are determined from the corresponding vehicle headings at P . The included angle φ and projected extent H are then calculated for the event. Therefore, the geometric construction accounts for the vehicle dimensions and local trajectory directions of each interacting vehicle pair [25].

The point at which the boundary of the conflict zone intersects the vehicle outline is defined as the invasion point I . Its coordinates are obtained by vector addition from the conflict-zone center P . As shown in Figure 2, the displacement from P to I consists of the displacement from P to the intermediate boundary point B and the displacement from B to I

$$\vec{PI} = \vec{PB} + \vec{BI}. \quad (1)$$

According to the geometric relationships of the parallelogram,

$$\vec{PB} = \frac{W_s}{2} \begin{bmatrix} \cos \theta_L \\ \sin \theta_L \end{bmatrix}, \vec{BI} = \frac{H}{2} \begin{bmatrix} \cos(\pi - \theta_s) \\ \sin(\pi - \theta_s) \end{bmatrix}. \quad (2)$$

Therefore, the coordinates of the invasion point I are calculated as:

$$x_I = x_P + \frac{W_s}{2} \cos \theta_L + \frac{H}{2} \cos(\pi - \theta_s), y_I = y_P + \frac{W_s}{2} \sin \theta_L + \frac{H}{2} \sin(\pi - \theta_s). \quad (3)$$

The remaining vertices of the parallelogram are obtained using the corresponding vector relationships. Together, these vertices define the conflict-zone polygon, denoted by $\mathcal{Z}$.

To determine the moments when the vehicles invade and leave $\mathcal{Z}$, each vehicle is represented by an oriented rectangular outline. Taking the left-turning vehicle as an example, $G = (x_G, y_G)$ denotes its center position, L_{left} and W_L denote its length and width, and γ denotes its instantaneous heading angle. The corner I' shown in Figure 2 can be calculated as:

$$x_{I'} = x_G - \frac{L_{\text{left}}}{2} \cos \gamma + \frac{W_L}{2} \sin \gamma, y_{I'} = y_G - \frac{L_{\text{left}}}{2} \sin \gamma - \frac{W_L}{2} \cos \gamma. \quad (4)$$

The other three vehicle corners are calculated using the corresponding combinations of the longitudinal and lateral offsets. The rectangular region occupied by the vehicle is then constructed from the four corner coordinates. The same procedure is applied to the opposing-through vehicle.

Let $u \in \{LT, OT\}$ denote an interacting vehicle, where LT represents the left-turning vehicle and OT represents the opposing-through vehicle. The rectangular spatial region occupied by vehicle u at time t is denoted by $R_u(t)$. A conflict-zone occupation indicator is defined as:

$$\chi_u(t) = \begin{cases} 1, & R_u(t) \cap \mathcal{Z} \neq \emptyset \\ 0, & R_u(t) \cap \mathcal{Z} = \emptyset \end{cases}. \quad (5)$$

A value of $\chi_u(t) = 1$ indicates that at least part of the vehicle outline overlaps the conflict zone. Accordingly, the entry and exit times of vehicle u are determined by

$$t_u^{\text{in}} = \min\{t : \chi_u(t) = 1\}, t_u^{\text{out}} = \max\{t : \chi_u(t) = 1\}. \quad (6)$$

The start of an unprotected left-turn interaction event is defined as the moment when the front outline of the left-turning vehicle first crosses the approach stop line, denoted by $t_{\text{LT}}^{\text{SL}}$. The interaction is considered complete when both interacting vehicles have left the conflict zone. Therefore, the temporal boundaries of an interaction event are defined as:

$$t_{\text{start}} = t_{\text{LT}}^{\text{SL}}, t_{\text{end}} = \max(t_{\text{LT}}^{\text{out}}, t_{\text{OT}}^{\text{out}}). \quad (7)$$

2.2. NHMM-Based Driving Primitive Segmentation

To analyze the dynamic interaction process of unprotected left turns without losing local behavioral heterogeneity, the continuous time-series data extracted from each event need to be decomposed into mid-granularity behavioral units [26]. This study employs a Non-homogeneous Hidden Markov Model to segment the complete left-turn process into a sequence of driving primitives [18]. Unlike the standard homogeneous HMM, the NHMM relaxes the time-homogeneity assumption and allows the state transition probabilities to vary over time as a function of time-varying exogenous covariates, thereby explicitly capturing how unfolding interaction dynamics drive changes in driving states [22].

For any given left-turn interaction event under analysis, let $O = \{o_1, o_2, \dots, o_t, \dots, o_T\}$ represent the observation sequence of a complete left-turn interaction event of duration T . The observation vector at time t , denoted as o_t , consists of the endogenous kinematic variables of the left-turning vehicle that directly reflect its physical control and motion state [27]

$$o_t = \{v_t, a_{\text{lon},t}, a_{\text{lat},t}, \omega_t\}, \quad (8)$$

where v_t is the instantaneous speed, $a_{\text{lon},t}$ is the longitudinal acceleration, $a_{\text{lat},t}$ is the lateral acceleration, and ω_t is the yaw rate.

The underlying, unobserved driving states are modeled as a hidden Markov chain $q = \{q_1, q_2, \dots, q_t, \dots, q_T\}$, where each state q_t belongs to a finite set of hidden states $S = \{S_1, S_2, \dots, S_N\}$, and K represents the total number of hidden states. The observation o_t at time t is assumed to be generated from the hidden state q_t according to a state-dependent emission probability distribution $b_k(o_t) = P(o_t | q_t = S_k, \theta)$, where θ denotes the parameters of the emission distribution, modeled here as a multivariate Gaussian distribution.

Assuming the continuous endogenous kinematic observation vector at time t given the hidden state q_t follows a multivariate Gaussian distribution, its emission probability density function $b_{q_t}(o_t)$ is explicitly defined as:

$$b_{q_t}(o_t) = P(o_t | q_t) = \frac{1}{(2\pi)^{d/2} |\Sigma_{q_t}|^{1/2}} \exp\left(-\frac{1}{2}(o_t - \mu_{q_t})^T \Sigma_{q_t}^{-1} (o_t - \mu_{q_t})\right), \quad (9)$$

where $d = 4$ represents the dimensions of the endogenous observation vector o_t ; μ_{q_t} denotes the d -dimensional mean vector, and Σ_{q_t} denotes the $d \times d$ covariance matrix corresponding to the hidden driving state q_t .

For a single isolated left-turn interaction event with a continuous observation sequence $O = \{o_1, o_2, \dots, o_t, \dots, o_T\}$ and the corresponding hidden Markov chain sequence $q = \{q_1, q_2, \dots, q_t, \dots, q_T\}$, the full joint probability distribution (likelihood function) parameterized by $\Theta = \{\pi, \zeta, \mu, \Sigma\}$ is mathematically formulated as:

$$L(\Theta | O, X) = P(q_1 | \pi) b_{q_1}(o_1) \prod_{t=2}^T a_{q_{t-1}q_t}(x_t) b_{q_t}(o_t), \quad (10)$$

where π is the initial state probability vector, and $a_{q_{t-1}q_t}(x_t)$ is the time-varying state transition probability dynamically modulated by the exogenous interaction covariates x_t .

The core expansion of the NHMM lies in modeling the transition matrix as a time-varying process influenced by external environmental stimuli. In an unprotected left-turn scenario, the driver's intent and state transitions are strongly conditioned by the spatial-temporal relationship with the oncoming traffic [28]. Therefore, a time-varying exogenous covariate vector x_t is constructed at each time step t :

$$x_t = \{\Delta x_{c,t}, \Delta v_{c,t}, l_t\}, \quad (11)$$

where $\Delta x_{c,t}$ represents the distance between the left-turning vehicle and the opposing through vehicle, $\Delta v_{c,t}$ represents the relative speed between the left-turning vehicle and the opposing vehicle, and l_t represents the remaining distance from the left-turning vehicle to the conflict zone. The time-varying transition probability a_{ijt} from state S_i at time $t - 1$ to state S_j at time t is modulated by x_t via a multinomial logistic link function:

$$a_{ijt} = P(q_t = S_j | q_{t-1} = S_i, x_t, \zeta) = \frac{\exp(\xi_{ij} + x_t^T \rho_j)}{\sum_{m=1}^N \exp(\xi_{im} + x_t^T \rho_m)}, \quad (12)$$

where ξ_{ij} represents the baseline transition intercept from state i to state j , ρ_j is the coefficient vector indicating the directional influence of the exogenous covariates on entering destination state j , and $\zeta = \{\xi_{ij}, \rho_j\}$ denotes the complete set of transition parameters. To intuitively illustrate the conditional dependencies and the time-varying nature of these state transitions, the complete structure of the proposed NHMM is depicted in Figure 3.

The optimal sequence of hidden states $\hat{q}$ was decoded from the estimated model parameters using the Viterbi algorithm. Rather than assigning a fixed, definitive semantic label directly to each individual hidden state at this stage, the hidden states are utilized purely to capture internally consistent kinematic characteristics. Continuous time steps sharing identical decoded hidden states are merged chronologically to partition the original observation sequence O into a sequence of K driving primitives, denoted as $\mathcal{P} = \{P_1, P_2, \dots, P_K\}$. The k -th driving primitive P_k is defined as:

$$P_k = \{o_{t_s}, o_{t_s+1}, \dots, o_{t_e}\} \text{ s.t. } q_{t_s} = q_{t_s+1} = \dots = q_{t_e}, \quad (13)$$

where t_s and t_e denote the start and end times of the k -th primitive, respectively. Consequently, a complete interaction event O is successfully transformed into a sequential chain of variable-length driving primitives, which serve as the fundamental motion units for the subsequent time-series pattern clustering.

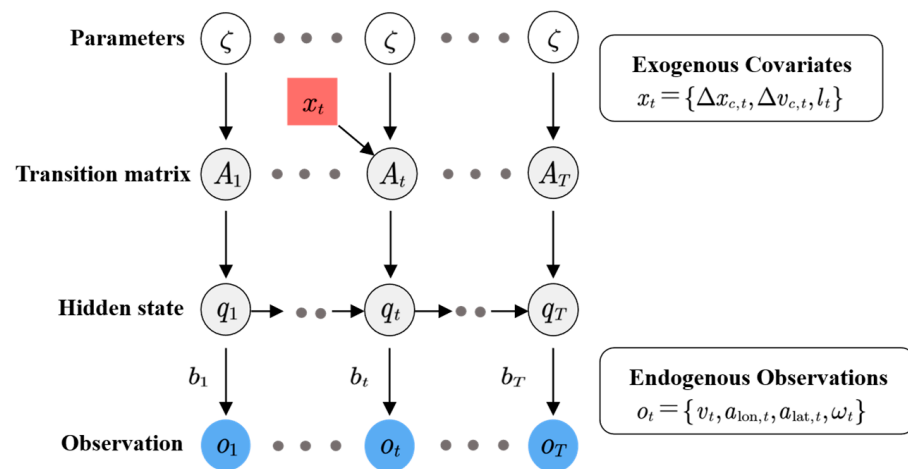


Figure 3. The graphical model of the NHMM.

2.3. Behavior Pattern Clustering Based on DTW-KMeans

Through the NHMM-based segmentation, the continuous left-turn interaction process is decomposed into a vast collection of sequential driving primitives. Although these primitives represent elementary motion units, individual primitives exhibit significant variability and do not intrinsically carry stable semantic meanings. To systematically interpret driver intent, it is necessary to identify recurring unprotected left-turn behavior patterns by grouping these extracted primitives.

A critical challenge in this clustering process is that the driving primitives inherently form variable-length time series, as drivers maintain specific behavioral states for different durations. Traditional clustering methods relying on Euclidean distance require interpolating sequences to a uniform length, which inevitably destroys the original duration attributes and distorts localized structural features. Therefore, a distance metric capable of evaluating the shape similarity of variable-length sequences is required.

Dynamic Time Warping provides a robust solution to this temporal mismatch [29]. By locally stretching or compressing the time axis, DTW searches for the optimal alignment path between two time series, effectively minimizing the cumulative distance between their corresponding points. This property is highly advantageous in traffic behavior analysis, as it successfully aligns primitives that share similar kinematic execution shapes but unfold at different speeds or exhibit localized temporal shifts [30].

Let $P_i = \{o_{i,1}, o_{i,2}, \dots, o_i\}$ and $P_j = \{o_{j,1}, o_{j,2}, \dots, o_j\}$ be two variable-length primitives. The DTW distance between P_i and P_j is defined by the minimum cumulative distance along the optimal warping path $\mathcal{W}$:

$$DTW(P_i, P_j) = \min_{\mathcal{W}} \sum_{k=1}^{|\mathcal{W}|} d(w_k), \quad (14)$$

where $w_k = (m, n)$ represents the alignment between the m -th data point in P_i and the n -th data point in P_j , and $d(w_k)$ denotes the local distance between these two multidimensional kinematic observations.

To computationally solve this optimal alignment path γ , a cumulative distance matrix $D \in \mathbb{R}^{M \times N}$ between the two variable-length empirical driving primitives P_1 (of length

M) and P_2 (of length N) is systematically constructed. The matrix element $D(m, n)$ represents the aligned dynamic cost and is evaluated via the following dynamic programming recurrence rule:

$$D(m, n) = d(p_{1,m}, p_{2,n}) + \min \begin{cases} D(m-1, n) & \text{(Temporal Compression)} \\ D(m, n-1) & \text{(Temporal Expansion)} \\ D(m-1, n-1) & \text{(Synchronous Match)} \end{cases}, \quad (15)$$

where $d(p_{1,m}, p_{2,n})$ denotes the squared Euclidean distance between the multidimensional kinematic observation vectors of the two primitives at time frames m and n , respectively. The final elastic distance is output as $DTW(P_1, P_2) = D(M, N)$.

To group the massive variable-length primitive sequences into finite, meaningful behavior patterns, this study applies the DTW-based time-series K-means clustering algorithm [31]. The objective is to partition all primitives $\mathcal{P} = \{P_1, P_2, \dots, P_K\}$ into C distinct behavior pattern clusters, denoted as $\mathcal{C} = \{C_1, C_2, \dots, C_C\}$. Let μ_c represent the centroid of cluster C_c . The algorithm iteratively updates the cluster assignments and recalculates the centroids to minimize the within-cluster sum of squares, defined as:

$$\min \sum_{c=1}^C \sum_{P_k \in C_c} DTW(P_k, \mu_c)^2. \quad (16)$$

Figure 4 illustrates this three-step clustering framework. First, the original variable-length primitives exhibit distinct temporal mismatches. Next, DTW performs non-linear temporal alignment to synchronize the intrinsic kinematic features across different primitives. Finally, the time-series K-means algorithm groups the aligned sequences to extract representative behavior patterns.

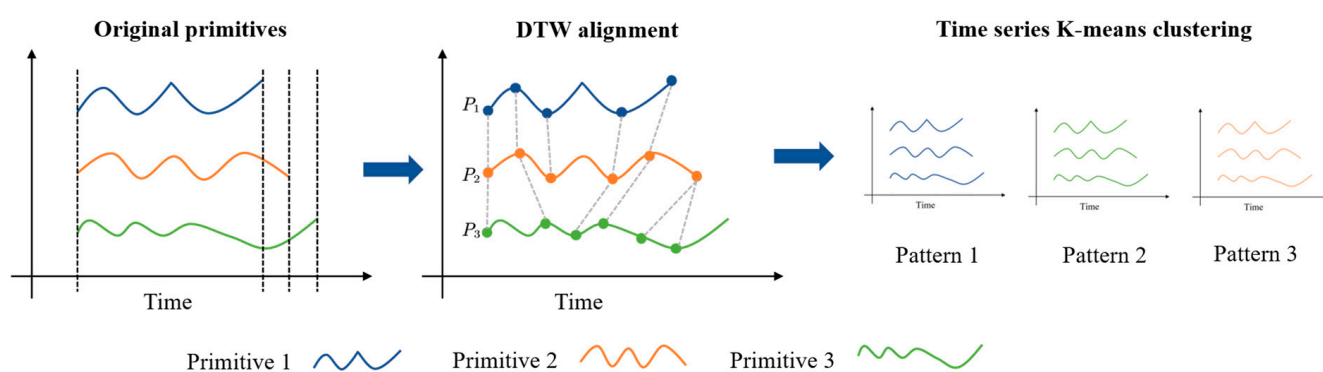


Figure 4. Schematic of the DTW-based time-series K-means clustering process.

By utilizing the DTW-based time-series K-means clustering, variable-length primitives with similar kinematic shapes and behavioral tendencies are robustly gathered into identical clusters. The resultant cluster centroids structurally characterize the representative driving maneuvers, providing a definitive basis for the subsequent semantic interpretation and pattern evolution analysis.

3. Data and Parameter Setting

3.1. Data Description and Processing

The trajectory data used in this study, hereafter referred to as the XJROAD dataset, were collected by unmanned aerial vehicles (UAVs) over a 12-h period at a two-phase signal-controlled intersection (Xiangjiang Road) in Shanghai, China. The intersection

features a four-lane bidirectional east–west approach and a two-lane bidirectional north–south approach. Comprising a total of 37,351 trajectories, the dataset captures over 99.8% of all traffic participants, including passenger cars, heavy vehicles, buses, motorcycles, and pedestrians. It records the frame-level motion information of all observed vehicles, including vehicle position, speed, acceleration, heading angle, and vehicle size. Figure 5 illustrates an aerial view of the studied intersection. Such high-resolution trajectory data provide the basis for reconstructing the continuous interaction process between left-turning vehicles and opposing through vehicles without visual occlusions.

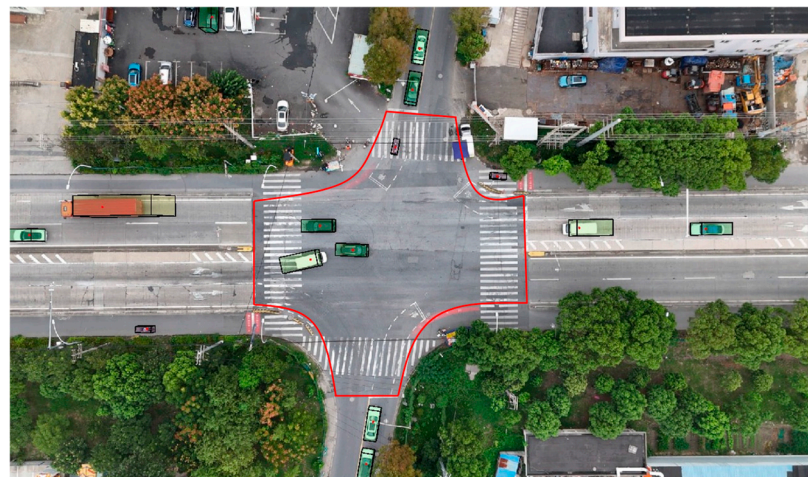


Figure 5. The Xiangjiang Road intersection and the extracted high-resolution vehicle trajectories.

Based on the conflict-zone extraction procedure in Section 2.1, unprotected left-turn interactions were identified from the UAV trajectories. To avoid the confounding effects of heterogeneous vehicle kinematics, heavy vehicles and buses were excluded to focus purely on passenger cars, and invalid or incomplete trajectories were removed to ensure data fidelity. Ultimately, 2490 valid interaction events were extracted. The event duration had a mean of 13.91 s, a standard deviation of 3.27 s, a median of 13.50 s, and a range from 6.90 to 30.80 s. For each frame, endogenous feature variables ($v, a_{lon}, a_{lat}, \omega$) and exogenous covariates ($\Delta x_c, \Delta v_c, l$) were calculated. All sequences were resampled to 10 Hz. The descriptive statistics of these variables are summarized in Table 1.

Table 1. Descriptive statistics of variables used in the model.

Variables	Description	Mean	S.D.	Min	Max
v	Speed of the left-turning vehicle (m/s)	4.454	2.345	0.003	12.032
a_{lon}	Longitudinal acceleration of the left-turning vehicle (m/s^2)	0.218	0.953	−5.518	2.479
a_{lat}	Lateral acceleration of the left-turning vehicle (m/s^2)	−0.502	0.559	−2.445	0.306
ω	Yaw rate of the left-turning vehicle (rad/s)	0.108	0.105	−0.056	0.426
Δx_c	Distance between the two interacting vehicles (m)	30.516	18.340	2.387	60.000
Δv_c	Relative speed between the two interacting vehicles (m/s)	1.793	3.519	−13.515	18.347
l	Remaining distance from the left-turning vehicle to the conflict zone (m)	14.156	9.979	0.008	35.000

Considering the spatial scale and effective observation range of the studied intersection, upper bounds were applied to the two distance covariates during data preprocessing.

The upper bound of Δx_c was set to 60 m. The upper bound of l was set to 35 m according to the upstream spatial range covered by the extracted left-turn interaction events.

3.2. Experiment and Parameter Settings

To systematically extract and analyze the behavioral patterns from the processed trajectory dataset, the experimental parameter configuration is conducted in two sequential stages: the determination of the hidden state number in the NHMM for primitive segmentation, and the selection of the optimal cluster number for the DTW-KMeans algorithm.

3.2.1. Driving Primitive Segmentation

The number of hidden states determines the segmentation granularity of the driving primitive sequence. If the number of hidden states is too small, distinct local motion processes may be prematurely merged into the same primitive. Conversely, if the number is too large, the model tends to generate highly fragmented primitives that carry redundant noise rather than stable behavioral information. Therefore, the hidden-state granularity must be systematically evaluated before final primitive segmentation.

In this study, the NHMM is implemented separately for each independent unprotected left-turn interaction event. For the i -th interaction event, a series of candidate models with the local state number K ranging from 2 to 7 ($K \in \{2, 3, \dots, 7\}$) are estimated, and the Bayesian Information Criterion (BIC) is adopted to select the optimal configuration. The event-level BIC is formulated as:

$$\text{BIC}(K) = -2 \ln L(K) + p(K) \ln T, \quad (17)$$

where $L(K)$ is the likelihood of the i -th event under the NHMM with K hidden states, $p(K)$ is the number of estimated parameters, and T is the sequence length of the event. The candidate value with the minimum BIC is selected as the optimal hidden-state number K for this event.

For each candidate model, the observation variables and exogenous covariates were standardized within the corresponding event. The parameters were initialized using a Gaussian HMM fitted to the observation sequence of the event. The Gaussian HMM was used only for initialization, with a maximum of 100 iterations and a convergence tolerance of 10^{-3} . The NHMM parameters were then estimated using the EM algorithm. In the E-step, the forward-backward algorithm was used to calculate the posterior probabilities of hidden states and state transitions. In the M-step, the initial-state probabilities, diagonal Gaussian emission parameters, and covariate-dependent transition coefficients were updated. The transition coefficients in the multinomial logistic function were optimized using the L-BFGS-B algorithm, with a maximum of 100 iterations and a tolerance of 10^{-5} . The maximum number of EM iterations for NHMM estimation was set to 20, and the stopping tolerance was 10^{-3} . In the baseline estimation, one HMM-based initialization was used for each candidate model, and fixed event- and K_i -specific random seeds were adopted.

The distribution of the selected hidden-state numbers is shown in Table 2. The optimal K varies across interaction events, indicating that different unprotected left-turn processes have different temporal structures. Most events are segmented with three or four hidden states, accounting for 34.38% and 37.35% of the samples, respectively. Events with $K = 5$ account for 17.51%, while only a small proportion of events select, $K = 6$, or $K = 7$. In particular, only 0.72% of the events reach the upper bound $K = 7$, suggesting that the candidate range $K = 2, \dots, 7$ is sufficient for the present dataset.

Table 2. Distribution of selected hidden-state numbers in NHMM.

<i>K</i>	2	3	4	5	6	7
Number of events	4	856	930	436	246	18
Percentage (%)	0.16	34.38	37.35	17.51	9.88	0.72

Across the 2490 interaction events, the event-specific NHMMs generated 12,704 driving primitives. The number of primitives per event had a mean of 5.10, a standard deviation of 1.42, and a range from 2 to 8. These event-level primitives provide the basic motion units for subsequent behavior pattern recognition.

Because each NHMM was estimated from a single interaction event, additional fitting diagnostics were conducted to examine the numerical stability of the event-level models. Table 3 reports the convergence status, state occupancy, covariance constraints, and unstable fitting cases. Candidate models that produced numerical errors or invalid probability estimates were recorded as fitting failures and excluded from BIC comparison. For the selected model of each event, hidden-state occupancy was calculated after Viterbi decoding. An empty hidden state indicates that no frame was assigned to that state, while low occupancy indicates that fewer than 1% or 5% of frames were assigned to the least occupied state. To avoid singular covariance estimates, the emission distribution was specified as a diagonal Gaussian distribution with a minimum variance floor of 10^{-3} .

Table 3. Fitting diagnostics of event-level NHMMs.

Diagnostic Aspect	Reported Item	Result
Model fitting	Candidate NHMM fits	14940
	Candidate fitting failures	15
Model selection	Events without valid selected model	0
	Selected models with empty hidden states	0
State occupancy	Events with minimum state occupancy < 1%	1
	Events with minimum state occupancy < 5%	45
Covariance constraint	Emission covariance structure	Diagonal Gaussian
	Minimum variance floor	10^{-3}
Model stability	Numerically unstable selected models	0

The diagnostic results show that all events retained at least one valid candidate model, and no selected model contained empty hidden states. Only 15 out of 14940 candidate fits failed, corresponding to 0.10% of all candidate models. In addition, only 45 events had a minimum state occupancy lower than 5%, accounting for 1.81% of the total events. No numerically unstable selected models were observed. These results indicate that the event-level NHMM fitting procedure was generally stable under the imposed covariance constraints.

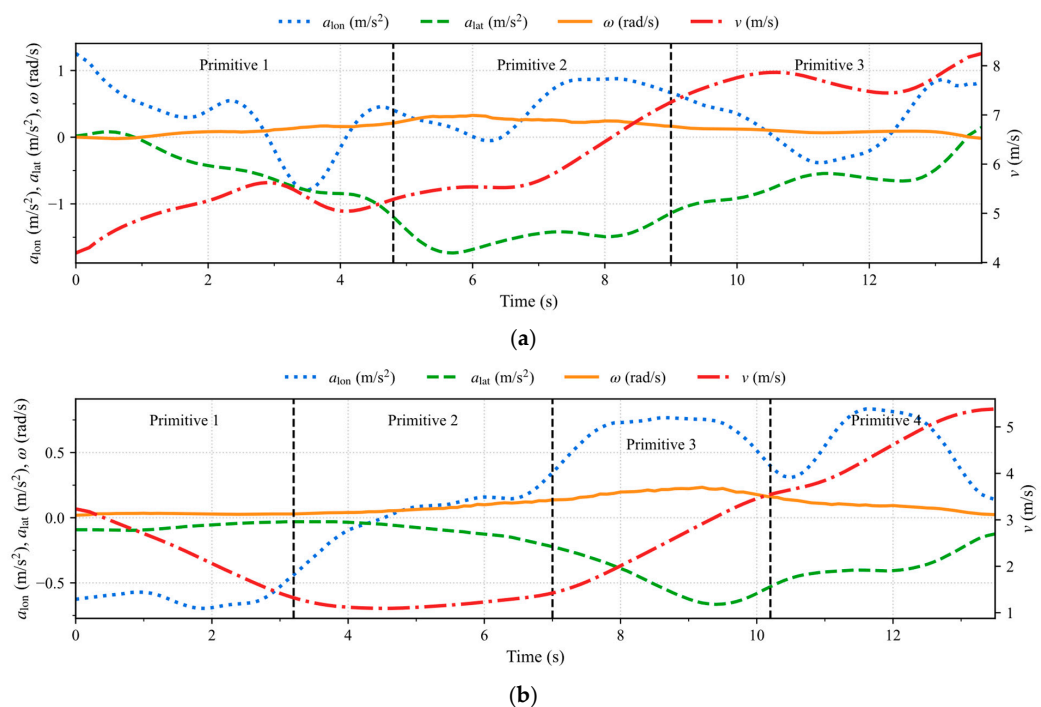
To further examine whether different starting values affect BIC-based model selection and primitive boundaries, a sensitivity analysis was conducted. Considering the high computational cost of repeatedly estimating event-level NHMMs under multiple random seeds, 400 interaction events were randomly selected from the full dataset for this analysis. Each selected event was repeatedly estimated using five different random seeds, and candidate models with $K_i = 2, \dots, 7$ were evaluated in each repetition. Only 3 out of 12,000 candidate estimations failed, and all event-seed runs retained at least one valid selected model. The results are reported in Table 4.

Table 4. Sensitivity analysis of event-level NHMM estimation.

Evaluation Metric	Result
Number of tested events	400
Number of random seeds	5
Candidate hidden-state range	2–7
Runs with unchanged selected K_i (%)	86.75
Runs with selected K_i within ± 1 of baseline (%)	96.38
Mean primitive-boundary deviation (s)	0.214
Median primitive-boundary deviation (s)	0.100
Runs with boundary deviation > 1.0 s (%)	2.13

The sensitivity analysis shows that the selected hidden-state number remained unchanged in most repeated estimations and was within ± 1 of the baseline value in 96.38% of the runs. The decoded primitive boundaries also showed small deviations, with a mean deviation of 0.214 s and a median deviation of 0.100 s. Only 2.13% of the repeated runs produced boundary deviations larger than 1.0 s. These results indicate that the event-level NHMM estimation was generally stable under different starting values.

Figure 6 presents two representative segmentation examples. In Figure 6a, the selected hidden-state number is $K = 3$, and the process is divided into three primitives. The first primitive corresponds to the early part of the left-turn interaction, during which the vehicle approaches the conflict area with a gradual increase in speed and relatively large fluctuations in longitudinal acceleration. The second primitive mainly covers the middle part of the maneuver, where the lateral acceleration decreases markedly, and the yaw rate remains at a relatively high level, reflecting the period in which the vehicle adjusts its turning motion. The third primitive appears in the later part of the interaction. In this segment, the speed continues to increase, and the lateral acceleration gradually recovers, indicating that the vehicle is leaving the conflict-related interaction process and entering a more stable motion state.

**Figure 6.** Segmentation results of an unprotected left-turn process. (a) Segmentation result of an event with $K = 3$. (b) Segmentation result of an event with $K = 4$.

In Figure 6b, the selected hidden-state number is $K = 4$, and the process is divided into four primitives. Compared with Figure 6a, this event shows a more detailed temporal structure. The first primitive corresponds to the initial approach part, in which the vehicle speed decreases and the longitudinal acceleration remains negative. The second primitive represents a transitional part before the main turning motion, where the speed stays at a relatively low level, and the yaw rate begins to increase. The third primitive captures the main turning-related part of the maneuver, characterized by a higher yaw rate and stronger lateral acceleration variation. The fourth primitive corresponds to the later part of the left-turn process, where the speed increases rapidly, and the yaw-rate variation gradually weakens.

These primitives provide the basic motion units for subsequent behavior pattern recognition. Based on the variable-length temporal profiles of the extracted primitives, the following section further applies DTW-based time-series K-means to identify representative unprotected left-turn behavior patterns.

3.2.2. Unprotected Left-Turn Behavior Pattern Clustering

After primitive segmentation, the valid event-level primitives extracted from all unprotected left-turn interaction events were pooled for behavior pattern clustering. Since these primitives differed in duration, conventional clustering based on point-to-point Euclidean distance could not adequately measure their temporal similarity. Therefore, DTW-based time-series K-means was applied. Each primitive was represented by a multivariate feature sequence consisting of speed, longitudinal acceleration, lateral acceleration, and yaw rate. Before clustering, the four feature dimensions were standardized to prevent differences in scale from dominating the distance calculation.

In the DTW-KMeans implementation, unconstrained DTW was used to accommodate the duration variation among the extracted primitives, and no Sakoe–Chiba warping window was imposed. Cluster centroids were computed using DTW Barycenter Averaging (DBA), which iteratively aligns the primitives assigned to each cluster and estimates their representative temporal profile. The clustering objective was defined using the squared DTW distance between each primitive and its assigned DBA centroid. Consequently, primitives with similar feature evolution profiles could be grouped into the same behavior pattern even when their durations and rates of evolution differed. The candidate number of clusters C was initially examined using the within-cluster DTW objective λ_w and its change rate, as shown in Figure 7.

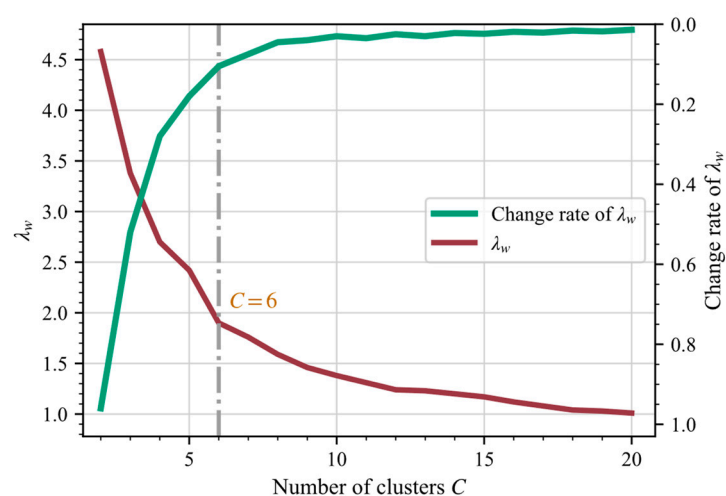


Figure 7. Selection of the optimal number of behavior pattern clusters.

Figure 7 shows that the normalized λ_w decreases as the number of clusters increases, indicating progressively greater within-cluster compactness. The reduction becomes more gradual around $C = 6$, while further increases in C produce smaller changes in the DTW objective. Candidate solutions from $C = 4$ to $C = 8$, covering the neighborhood of this change in trend, were therefore subjected to additional cluster validity and stability analyses.

For each candidate value of C , DTW-based time-series K-means was fitted using 10 random initializations, and the solution with the smallest within-cluster objective was retained. The silhouette score and Davies–Bouldin index were used to assess cluster separation and compactness. A larger silhouette score indicates stronger separation between clusters, whereas a smaller Davies–Bouldin index indicates a more compact and better-separated clustering solution. Clustering stability was further evaluated through 20 event-level resampling runs. In each run, 80% of the interaction events were sampled without replacement, and all primitives extracted from the selected events were retained together. This procedure preserved the dependence among primitives belonging to the same interaction event. The adjusted Rand index (ARI) was calculated between each resampled solution and the full-data reference solution for their shared primitives. A larger ARI indicates greater clustering stability. The results are presented in Table 5.

Table 5. Cluster validity and stability under different numbers of behavior patterns.

Number of Clusters C	Silhouette Score	Davies–Bouldin Index	ARI Stability
4	0.386	1.138	0.803
5	0.421	1.014	0.841
6	0.446	0.902	0.879
7	0.452	0.925	0.861
8	0.431	0.963	0.832

As shown in Table 5, the six-cluster solution provides a favorable overall balance among the candidate solutions, with the lowest Davies–Bouldin index and the highest ARI stability. Although $C = 7$ yields a slightly higher silhouette score, this gain in cluster separation is marginal and is offset by weaker compactness and lower stability. Increasing the cluster number also raises the computational cost of DTW-based clustering and reduces the parsimony of the behavioral representation. Therefore, considering the DTW objective, cluster validity, clustering stability, model parsimony, computational efficiency, and behavioral interpretability, $C = 6$ was selected as the final number of unprotected left-turn behavior patterns.

4. Results and Discussion

4.1. Semantic Representation of Unprotected Left-Turn Behavior Patterns

After the primitive segmentation, DTW-based time-series K-means clustering was applied to all valid primitives extracted from the studied passenger-car interaction events, and six representative unprotected left-turn behavior patterns were identified. Figure 8 presents the schematic diagram of these six patterns. To facilitate semantic interpretation, this study uses the mean values of the cluster centroids to characterize each type of unprotected left-turn behavior pattern. In each subfigure, the arrows represent the mean kinematic characteristics of the left-turning vehicle, including speed, longitudinal acceleration, lateral acceleration, and yaw rate. The direction of each arrow indicates the direction or sign of the corresponding variable, while the arrow length represents its relative magnitude. The colored bar above each subfigure denotes the identity color of the corresponding behavior pattern, which is also used in the subsequent case analysis.

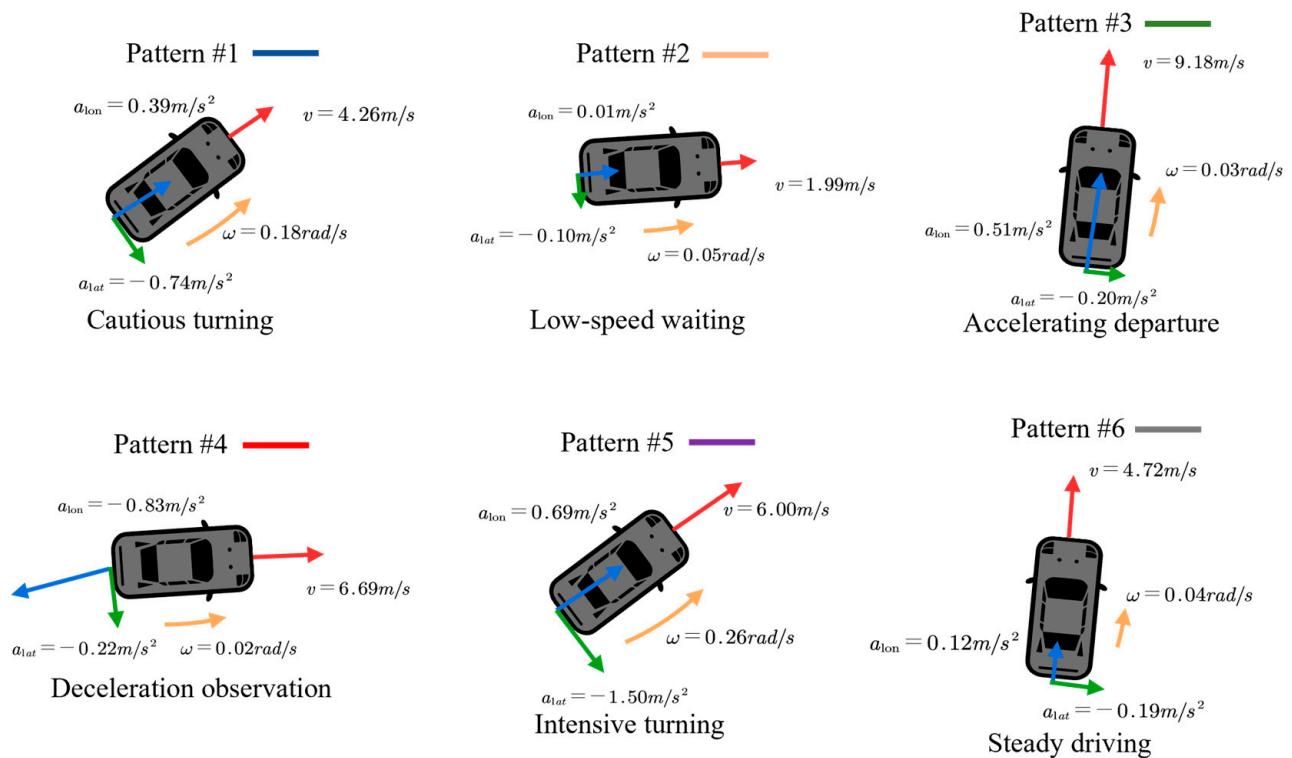


Figure 8. Schematic diagram of the six representative unprotected left-turn behavior patterns. The blue, green, orange, and red arrows represent longitudinal acceleration, lateral acceleration, yaw rate, and speed, respectively.

To support the semantic interpretation of the clustering results, the temporal location of each behavior pattern within the complete left-turn process was further examined. The early, middle, and late stages were defined according to the cumulative heading-angle change of the left-turning vehicle. For each event, the cumulative heading-angle change ratio at time t was calculated as

$$r_t = \frac{|\theta_t - \theta_{\text{start}}|}{|\theta_{\text{end}} - \theta_{\text{start}}|}, \quad (18)$$

where θ_t is the heading angle of the left-turning vehicle at time t , and θ_{start} and θ_{end} are the heading angles at the beginning and end of the corresponding interaction event, respectively. Based on r_t , the start of the main turning stage was defined as the first time step at which r_t reached 0.2, and the end of the main turning stage was defined as the first time step at which r_t reached 0.8. Therefore, the temporal stage G_t at time t was defined as

$$G_t = \begin{cases} \text{early stage,} & r_t < 0.2, \\ \text{middle stage,} & 0.2 \leq r_t \leq 0.8, \\ \text{late stage,} & r_t > 0.8. \end{cases} \quad (19)$$

Each primitive was assigned to one of the three stages.

As shown in Figure 8 and Table 6, Pattern #2 mainly appears in the early stage and is characterized by the lowest speed and weak acceleration variation. This pattern indicates that the left-turning vehicle moves slowly or waits before accepting a suitable gap. Therefore, it is interpreted as low-speed waiting. Pattern #4 also mainly appears in the early stage, but it has a relatively higher speed and a negative longitudinal acceleration. This indicates that the vehicle is still approaching the conflict area but begins to decelerate in response to the opposing traffic. Thus, Pattern #4 is interpreted as deceleration observation.

Table 6. Temporal distribution of the six unprotected left-turn behavior patterns.

Pattern	Behavior Pattern	Early (%)	Middle (%)	Late (%)	Dominant Stage
#1	Cautious turning	10.8	75.6	13.6	Middle
#2	Low-speed waiting	83.4	13.2	3.4	Early
#3	Accelerating departure	2.8	4.7	92.5	Late
#4	Deceleration observation	81.6	12.5	5.9	Early
#5	Intensive turning	7.5	78.9	13.6	Middle
#6	Steady driving	38.8	8.5	52.7	Early/Late

Pattern #1 and Pattern #5 mainly appear in the middle stage of the left-turn process. Pattern #1 shows moderate speed, evident yaw-rate variation, and moderate lateral acceleration, suggesting that the vehicle is executing the turn in a relatively smooth and controlled manner. Therefore, it is interpreted as cautious turning. Pattern #5 has stronger lateral acceleration and the largest yaw rate among the six patterns, indicating a more intensive heading change during the main turning process. Accordingly, Pattern #5 is interpreted as intensive turning.

Pattern #3 is highly concentrated in the late stage. It has the highest speed, positive longitudinal acceleration, and a small yaw rate, indicating that the vehicle has completed the major heading change and is accelerating away from the conflict area. Therefore, Pattern #3 is interpreted as accelerating departure. Pattern #6 appears in both the early and late stages. Its acceleration and yaw-rate variations are relatively weak, indicating a stable motion state. This pattern may correspond to steady approach before the main interaction or stable driving after the conflict has been cleared. Therefore, Pattern #6 is interpreted as steady driving.

Overall, the six patterns describe different local motion units within the unprotected left-turn process. The results indicate that an unprotected left-turn maneuver is not a single static decision, but a continuous process composed of several interpretable behavior patterns, including waiting, observation, turning, departure, and steady driving. These pattern labels provide the basis for analyzing behavior evolution chains in representative interaction processes.

4.2. Pattern Transitions and Interaction Mechanism

4.2.1. Overall Evolution of Behavior Patterns

To examine the overall organization of unprotected left-turn behavior, the identified patterns within each interaction event were arranged chronologically. Consecutive primitives assigned to the same pattern were merged, and transitions between adjacent patterns were counted across all valid events. Figure 9 presents the resulting row-normalized transition probability matrix, in which each row denotes the current pattern at time t , and each column denotes the subsequent pattern at time $t + 1$. The outgoing transition total N_i , shown beside each row, indicates the number of transitions originating from the corresponding pattern.

Several dominant transition relationships can be observed. Pattern #2 (low-speed waiting) is most frequently followed by Pattern #1 (cautious turning), indicating that vehicles commonly initiate the turning maneuver cautiously after waiting for an acceptable opportunity. Pattern #4 (deceleration observation) has three principal transition directions: Pattern #5 (intensive turning), Pattern #1 (cautious turning), and Pattern #2 (low-speed waiting). This branching structure suggests that, after decelerating to assess opposing traffic, drivers may execute the turn directly, initiate it cautiously, or continue waiting when the available gap remains insufficient.

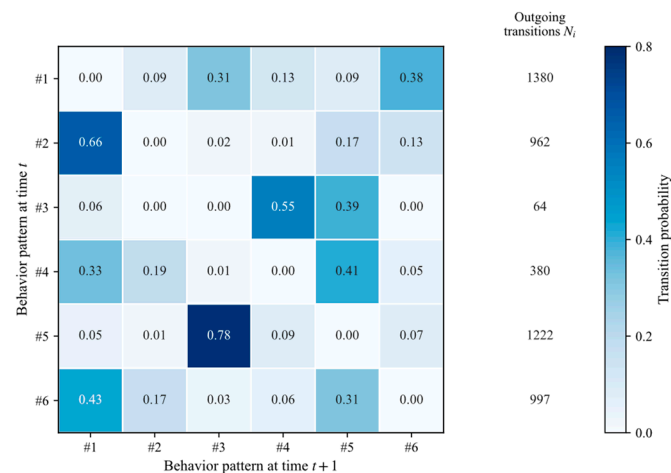


Figure 9. Transition probability matrix of unprotected left-turn behavior patterns.

Although the row-normalized probabilities from Pattern #3 to Patterns #4 and #5 are relatively high, these transitions should be interpreted cautiously. The outgoing transition total for Pattern #3 is only 64 because this pattern generally occurs near the end of the left-turn process, leaving relatively few observations with a subsequent pattern. These transitions therefore represent occasional short-term adjustments following an acceleration segment rather than a common return from departure to the earlier decision or turning stages.

Overall, the transition matrix derived from the studied events reveals several recurrent but non-unique evolution paths of unprotected left-turn behavior. In the analyzed samples, waiting and observation patterns generally precede turning patterns, while turning patterns are commonly followed by steady driving or accelerating departure. Meanwhile, the branching transitions indicate that the observed evolution process is not represented by a single fixed sequence. The event-level analyses in the following section further illustrate how these pattern combinations develop under different interaction conditions.

4.2.2. Pattern Evolution Under Interaction Conditions

While the transition probability matrix provides a population-level view of recurrent behavior-pattern transitions, it does not fully explain how these transitions unfold within individual interaction processes. To further interpret the mechanism underlying pattern evolution, this section examines representative event-level cases by jointly considering the endogenous kinematic profiles of the left-turning vehicle and the exogenous interaction covariates. Figures 10 and 11 present a three-pattern process and a four-pattern process, respectively. Consistent colors are used in the spatial trajectory, feature-variable profiles, and covariate panels to indicate the spatial distribution and temporal boundaries of the patterns. Tables 7 and 8 present the population-level marginal effects of the exogenous covariates on the pattern transitions observed in the two cases, calculated from all event-level NHMMs containing the corresponding transitions.

Figure 10 presents a process following the pattern #6 to #5 to #3. During Pattern #6 (steady driving), the left-turning vehicle approaches the interaction area with a relatively stable yaw rate and limited lateral motion. Its speed initially increases and then remains approximately stable. Meanwhile, Δx_c and l gradually decrease, indicating that the two vehicles are approaching the interaction area and that the available spatial margin is being reduced.

At approximately 6 s, the vehicle transitions to Pattern #5. The yaw rate increases markedly, while the lateral acceleration reaches a larger magnitude, reflecting the initiation of a decisive turning operation. During this stage, l decreases to its minimum and then

increases after the vehicle passes the conflict-zone center. The inter-vehicle distance Δx_c also changes from a decreasing to an increasing trend, indicating that the vehicles have passed their closest interaction condition and begun to separate. After the principal heading change, the vehicle enters Pattern #3 (accelerating departure), where the yaw rate and lateral acceleration weaken while the speed increases continuously.

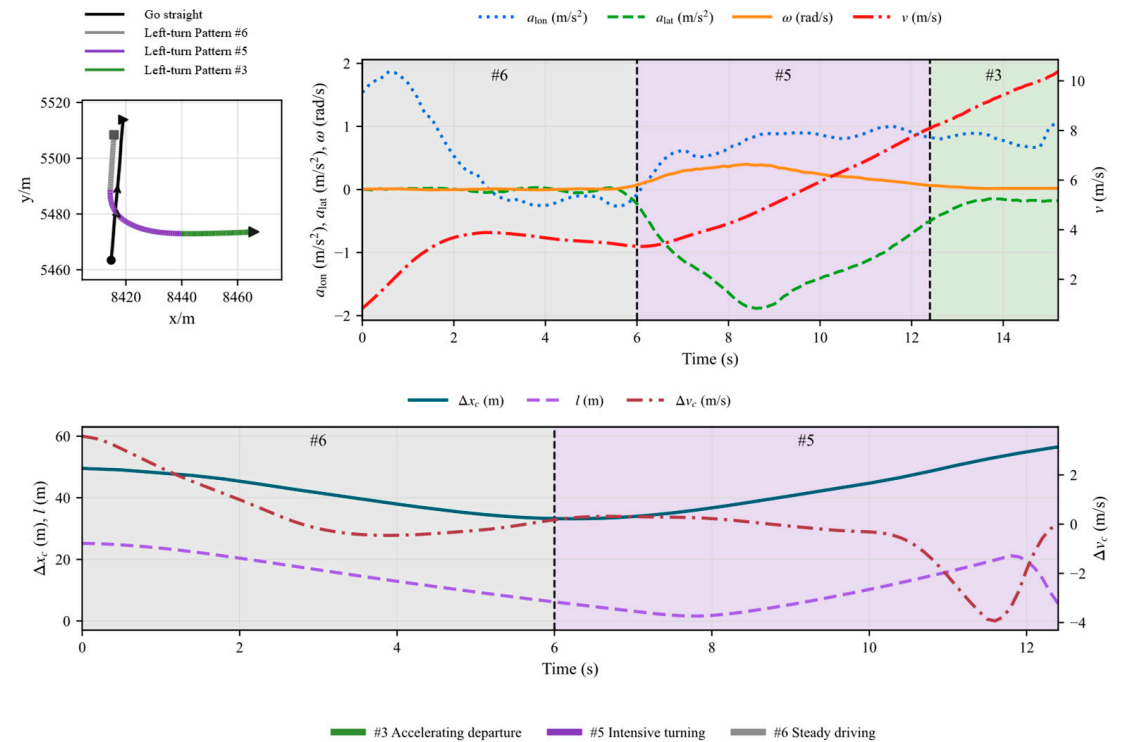


Figure 10. Evolution of behavior patterns and interaction covariates in a three-pattern left-turn case.

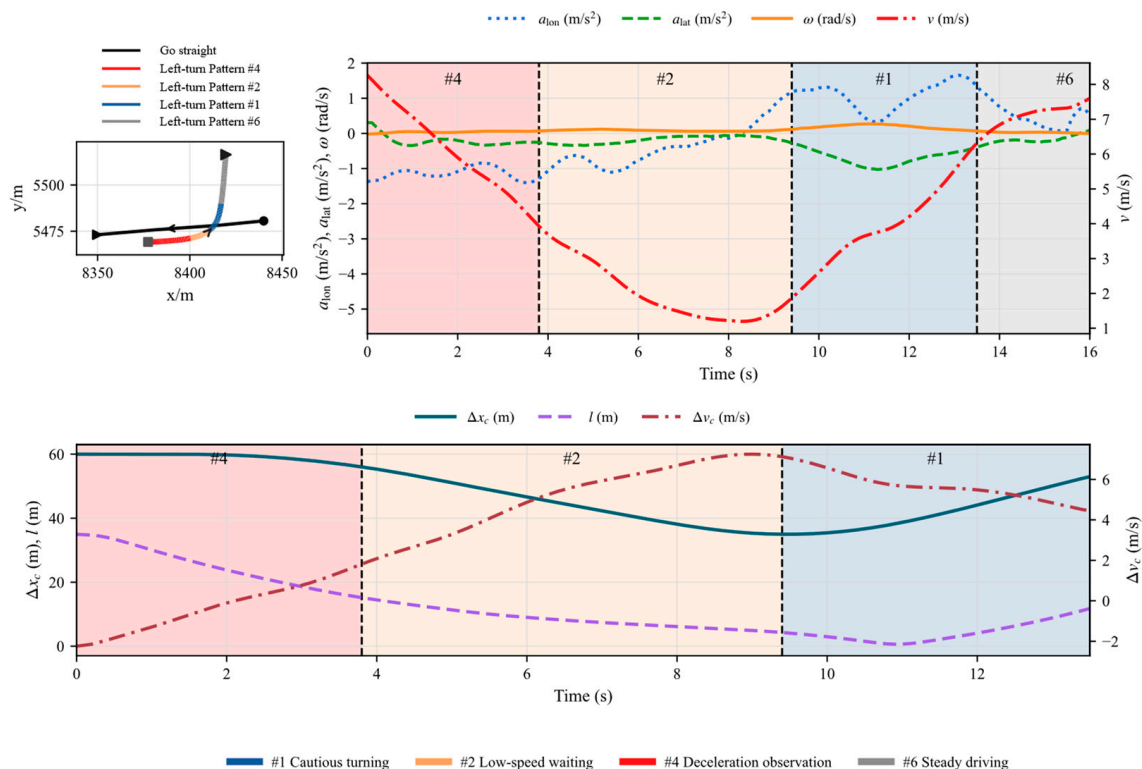


Figure 11. Evolution of behavior patterns and interaction covariates in a four-pattern left-turn case.

Table 7. Effects of exogenous covariates on transitions in the three-pattern process.

Transition	Δx_c	Δv_c	l
#6 to #5	−0.079	−0.128	−0.515 *
#5 to #3	−0.280 *	+0.173 *	+0.309 *

Note: * indicates statistical significance at the 5% level.

Table 8. Effects of exogenous covariates on transitions in the four-pattern process.

Transition	Δx_c	Δv_c	l
#4 to #2	−0.203	+0.694 *	−0.830 *
#2 to #1	+0.009	−0.203 *	−0.506 *
#1 to #6	−0.148 *	+0.109	+0.634 *

Note: * indicates statistical significance at the 5% level.

For the transition from Pattern #6 to Pattern #5, l exhibits a significant negative marginal effect, indicating that the likelihood of intensive turning increases as the left-turning vehicle approaches the conflict-zone center. For the subsequent transition from Pattern #5 to Pattern #3, Δx_c , Δv_c , and l all show significant effects. The negative effect of Δx_c and the positive effect of Δv_c characterize the changing interaction state between the two vehicles, while the positive effect of l indicates an increased likelihood of accelerating departure as the left-turning vehicle moves away from the conflict-zone center. These results quantify the association between the exogenous interaction conditions and the progression from steady driving through intensive turning to departure.

Figure 11 illustrates a more gradual process following the sequence #4 to #2 to #1 to #6. During Pattern #4, the vehicle speed decreases continuously, accompanied by negative longitudinal acceleration and a relatively small yaw rate. Over the same period, Δx_c and l decrease while Δv_c increases, reflecting the strengthening interaction between the left-turning and opposing vehicles.

The vehicle subsequently enters Pattern #2. Its speed remains at a low level, while the yaw rate and lateral motion remain limited. During this stage, the inter-vehicle distance continues to decrease, and the relative speed reaches a comparatively high level, indicating that the opposing vehicle continues to constrain the left-turning maneuver. At approximately 9.4s, the vehicle transitions to Pattern #1. The longitudinal acceleration becomes positive, the speed begins to recover, and the yaw rate and lateral acceleration exhibit more evident changes. Meanwhile, Δx_c reaches its minimum and subsequently increases, while Δv_c decreases from its previous high level. After completing the main turning motion, the vehicle enters Pattern #6, in which the lateral motion weakens and the vehicle returns to a stable driving state.

The marginal effects are consistent with the temporal changes shown in Figure 11. The positive effect of Δv_c and the negative effect of l on the transition from #4 to #2 indicate that increasing relative-speed pressure and greater proximity to the conflict-zone center are associated with low-speed waiting. For the transition from #2 to #1, the negative effects of Δv_c and l show that cautious turning becomes more likely as the relative-speed constraint weakens and the vehicle approaches the conflict zone. Finally, the positive effect of l on the transition from #1 to #6 corresponds to the vehicle moving away from the conflict-zone center and entering stable driving.

The two representative cases further illustrate how different pattern sequences appear in the UAV trajectory data collected at the studied Shanghai intersection. The transition from observation or waiting to turning is accompanied by coordinated changes in Δx_c , Δv_c , and l , while the subsequent weakening of the interaction constraint allows the vehicle to complete the turn and depart. These results show how the identified behavior patterns are

sequentially organized under changing opposing-traffic conditions in the studied dataset, providing a process-level interpretation of the observed unprotected left-turn behavior evolution at this intersection.

5. Conclusions

This study investigated the process-level evolution of unprotected left-turn interactions by decomposing continuous vehicle trajectories into interpretable driving primitives. Different from studies that mainly focus on gap acceptance results, conflict indicators, or final maneuver outcomes, this study investigates how left-turning behavior unfolds and evolves during the continuous interaction with opposing through vehicles. A conflict-zone-based event extraction procedure was first developed to determine the interaction window between the left-turning vehicle and the opposing through vehicle. Then, a Non-Homogeneous Hidden Markov Model was used to segment each complete left-turn maneuver into variable-length driving primitives, with time-varying interaction covariates incorporated into the state transition process. Finally, DTW-based time-series K-means clustering was applied to identify recurrent behavior patterns from the extracted primitives.

The empirical results from the studied intersection show that the observed unprotected left-turn maneuvers are not homogeneous driving processes, but are composed of several interpretable behavioral units. Six representative behavior patterns were identified, namely cautious turning, low-speed waiting, accelerating departure, deceleration observation, intensive turning, and steady driving. These patterns correspond to different local motion strategies during the left-turn process. Specifically, low-speed waiting and deceleration observation mainly appear in the early stage of the maneuver, reflecting gap-searching and risk-assessment behavior before entering the conflict area. Cautious turning and intensive turning are concentrated in the middle stage, representing different levels of turning adjustment under interaction pressure. Accelerating departure is mainly observed in the late stage, indicating the recovery of speed after the potential conflict has been resolved. Steady driving appears in both the early and late stages, suggesting that some left-turning vehicles may experience relatively smooth approach or departure processes.

More importantly, the results demonstrate that a complete unprotected left-turn maneuver can be understood as a sequential evolution chain of multiple driving primitives rather than a single discrete decision. The transition from waiting or observation to turning, and then to departure, reflects how drivers continuously adjust their longitudinal and lateral control in response to the changing spatial-temporal relationship with opposing vehicles. The inclusion of exogenous interaction covariates further indicates that primitive transitions are not determined only by the kinematic state of the left-turning vehicle itself, but are also influenced by the distance, relative speed, and conflict-zone proximity associated with the opposing through vehicle. Therefore, the proposed primitive-based perspective provides a more detailed explanation of how interaction pressure is transformed into observable motion adjustment during unprotected left turns.

Taken together, the main contributions of this study can be summarized at three levels. First, the event-specific NHMM framework accommodates differences in the temporal complexity of unprotected left-turn interactions by selecting the segmentation granularity separately for each event, rather than imposing an identical hidden-state structure on all maneuvers. Second, the combination of event-level segmentation and cross-event DTW-based clustering establishes a connection between variable-length local motion units and shared behavior patterns, enabling consistent semantic interpretation across heterogeneous interaction processes. Third, the reconstruction of behavior-pattern transition sequences, together with the analysis of exogenous interaction covariates, links local vehicle motion characteristics to the evolution of complete left-turn interactions. These contributions

extend unprotected left-turn analysis from static outcomes or isolated safety indicators to an interpretable representation of within-maneuver behavioral evolution.

The findings of this study have potential implications for both traffic safety analysis and autonomous driving applications. For traffic safety analysis, the identified behavior patterns can help describe the microscopic formation process of left-turn conflicts, rather than evaluating risk only after a conflict indicator has been observed. For human-driven vehicles, the practical benefit is mainly reflected in intersection management and infrastructure improvement. Transition sequences in which drivers move from deceleration observation or low-speed waiting to intensive turning under constrained interaction conditions can help identify approaches or time periods with recurrent left-turn pressure. Such evidence could support the optimization of warning signs, sight distance, protected left-turn phases, and signal timing, thereby reducing the decision burden and potential conflict exposure of human drivers. These applications require further validation across multiple intersections and a quantitative assessment of their relationship with safety outcomes before implementation. For autonomous driving, if similar behavior patterns and transition relationships can be consistently identified across intersections with different geometric layouts and traffic conditions, the primitive evolution chains could provide interpretable behavioral priors for unprotected left-turn decision making. For example, an automated left-turning vehicle could compare its current kinematic state and interaction condition with the identified evolution chains to determine whether to continue waiting, initiate a cautious turn, or complete the maneuver within an available gap. This representation could allow the decision-making system to update its maneuver strategy progressively as the inter-vehicle distance, relative speed, and conflict-zone proximity change. Further multi-intersection validation is required before these behavior patterns can be incorporated into operational trajectory-prediction and motion-planning models.

Several limitations should also be acknowledged. First, the transferability of the identified behavior patterns to intersections with different geometric layouts, signal settings, and traffic compositions needs further validation. Second, the dataset did not include systematic observations under adverse weather or low-visibility conditions; therefore, the applicability of the identified patterns under conditions such as fog, frost, or reduced visibility requires further validation. Third, this study focused on vehicle–vehicle interactions and did not explicitly consider behavioral differences involving heavy vehicles, buses, motorcycles, pedestrians, or cyclists. Fourth, although the proposed framework reveals the sequential structure of left-turn interactions, it has not yet been directly integrated into a predictive or planning model. Future research will extend the framework to more diverse intersection and environmental conditions, incorporate heterogeneous traffic participants, and investigate how the extracted driving primitives and evolution chains can be embedded into trajectory-prediction, conflict-risk-assessment, and automated decision-making models.

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References

1. Mozaffari, S.; Al-Jarrah, O.Y.; Dianati, M.; Jennings, P.; Mouzakitis, A. Deep learning-based vehicle behavior prediction for autonomous driving applications: A review. *IEEE Trans. Intell. Transp. Syst.* **2020**, *23*, 33–47.
2. Karle, P.; Geisslinger, M.; Betz, J.; Lienkamp, M. Scenario understanding and motion prediction for autonomous vehicles—Review and comparison. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 16962–16982. [\[CrossRef\]](#)
3. Huang, Y.; Du, J.; Yang, Z.; Zhou, Z.; Zhang, L.; Chen, H. A survey on trajectory-prediction methods for autonomous driving. *IEEE Trans. Intell. Veh.* **2022**, *7*, 652–674. [\[CrossRef\]](#)
4. Wang, W.; Wang, L.; Zhang, C.; Liu, C.; Sun, L. Social interactions for autonomous driving: A review and perspectives. *Found. Trends Robot.* **2022**, *10*, 198–377. [\[CrossRef\]](#)
5. Fang, J.; Wang, F.; Xue, J.; Chua, T.-S. Behavioral intention prediction in driving scenes: A survey. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 8334–8355. [\[CrossRef\]](#)
6. Ding, Z.; Zhao, H. Incorporating driving knowledge in deep learning based vehicle trajectory prediction: A survey. *IEEE Trans. Intell. Veh.* **2023**, *8*, 3996–4015. [\[CrossRef\]](#)
7. Zhao, J.; Knoop, V.L.; Sun, J.; Ma, Z.; Wang, M. Unprotected left-turn behavior model capturing path variations at intersections. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 9016–9030. [\[CrossRef\]](#)
8. Han, X.; Liu, P.; He, Y.; Shafique, M.A.; Zhao, J. Exploring Driver Trajectory Preferences for Unprotected Left Turns and the Impact on Traffic Safety. *Promet-Traffic Transp.* **2025**, *37*, 1269–1285. [\[CrossRef\]](#)
9. Pawar, N.M.; Velaga, N.R. Analyzing the impact of time pressure on drivers’ safety by assessing gap-acceptance behavior at un-signalized intersections. *Saf. Sci.* **2022**, *147*, 105582. [\[CrossRef\]](#)
10. Chen, Y.; Zou, Y.; Liu, J.; Xie, Y.; Tang, J. Modeling decision-making during unprotected left turns using interpretable deep learning and uncertainty quantification. *Accid. Anal. Prev.* **2025**, *220*, 108136. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Zheng, O.; Abdel-Aty, M.; Yue, L.; Abdelraouf, A.; Wang, Z.; Mahmoud, N. CitySim: A drone-based vehicle trajectory dataset for safety-oriented research and digital twins. *Transp. Res. Rec.* **2024**, *2678*, 606–621.
12. Tan, H.; Fang, C.; Shen, J.; Alam Bhuiyan, Z.; Wu, Q.M.J. Cross-Domain Heterogeneous Data Aggregation with Dynamic Group Key Agreement for Hybrid Satellite Networks. *IEEE Trans. Dependable Secur. Comput.* **2025**, *23*, 4830–4844.
13. Sen, M.A.; Al-Rubaye, S.; Tsourdos, A. Securing uav flying ad hoc wireless networks: Authentication development for robust communications. *Sensors* **2025**, *25*, 1194. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Zhang, Y.; Zou, Y.; Wang, Y.; Wu, L.; Han, W. Understanding the merging behavior patterns and evolutionary mechanism at freeway on-Ramps. *J. Intell. Transp. Syst.* **2023**, *27*, 573–586.
15. Xu, Y.; Shao, W.; Li, J.; Yang, K.; Wang, W.; Huang, H.; Lv, C.; Wang, H. SIND: A drone dataset at signalized intersection in China. *arXiv* **2022**, arXiv:2209.02297.
16. Ma, W.; Zhong, H.; Wang, L.; Jiang, L.; Abdel-Aty, M. MAGIC dataset: Multiple conditions unmanned aerial vehicle group-based high-fidelity comprehensive vehicle trajectory dataset. *Transp. Res. Rec.* **2022**, *2676*, 793–805. [\[CrossRef\]](#)
17. Nasernejad, P.; Sayed, T.; Alsaleh, R. Multiagent modeling of pedestrian-vehicle conflicts using Adversarial Inverse Reinforcement Learning. *Transp. A Transp. Sci.* **2023**, *19*, 2061081. [\[CrossRef\]](#)
18. Ding, L.; Zhu, T.; Wang, Y.; Zou, Y. Finite mixture of the hidden Markov model for driving style analysis. *J. Adv. Transp.* **2022**, *2022*, 4989947. [\[CrossRef\]](#)
19. Jing, D.; Yao, E.; Chen, R. Driving style recognition based on a Bayesian belief-renewing method. *Transp. A Transp. Sci.* **2025**, *1*–24. [\[CrossRef\]](#)
20. Guo, Y.; Gu, X.; Chen, Y.; Guo, J.; Wan, H.; Zhou, Y. Lane change behavior patterns and risk analysis in expressway weaving areas: Unsupervised data-mining method. *J. Transp. Eng. Part A Syst.* **2024**, *150*, 04024071. [\[CrossRef\]](#)
21. Yin, C.; Cecotti, M.; Auger, D.J.; Fotouhi, A.; Jiang, H. Deep-learning-based vehicle trajectory prediction: A review. *IET Intell. Transp. Syst.* **2025**, *19*, e70001. [\[CrossRef\]](#)
22. Yuan, Y.; Wang, X.; Calvert, S.; Happee, R.; Wang, M. A risk-based driver behaviour model. *IET Intell. Transp. Syst.* **2024**, *18*, 88–100. [\[CrossRef\]](#)
23. Zhao, J.; Harris, A.; Sartipi, M. Quality assessment of large-scale vehicle and pedestrian trajectories at intersections. *Transp. Res. Rec.* **2023**, *2677*, 53–63. [\[CrossRef\]](#)

24. Mi, T.; Takács, D.; Liu, H.; Orosz, G. Capturing the true bounding boxes: Vehicle kinematic data extraction using unmanned aerial vehicles. *J. Intell. Transp. Syst.* **2025**, *29*, 566–578. [[CrossRef](#)]
25. Zhao, J.; Ma, R.; Wang, M. A behaviourally underpinned approach for two-dimensional vehicular trajectory reconstruction with constrained optimal control. *Transp. Res. Part C Emerg. Technol.* **2024**, *159*, 104489. [[CrossRef](#)]
26. Zou, Y.; Wu, S.; Ding, L.; Zhang, Y.; Zhang, S.; Wu, L. Analyzing mandatory and discretionary lane change interaction patterns using hidden Markov model-based approaches. *Adv. Eng. Inform.* **2025**, *66*, 103404. [[CrossRef](#)]
27. Gipps, P.G. A behavioural car-following model for computer simulation. *Transp. Res. Part B Methodol.* **1981**, *15*, 105–111. [[CrossRef](#)]
28. Jia, L.; Yang, D.; Ren, Y.; Qian, C.; Feng, Q.; Sun, B. A dynamic driving-style analysis method based on drivers' interaction with surrounding vehicles. *J. Transp. Saf. Secur.* **2024**, *16*, 972–995. [[CrossRef](#)]
29. Sakoe, H.; Chiba, S. Dynamic programming algorithm optimization for spoken word recognition. *IEEE Trans. Acoust. Speech Signal Process.* **1978**, *26*, 43–49. [[CrossRef](#)]
30. Holder, C.; Middlehurst, M.; Bagnall, A. A review and evaluation of elastic distance functions for time series clustering. *Knowl. Inf. Syst.* **2024**, *66*, 765–809. [[CrossRef](#)]
31. Vera, J.F.; Angulo, J.M. An MDS-based unifying approach to time series K-means clustering: Application in the dynamic time warping framework. *Stoch. Environ. Res. Risk Assess.* **2023**, *37*, 4555–4566.

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