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Research Article

Humanoid cognition-based approach: Lane-changing decision making and dynamic trajectory planning for autonomous driving

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ABSTRACT: Autonomous lane-changing decision making and planning represent a fundamental aspect of advanced driving technologies, playing a pivotal role in improving operational safety, enhancing passenger comfort, and optimizing traffic flow. Current research predominantly emphasizes environmental perception and path planning, yet systematically modeling human behavioral patterns during lane changes remains underexplored, leading to inadequate anthropomorphic decision-making capabilities. Moreover, the conventional fragmented approach to implementing decision-making, trajectory planning, and interaction signaling modules results in insufficient coordination and feedback mechanisms, ultimately compromising dynamic adaptability in real-world driving scenarios. To solve these problems, this study systematically investigates driver behavior patterns through naturalistic driving data analysis, establishes a taxonomy of lane-changing scenarios, and develops a human-like decision architecture incorporating cognitive mechanisms. The model consists of a multilayered decision framework encompassing lane-changing motivation recognition, lane selection, feasibility evaluation, and risk assessment. Furthermore, an information feedback mechanism is established between the decision-making and trajectory planning modules, enabling dynamically coupled and closed-loop control. Simulation experiments conducted on the Prescan/Simulink platform confirm that the proposed method significantly enhances the naturalness and safety of lane-changing behavior in complex traffic environments. This study provides both theoretical support and technical guidance for the development of intelligent lane-changing systems that emulate human cognitive characteristics.

KEYWORDS: autonomous vehicles (AVs); lane-changing decision; dynamic trajectory planning; human-like decision; driving behavior

1 Introduction

The synergistic integration of vehicle-to-everything (V2X) communication systems, edge-computing-enhanced big data analytics, and deep neural network-driven artificial intelligence is fundamentally reconfiguring cyber-physical architectures within modern vehicular ecosystems. This shift catalyzes a paradigm change from mechanical-centric to software-defined vehicle development frameworks. Autonomous vehicles (AVs) have thus become a strategic cornerstone of the industrial field (Bevly et al., 2016; Hula et al., 2023; Sheng et al., 2024). Autonomous vehicle decision-making is a key research frontier in intelligent transportation systems (ITSs), revolutionizing mobility through traffic optimization and human–machine coexistence. Autonomous driving technology has the potential to liberate drivers from the closed-loop system of "human–vehicle–road". This technology can mitigate traffic accidents caused by human error, significantly enhancing driving safety and improving overall road traffic efficiency (Hulse et al., 2018; Yi et al., 2024; Zheng et al., 2025). Although autonomous driving technology holds significant potential in reducing traffic accidents caused by human error and improving road traffic efficiency, its application in complex traffic environments still faces numerous challenges.

Traditionally, human-controlled lane-changing decisions have now become a key challenge for autonomous vehicles, and integrating decision-making processes similar to those of humans is crucial for ensuring safe, efficient, and context-aware lane-change operations (Azadani and Boukerche, 2024). Moreover, according to the standards set by the society of automotive engineers (SAE) for autonomous driving, most existing systems

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remain at levels L1–L2 of driving assistance, and transitioning to fully autonomous driving at levels L3 and above requires more advanced decision-making and planning capabilities. Despite extensive research dedicated to the development of lane-changing technologies for autonomous driving, current solutions still face limitations, especially in simulating human driving behavior and adapting to complex traffic environments (Yang et al., 2025).

Lane-changing is a fundamental maneuver for autonomous vehicles in complex traffic environments, and the decision-making process directly affects vehicle safety, efficiency, and its impact on surrounding traffic flow (Zhang et al., 2015). Studies have shown that improper lane-changing behavior is one of the leading causes of traffic accidents and congestion, accounting for 75% of traffic accidents (Weng et al., 2012). Therefore, developing decision models that accurately assess the necessity of lane changes, select the appropriate target lane, and ensure operational safety is critical for the widespread adoption of autonomous vehicles (Wang et al., 2019; Ma and Li, 2023). Additionally, the complexity of lane-changing decisions lies in the need to consider multiple factors, including vehicle dynamics constraints, dynamic changes in the traffic environment, trajectory prediction and the intentions and behavioral patterns of drivers (Li and Shun, 2022; Zhang et al., 2013).

Fig. 1 illustrates the process of autonomous lane changing performed by vehicle A. Initially, vehicle A travels in Lane 2, generates the intention to change lanes, crosses the target lane line, and subsequently moves into Lane 1. Additionally, the operating states of vehicle B and vehicle E are crucial in determining whether vehicle A can safely execute lane-changing. The lateral maneuver requires evaluating vehicular dynamics constraints and ensuring compliance with safety metrics. The interaction of operating states across multiple vehicles introduces a risk factor, making lane changing a multivehicle dynamic that requires careful coordination.

Despite extensive research dedicated to the development of lane-changing technologies for autonomous driving, existing solutions still face limitations. Traditional rule-based lane-changing models are often confined to specific scenarios and lack adaptability (Gipps, 1986; Yang et al., 1996). While machine learning-based approaches can simulate the decision-making logic of drivers, they often suffer from issues such as poor interpretability and limited generalization capability (Yang et al., 2024; Yoo et al., 2013; Zhao et al., 2025). Furthermore, the fragmented implementation of existing decision-making, trajectory planning, and signal interaction modules leads to inadequate coordination and feedback mechanisms between these modules, thereby weakening the system's dynamic adaptability in real-world driving scenarios (Selvi et al., 2024; Shao et al., 2022).

Since highway driving environments are predominantly dominated by human-driven vehicles (HVs), these vehicles are more susceptible to human factors. Additionally, HVs have a larger perception threshold, meaning that vehicles following an AV can only detect the AV's intention to change lanes after the AV has already covered a longer distance. At the operational control level, the lateral maneuvering of the vehicle still depends on the driver. Understanding drivers' motivations for lane-changing and their associated behaviors is crucial for developing models that inform lane-changing decision-making strategies. Therefore, it is essential to analyze both the driver's operational behavior and lane-changing scenarios during the system design process. Furthermore, with the development of intelligent connected vehicle technology, especially the emergence of V2X and C-V2X technologies, the decision-making architecture for autonomous driving has undergone profound changes (Zheng et al., 2024). V2X and C-V2X technologies enable real-time data exchange between vehicles and infrastructure (such as road signs, traffic signals, and congestion alerts), as well as between vehicles themselves, providing a rich contextual foundation for safer and more coordinated lane-changing operations (Bréhon-Grataloup et al., 2023; Takacs and Haidegger, 2024; Zheng et al., 2024). By leveraging the low-latency, high-reliability communication, and multisource information fusion provided by V2X/C-V2X, the proposed human-like decision framework can dynamically adjust incentive thresholds, enhance situational awareness, and improve risk prediction during lane-changing operations. This deep integration ensures that autonomous vehicles not only respond to the immediate environment but also proactively coordinate with the broader traffic system (Kuang et al., 2024; Lin et al., 2025).

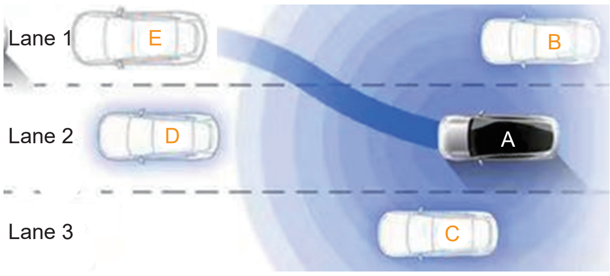


Fig. 1 Autonomous lane-changing process.

Based on the analysis above, this study develops a lane-changing decision system architecture from the driver's perspective. The comprehensive decision-making and planning framework for autonomous lane-changing is schematically illustrated in Fig. 2.

The key contributions of this study are as follows:

- Identifying typical lane-changing scenarios is essential for developing autonomous decision models. Preliminary research categorizes scenarios into three types: static obstacles ahead, no commercial vehicles ahead, and passenger vehicles ahead. By analyzing driver intent and behavior, these scenarios are further subclassified into six categories based on whether the vehicle achieves the desired speed.
- Building on the research and analysis of driver behavior, two decision-making methods are proposed: changing lanes at the current speed when the vehicle reaches a speed near the desired speed and incorporating the degree of attraction of adjacent lanes alongside the driver's dissatisfaction with the current lane. Considering the multifaceted factors that influence lane-changing decision-making, a series of autonomous lane-changing decision-making models is developed from a driver-centric perspective. These models integrate both the behavioral patterns observed in human drivers and the contextual awareness of the traffic environment.
- The system architecture for lane-changing decision-making and trajectory planning has been developed. This involves analyzing the interconnection and feedback mechanisms between the lane-changing decision-making module and the trajectory planning module. The integrated system for lane-changing decision-making and trajectory planning is built on the Prescan/Simulink joint simulation platform. In typical lane-changing scenarios, the proposed autonomous lane-changing decision-making system is evaluated through simulation and analysis. The results indicate that the proposed algorithm effectively manages lane-changing behavior under standard conditions, thus validating its feasibility and rationality.

This paper is organized as follows: Section 2 presents a

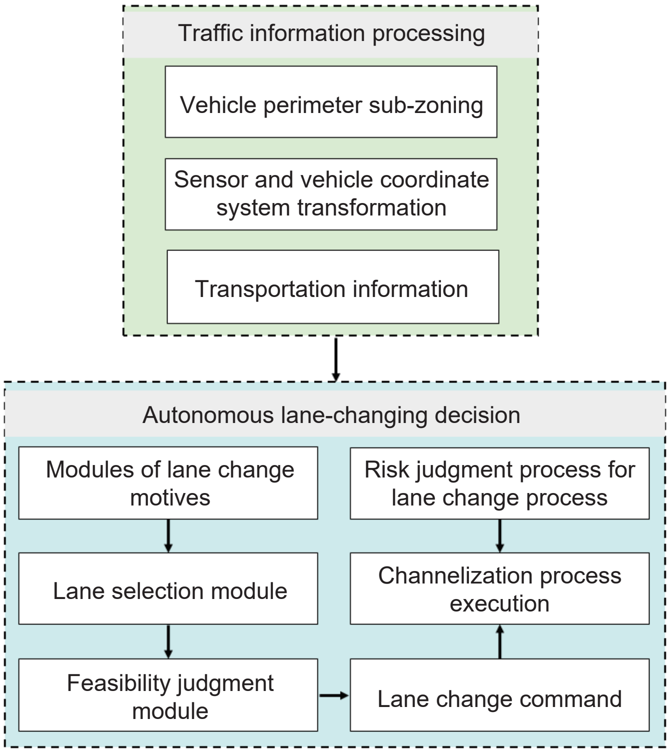


Fig. 2 Logic diagram of autonomous lane-changing decision.

literature review of lane-changing decision-making algorithms. Section 3 describes the methodology used in this study. Section 4 details the construction of the Prescan/Simulink joint simulation platform. Sections 5 and 6 summarize the key contributions and outline future research directions.

2 Literature review

Autonomous lane changing in AVs refers to the process by which intelligent vehicles safely transition from one lane to another within a controlled environment. The decision-making model involved in this process is inherently complex. Current research on decision-making algorithms for lane-changing in intelligent vehicles can be broadly classified into two main categories. The first category includes rule-based algorithms, which are primarily designed to assess the feasibility of lane changes and evaluate driver preferences. These algorithms rely on predefined logical rules to make decisions based on environmental and vehicle conditions. The second category encompasses machine learning-based decision-making frameworks, which leverage large volumes of historical lane-changing trajectory data to build models that analyze and predict lane-changing behavior. These models are more adaptive, utilizing patterns identified in the data to improve decision-making capabilities over time.

2.1 Rule-based decision algorithm

The rule-based lane-changing decision algorithm simulates a driver's lane-changing strategy by considering factors such as motivation, target lane priority, and feasibility. One of the earliest rule-based lane-changing decision models was proposed by Gipps (1986). This model follows a workflow that begins with selecting the target lane, followed by judging and executing the lane-changing operation based on a set of refined lane-changing feasibility criteria. Yang et al. (1996) introduced the MITSIM model, an enhancement of the Gipps model, which divides the lane-changing process into three steps: (1) determining the necessity of lane-changing, (2) selecting the target lane, and (3) assessing whether a safe distance exists for lane-changing. Subsequently, Halati et al. (1997) proposed the SITRAS model, an iteration of the MITSIM model. The primary distinction of the SITRAS model lies in its increased emphasis on evaluating driving stability and comfort.

The finite-state machine (FSM) has been widely adopted to model discrete behavioral switches during lane changing. For example, Talebpour et al. (2015) developed a hierarchical logic framework based on FSM for autonomous driving decision-making. Selvi et al. (2024) further introduced submodule prioritization within this framework to resolve state conflicts and maintain decision-making consistency through real-time state estimation. Additionally, vehicle spacing is considered a key factor (Peng et al., 2020). Selvi et al. (2024) highlighted the impact of longitudinal-horizontal coupling on safety distance, suggesting the maintenance of a dynamic relative distance between the front and rear vehicles during the lane-changing process. Deng et al. (2019) decomposed the decision-making process into two levels of screening: "internal intention" and "external environment". Lane changing is initiated only when both levels meet the safety threshold. To align more closely with human gap acceptance behavior, Keyvan-Ekbatani et al. (2016) developed a gap acceptance model for assessing the feasibility of lane changing, incorporating factors such as relative speed, obstacle location, and reachable acceleration. Moreover, Shao et al. (2022) enhanced the STNS rule based on metacellular automata, quantifying the guiding effect of the turn signal cue on the actions of nearby vehicles.

In recent years, the application of rule-based approaches in interconnected environments has continued to grow. Xiang et al. (2024) introduced the dynamic intelligent connected dedicated lane (IC-DL) cooperative lane-changing strategy for C-V2X scenarios. This strategy minimizes overall braking while maintaining dedicated lane saturation by incorporating a system-level lane prioritization mechanism and a dual-vehicle cooperative control approach into the traditional MOBIL framework. The decisions made by this method effectively reduce braking and ensure the maintenance of dedicated lane saturation. Sun et al. (2021) presented a two-stage optimization strategy for dynamically prioritizing target lanes based on real-time speed differences and vehicle-road communication data. This approach significantly improves the lane-changing execution rate and efficiency of dual lanes, particularly under mixed traffic conditions.

2.2 Machine learning-based decision algorithm

The Gipps model’s lane-changing process operates based on predetermined rule conditions, resulting in a binary decision: either “change lane” or “remain in the current lane”. With advancements in in-vehicle sensing and computing capabilities, researchers have increasingly focused on capturing the implicit decision-making logic inherent in human driving through data-driven approaches. For example, Yoo et al. (2013) incorporated game theory into their driving behavior models to examine driver cooperation and competition during lane changes. Yin et al. (2025) extended this by proposing a dynamic game framework to generate a human-like driving model that adapts to individual driving preferences. Furthermore, Yu et al. (2023) developed a multiplayer dynamic game for hybrid traffic flows involving AVs and HVs, demonstrating that cooperative communication can significantly reduce conflict rates.

The advent of fuzzy logic and probabilistic reasoning has broadened the ability of models to handle uncertainty. Balal et al. (2016) integrated fuzzy reasoning into a rule-based framework to express the nonlinear relationship between safety distance and speed differential through an affiliation function. In contrast, Schmidt et al. (2016) used a Markov decision process (MDP) to evaluate risks and benefits. Wen et al. (2025) employed a Gaussian mixture model-hidden Markov model (GMM-HMM) to recognize driver intentions and predict lane-changing behavior in real time. Additionally, Bayesian model and Support Vector Machine (SVM) model (Morris et al., 2011) have been used for intention recognition and safety assessments.

The emergence of deep learning has introduced end-to-end methods for lane-changing decision-making. For instance, Xie et al. (2019) used a deep belief network (DBN) to identify lane-changing intentions. Yang et al. (2024) introduced the LSTM-DDPG model to integrate trajectory prediction and strategy optimization using the NGSIM dataset. Zou et al. (2019) incorporated the states of neighboring vehicles with social-LSTM for intention prediction. They also combined convolutional neural networks (CNNs) with proportional-integral-derivative (PID) control for active steering in emergency situations. More recently, Schwarting et al. (2019) integrated a recurrent neural network within a Bayesian game framework to enable online inference of an opponent’s vehicle strategy. The continued expansion of deep learning technologies has motivated scholars to apply these methods to further explore lane-changing decisions (Fan et al., 2022; Gao et al., 2025; Wang et al., 2024; Zhang et al., 2023; Zhou et al., 2022).

Table 1 presents a summary of the literature on lane-changing decision-making algorithms. Most lane-changing decision models focus on microtraffic or vehicle behavior. They perform well in ideal settings but struggle to handle complex human-vehicle interactions on real roads. This is especially true on highways dominated by non-AVs. If autonomous systems ignore human driving behavior, they will have trouble integrating into traffic (Hao et al., 2024; Li et al., 2024; Liu et al., 2023). Rule-based models lack human-like qualities, falling short in naturalness and acceptability. Machine-learning-based models, despite their learning ability, often have poor interpretability, trouble transferring to new settings, and a strong dependency on high-quality training data. They also struggle with real-time, stable inference under limited computing power (Li et al., 2025). Currently, due to the constraints of on-board chip processing capabilities and the inherent risks and costs associated with mass production and deployment in vehicular systems, the lane-changing decision-making process in mass-produced vehicles remains primarily rule-based. However, in specific environments, such as driverless demonstration zones, machine learning-based models are typically employed for lane-changing decision-making. Therefore, a key research priority is developing lane-changing models from a driver’s perspective. These models should have human-like cognition, ensuring natural behavior, good interpretability, and practicality for real-world use.

This study focuses on the lane-changing decision-making model within the context of a highway environment, where a rule-based approach is used for model analysis. The primary objective of this study is to examine autonomous lane-changing from the driver’s perspective, analyze the motivations and behaviors associated with lane changes, and design a set of lane-changing decision-making algorithms based on the decision tree. Furthermore, it proposes a hierarchical decision-trajectory coordination architecture designed to ensure human-like behavioral consistency, compliance with functional safety standards, and system robustness for the lateral maneuvering system of intelligent vehicles.

3 Methodology

This section focuses on the lane-changing decision-making model for self-driving vehicles. At the micro level, the vehicle’s autonomous lane-changing behavior is influenced by driver intentions, while at the macro level, the surrounding traffic environment also affects lane-changing decisions. Fig. 3 presents

Table 1 Literature review of lane-changing decision-making algorithms

Research	Ref.	Method	Consider driver factor	Consider modules interaction
Rule-based decision algorithm	Gipps et al. (1986)	Rule threshold	×	×
	Shao et al. (2022)	Improved STNS model	√	×
	Selvi et al. (2024)	FSM	×	×
	Keyvan-Ekbatani et al. (2016)	Rule threshold	√	×
	Xiang et al. (2024)	Collaboration rules	×	√
Machine learning decision algorithm	Yoo et al. (2013)	Game theory	×	×
	Yang et al. (2024)	LSTM-DDPG algorithm	×	×
	Wen et al. (2025)	Markov decision process	√	×
Rule-based decision algorithm	This study	The decision tree	√	√

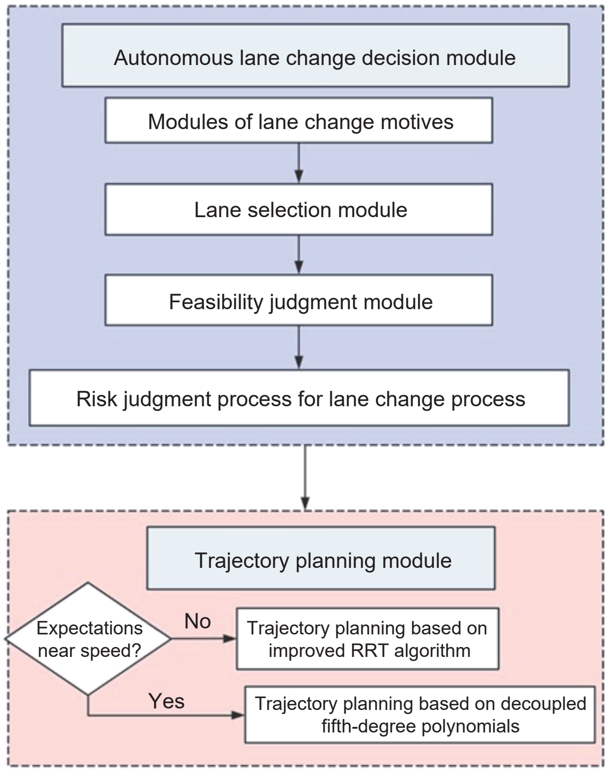


Fig. 3 Methodology logic diagram.

the logic diagram of the proposed lane-changing decision-making approach.

3.1 Driver behavior analysis

To achieve a "human-like" functionality in the lane-changing decision-making system, this study is conducted in two distinct phases aimed at identifying the critical factors that influence lane-changing decisions. The first phase involves administering a structured questionnaire to a sample of 120 drivers. In the second phase, driving data are collected from 20 experienced drivers through a field experiment.

Stage 1: Preliminary questionnaire survey

To investigate the motivations and influencing factors behind active lane-change behavior, a questionnaire was designed and supported by interviews with 10 drivers with more than three years of driving experience. The questionnaire included multiple-choice and Likert-scale questions focusing on drivers' responses to various highway traffic conditions, such as the presence of static obstacles, large vehicles, and slow-moving leading cars, as well as the relative efficiency of adjacent lanes. A total of 120 valid responses were collected. Among them, 60 were from testing personnel at a vehicle R&D center in Guangzhou, and 60 were from other drivers recruited online and through local driving schools. Of the total respondents, 87 (72.5%) had over 3 years of driving experience, while 33 (27.5%) had less than 3 years.

The interview results revealed that approximately 30% of drivers were inclined to change lanes when a vehicle was at a manageable distance ahead, especially if neighboring lanes demonstrated superior travel efficiency. These initial insights guided the development of a structured questionnaire designed to further quantify and validate the influence of various factors on drivers' lane-changing behavior. A total of 120 valid questionnaires were returned—60 from test staff at a vehicle research institute in Guangzhou and 60 from drivers in other regions. The data revealed that 72.5% (87) of respondents had accumulated over three years of driving experience, while 27.5% (33) had less than three years of driving experience.

The analysis of the questionnaire data shows that (1) the vast majority of drivers tend to change lanes when there is a large vehicle or stationary obstacle in front of them; (2) the slower speed of the vehicle ahead is a significant factor influencing the decision to change lanes; and (3) the higher driving efficiency of neighboring lanes has a noticeable impact on drivers' lane-changing decisions.

Stage 2: Field experiments

To corroborate the findings from the questionnaire survey, this study further investigates drivers' lane-changing behavior and the underlying motivations through field experiments. The chosen experimental site was a specific section of the Nanda Trunk Road in Panyu District, Guangzhou City. The experiments were conducted between 17:30 and 18:30 on roads without speed limits or traffic lights. To ensure sample representativeness and consistency in driving operations, participants were selected from 20 drivers, each with at least three years of driving experience.

The study examined a series of standard lane-changing scenarios, which included situations with commercial vehicles ahead, slower-moving vehicles in front, and more efficient adjacent lanes. In these scenarios, we meticulously recorded each driver's lane-changing behavior and analyzed a range of factors influencing their decisions. The empirical findings, presented in Table 2, substantiate the key factors influencing lane changes that were identified in the questionnaire survey.

Through a comprehensive analysis of questionnaires and field experiments, this study summarizes the typical behavioral patterns of drivers when changing lanes: (1) generating the motivation to change lanes, (2) observing the surrounding environment, such as distance and speed conditions, (3) activating the turn indicators, and (4) selecting different lane-changing methods based on surrounding environmental conditions.

Additionally, the experiment revealed that most drivers change lanes at a constant speed when their speed reaches 100 km/h or higher. Based on these findings, it is evident that when changing lanes at higher speeds, most drivers adopt an even-speed lane-changing method. In contrast, at lower speeds, the lane-changing speed is determined by the driver based on the specific scenario, leading to some variability. Therefore, this study proposes a second decision-making method: lane-changing is performed based on the current speed when the target vehicle's speed is close to the desired speed.

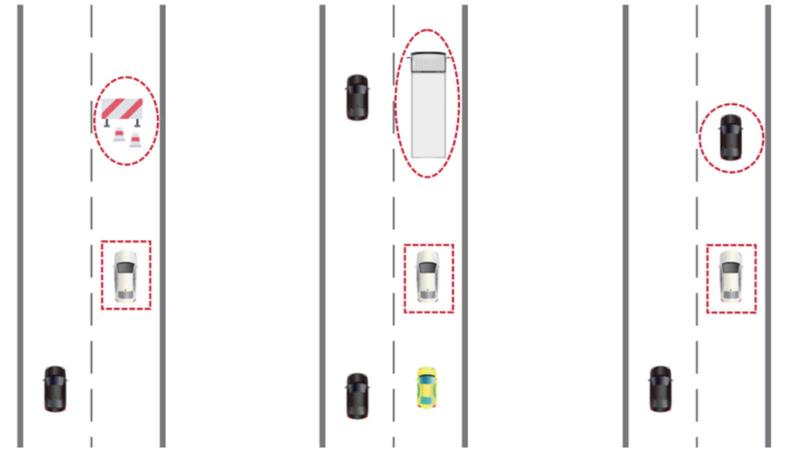
Drawing from previous related studies and experimental investigations, the typical working conditions for lane-changing are categorized into three types, as shown in Fig. 4:

By analyzing drivers' motivations to change lanes and their lane-changing behavior, based on whether the vehicle has reached the desired speed, the typical working conditions for lane-changing can be further classified into the following six types:

1) The vehicle has reached the desired speed, and there is a

Table 2 Results of various factors influencing drivers to change lanes

Category	Static obstacle ahead	Commercial vehicle ahead	Slower travel speeds in front	Adjacent lanes travel efficiently
Questionnaire survey	100%	93.3%	83.3%	40.0%
Field experiments	—	95.0%	85.0%	35.0%



(a) Static obstacle ahead (b) Commercial vehicle ahead (c) Passenger car ahead

Fig. 4 Autonomous lane-changing working condition diagram.

static obstacle ahead;

2) The vehicle has reached the desired speed, with a commercial vehicle ahead;

3) The vehicle is at the desired speed, with a passenger vehicle ahead;

4) The vehicle has not reached the desired speed, and there is a static obstacle ahead;

5) The vehicle has not reached the desired speed, with a commercial vehicle ahead;

6) The vehicle has not reached the desired speed, and there is a passenger vehicle ahead.

3.2 Lane-changing decision model

The lane-changing decision algorithm presented in this study is primarily based on the decision tree approach. The first phase of the algorithm determines the motivation value for lane-changing, which is influenced by two factors: driver dissatisfaction and the attractiveness of adjacent lanes. Once the motivation value exceeds a predetermined threshold, the algorithm moves to the second phase, where the target lane is selected based on three evaluation criteria: maximum safe speed, average driving speed, and heavy vehicle ratio. In the third and final phase, the feasibility of lane changing is assessed using gap acceptance theory. The algorithm then determines the target lane and issues the lane-changing instruction by analyzing the gap in front of and behind the target lane.

The lane-changing decision model can be categorized into the following four parts:

Step 1: Calculate the lane-changing motivation value

When an automated vehicle drives on a highway, it receives a desired speed set by the driver, while the actual speed is constrained by several factors, leading to dissatisfaction with the surrounding environment. The driver's dissatisfaction with the current lane and the driving efficiency of neighboring lanes are the main motivations for lane-changing. Therefore, the lane-changing motivation model at time t is

$$F(t)=\begin{cases}\alpha\cdot D_f(t)+\beta\cdot U_{\mathrm{Lann}}(t), & \dfrac{v}{v_q}<0.95 \text{ and } S_{\mathrm{rd}}\le S_{\mathrm{mf}} \text{ and } Obj_{\mathrm{type}}=2\\ F_{\mathrm{thr}}, & \dfrac{v}{v_q}\ge 0.95 \text{ and } S_{\mathrm{rd}}\le S_{\mathrm{mf}} \text{ and } S_{\mathrm{rd}}\downarrow \text{ and } Obj_{\mathrm{type}}=2\\ F_{\mathrm{thr}}, & Obj_{\mathrm{type}}\in (0,1)\end{cases} \tag{1}$$

where $F(t)$ is the value of lane-changing motivation at moment t, D_f denotes the degree of dissatisfaction of the driver of this vehicle with the current environment, U_{Lann} denotes the degree of attraction of the neighboring lanes to the driver, α and β are the weights of each subitem, F_{thr} is the set threshold, and S_{rd} denotes the relative distance between this vehicle and the vehicle in front of it.

$$S_{\mathrm{mf}}=S'+\varepsilon \tag{2}$$

$$D_f=(v_q-v)/v_q \tag{3}$$

$$U_{\mathrm{Lann}}=(\overline{v_{\mathrm{Lann}}}-v)/v_q \tag{4}$$

where S_{mf} denotes the minimum safe following distance defined in this study, S' represents the minimum safe distance for a following vehicle to maintain behind a leading vehicle; ε indicates the set safety distance margin, U_{Lann} represents the attractiveness of adjacent lanes to drivers, v_q is the desired speed set for the subject vehicle, v is the current speed of the subject vehicle, and $\overline{v_{\mathrm{lann}}}$ denotes the average speed of the lane numbered n.

Driver dissatisfaction with the environment accumulates over time rather than in a split second. Therefore, the concept of the decision time domain is introduced, and the sampling step is set to k. The method of calculating the value of lane-changing motivation in the decision time domain T is as

$$T=\{\text{Environmental Information}|t\in[t_{\mathrm{current}},t_{\mathrm{current}}+T]\} \tag{5}$$

$$F'=\sum_{t}^{T+t}F=\sum_{n=0}^{T/k}F(t+n\cdot k) \tag{6}$$

where T represents the duration of the decision time domain, and t_{current} is the current time.

Step 2: Selection of the target lane

Lane selection is primarily determined by evaluating various metrics, starting with the average speed of all vehicles in the lane-aware region during the decision time domain, which reflects the operational efficiency of the vehicles. The lower the average speed of the vehicles is, the higher the travel cost. In this context, lane selection should encourage the main vehicle to avoid following heavy vehicles, allowing it to reach its maximum safe speed after changing lanes. Based on the minimum safe distance, the maximum safe speed is calculated as

$$v_1(t) \le b_1\tau_1 + \left\{ b_1^2{\tau_1}^2 - b_1 \left[2(S' + \varepsilon) - v_2(t)\tau_1 - \frac{v_2(t)^2}{b_2} \right] \right\}^{1/2} \tag{7}$$

Replace the minimum safe distance S' with the actual relative distance S_{rd}:

$$v_1(t) \le b_1\tau_1 + \left[b_1^2{\tau_1}^2 - b_1 \left(2S_{\mathrm{rd}} - v_2(t)\tau_1 - \frac{v_2(t)^2}{b_2} \right) \right]^{1/2} \tag{8}$$

where $v_1(t)$ and $v_2(t)$ represent the velocities of the front and rear vehicles at time t, respectively; b_1 and b_2 denote the maximum deceleration of the front and rear vehicles during emergency braking, respectively; and τ_1 represents the reaction time of the rear driver.

Define lane cost to denote lane travel efficiency:

$$Q = 1/\left(\lambda_1 \cdot w_i \cdot \frac{\overline{v_{\mathrm{Lann}}}}{120} + \lambda_2 \cdot w_i \cdot \frac{1}{q_m + 0.5} + \lambda_3 \cdot w_i \cdot \frac{v'_{\mathrm{Lann}}}{120} \right) \tag{9}$$

where v'_{Lann} denotes the maximum safe speed for lane number n; i denotes environmental input data in the decision time domain T; $\lambda_1, \lambda_2, \lambda_3$ are the weights of each subcomponent, which denote the proportion that each variable occupies to the lane selection strategy; q_m denotes the proportion of the heavy vehicle; and w_i is the weights of the observations of each subcomponent, which denotes that the closer to the point in time when the decision is made, the higher the importance of the observed data is, taken:

$$w_i = i/\sum_{j=1}^{T/k} j \tag{10}$$

By calculating the lane costs of neighboring lanes, the lane with the lowest cost is selected as the target lane.

Step 3: Lane-changing feasibility analysis

After determining the target lane, the feasibility of lane-changing must be assessed. When the target lane complies with traffic rules, lane-changing is considered feasible. Based on gap acceptance theory, the safety gap of the target lane is evaluated, typically considering two scenarios: one where the vehicle is positioned in the middle of the target lane and another where the vehicle is positioned toward the middle of the target lane.

From Fig. 5, vehicle A is the target vehicle, with commercial vehicle B ahead. The target lane is situated in front of vehicle C and behind vehicle D:

$$S_{\mathrm{cf}} = \frac{v_1^2(t)}{2b_1} - \frac{v_2^2(t)}{2b_2} + \frac{\tau_1}{2}\left(2v_1(t) - a_1\tau_1\right) \tag{11}$$

Similarly, the current gap to the vehicle in the target lane is measured:

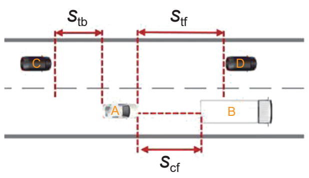


Fig. 5 No vehicles are in the middle of the target lane.

$$\begin{cases} S_{\mathrm{tf}} = \dfrac{v_1^2(t)}{2b_1} - \dfrac{v_3^2(t)}{2b_3} + \dfrac{\tau_1}{2}\left(2v_1(t) - a_1\tau_1\right) \\ S_{\mathrm{tb}} = \dfrac{v_4^2(t)}{2b_4} - \dfrac{v_1^2(t)}{2b_1} + \dfrac{\tau_4}{2}\left(2v_4(t) - a_4\tau_4\right) \end{cases} \tag{12}$$

Based on this, the study establishes the feasibility conditions required for lane-changing. The current clearance must meet the following criteria: the gap between the vehicle and the front of the target lane, the gap between the vehicle and the rear of the target lane, the length of the vehicle, and a defined safety margin.

$$S \ge S_{\mathrm{tb}} + S_{\mathrm{tf}} + l_1 + 2\varepsilon \tag{13}$$

where S_{tf} represents the gap between the subject vehicle, S_{tb} denotes the gap between the subject vehicle and the trailing vehicle in the target lane, S indicates the current gap, and l_1 refers to the length of the subject vehicle.

If the current gap meets the feasibility conditions, it is designated as the driving space for trajectory planning. When a vehicle occupies the middle position of the target lane, selecting the front gap for lane-changing may lead to various risks, including rear-end or side collisions with the front vehicle in the current lane, the rear vehicle in the target lane, or the front vehicle in the target lane. Therefore, the rear-positioned gap is chosen as the target gap.

It is necessary to continuously assess the safety of lane-changing throughout the process. To address potential risks, the longitudinal trajectory of the target vehicle is projected onto the Frenet coordinate system. A virtual synchronized vehicle is then generated in the target lane to evaluate the interaction. The risk value, f_{risk}, is defined to assess lane-changing safety, representing the ratio between the actual relative distance and the minimum safe following distance. The virtual synchronized vehicle is designed to maintain the required safety gap.

$$\begin{cases} f_{\mathrm{risk}f} = S_{\mathrm{tf}}/S_{\mathrm{rd}f} \\ f_{\mathrm{risk}b} = S_{\mathrm{tb}}/S_{\mathrm{rd}b} \end{cases} \tag{14}$$

where $f_{\mathrm{risk}f}$ is the risk value between the virtual synchronized vehicle and the vehicle in front of the target lane and $f_{\mathrm{risk}b}$ is the risk value between the virtual synchronized vehicle and the vehicle behind the target lane. $S_{\mathrm{rd}f}$ denotes the actual relative distance between the virtual synchronized vehicle and the front vehicle, while $S_{\mathrm{rd}b}$ denotes the actual relative distance between the virtual synchronized vehicle and the rear vehicle. The risk function for the lane-changing process is defined as

$$f_{\mathrm{risk}} = \max\left(f_{\mathrm{risk}f}, f_{\mathrm{risk}b}\right) \tag{15}$$

In the early stage of lane-changing, the risk value can be calculated using the virtual synchronized vehicle model. If the risk value is greater than or equal to 1, it indicates that the gap in front of or behind the target lane does not meet the minimum safety distance. In this case, lane-changing should be aborted, and the vehicle should continue driving in the current lane. However, at the end of the lane-changing stage, the gaps between the front and rear vehicles cannot be used to assess the risk of lane-changing.

Step 4: Output target lane and lane-changing command

Based on the analysis of lane-changing motivation, the calculated lane costs, and the feasibility of lane-changing, the vehicle outputs the target lane indicator and initiates the lane-changing instruction.

3.3 Trajectory planning module

The trajectory planning module described herein operates under several key assumptions that define its operational domain and focus. The model presupposes ideal road conditions (i.e., dry surfaces with clear markings), a traffic environment composed primarily of standard passenger vehicles, and moderate traffic density. Consequently, its direct application is best suited for these conditions, and adaptation would be required for scenarios involving adverse weather, heavy vehicles, or extreme traffic densities.

Within this operational context, a staged planning strategy is designed to accommodate different traffic conditions during lane changes. When the vehicle has not yet reached its desired speed, it is typically situated in a complex traffic environment. To balance search efficiency, path feasibility, and lane-change safety, a coupled path-speed planning approach is adopted. The path is generated using a modified rapidly exploring random tree (RRT) algorithm developed in our previous work (Wu et al., 2022), which integrates progressive region sampling and goal-biased sampling strategies to improve directionality and mitigate the high randomness and tortuosity commonly observed in standard RRTs. During path expansion, lateral deviation, path cost, vehicle geometry, and front wheel angle constraints are incorporated to ensure feasibility. A postprocessing step using a greedy selection strategy and cubic B-spline smoothing is applied to enhance continuity. The resulting path is then projected into the spatiotemporal (S–T) domain, where dynamic obstacle interactions are evaluated through a cost function, and the optimal velocity profile is determined via heuristic search. The final trajectory is smoothed using polynomial regression to improve robustness and ride comfort.

When the vehicle approaches the desired speed and the traffic environment becomes relatively simple, a decoupled quintic polynomial planning method is employed to reduce computational overhead. A set of candidate lane-change trajectories is generated over discrete time steps and evaluated using a composite cost function. The trajectory with the optimal balance of smoothness, comfort, and execution stability is selected.

4 Case study

Based on the AV-HV hybrid traffic environment, a lane-changing decision-making and trajectory planning system is proposed. The feasibility and effectiveness of the lane-changing decision algorithm are verified using a Prescan/Simulink cosimulation platform. In this setup, Prescan is used to design the experimental road, vehicle models, and typical lane-changing scenarios, while Simulink is responsible for designing the complete autonomous lane-changing decision-making system. The correctness of the algorithm is validated through the integrated cosimulation platform.

4.1 Design of the simulation system

Simulink is a graphical simulation platform integrated with MATLAB, while Prescan is a software platform specifically developed for vehicle simulation and testing. Prescan allows users to create customized test scenarios by defining road layouts, vehicle models, and surrounding environments. In Fig. 6, environmental information is fed into the autonomous lane-changing decision-making system, which then outputs a lane-changing trajectory to the downstream control layer. The overall architecture of the autonomous lane-changing decision-making system consists of four main modules: the environment sensing module, the autonomous decision-making module, the trajectory planning module, and the control execution module.

Environment perception module: The traffic environment surrounding the target vehicle, along with the vehicle's motion

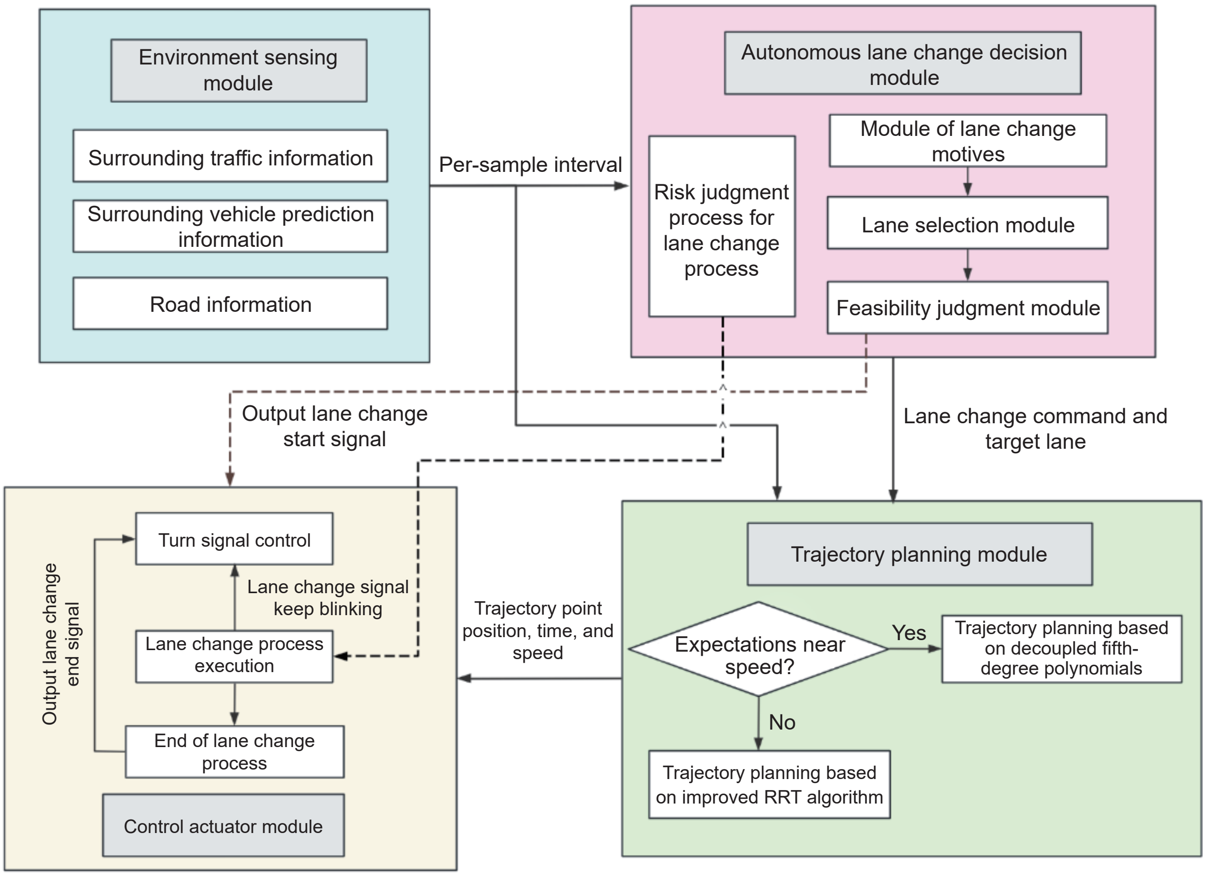


Fig. 6 Autonomous lane-changing decision system architecture.

state, is collected by the environment sensing and prediction module, while road information is obtained directly. These data are sampled at regular intervals and then fed into the lane-changing decision-making and trajectory planning module.

Autonomous lane-changing decision module: This module enables the vehicle to assess the motivation for lane changes, analyze their feasibility, and evaluate the associated risk level to determine whether a lane-changing should be executed. The specific algorithm is outlined in Section 3.2.

Trajectory planning module: The trajectory planning algorithm discussed in this study pertains to the enhanced rapidly expanding random tree algorithm (RRT) algorithm proposed by Wu et al. (2022). Based on environmental information and lane-changing instructions, the module conducts trajectory planning using different algorithms depending on whether the vehicle has reached the desired speed and generates a safe and efficient trajectory.

Control execution module: The trajectory planning module outputs trajectory points—including position, time, and speed—which are subsequently provided to the lane-changing control model based on prior feasibility and risk assessments.

4.2 Input of parameters

The road environment is constructed, and parameters are set in Prescan, where a two-way, three-lane highway environment is created in the simulation platform. The parameters of the road environment are presented in Table 3.

After the road environment parameters are set, the vehicle model that comes with Prescan is selected, and the target vehicle information is shown in Table 4.

For sensor selection, the TIS sensor provided by Prescan is chosen, and three millimeter-wave radars are deployed. The radar-related parameters are detailed in Table 5.

Table 3 Road parameters

Parameter	Value
Lane number	3 × 2
Lane width (m)	3.75
Road shape	Straightness
Lane line	Dotted line
Road length (m)	1000
Elevation	—
Road origin coordinates (x, y, z)	(0,0,0)

Table 4 Target vehicle information

Parameter	Value
Captain (m)	5.21
Width (m)	2.04
Height (m)	1.44
Vehicle mass (kg)	1820
Maximum acceleration (g)	0.3
Maximum deceleration (g)	1

Table 5 Radar setup parameters

Type	Parameter	Value
Millimeter-wave radar1	Detection distance (m)	150
	Detection angle (°)	60
Millimeter-wave radar2	Detection distance (m)	100
	Detection angle (°)	180
Millimeter-wave radar3	Detection distance (m)	100
	Detection angle (°)	−180

After the parameter settings are completed, traffic participants such as commercial vehicles, small cars, and obstacle vehicles are imported using Prescan. The testing process commences once the simulation platform is constructed.

4.3 Result analysis

The entire lane-changing planning process is simulated by designing the simulation system logic and inputting the relevant parameters. As discussed in Section 3, typical lane-changing conditions are classified into six scenarios, depending on whether the target vehicle reaches the desired speed and the type of preceding vehicle. Since the lane-changing logic remains consistent when the preceding vehicle is either a static obstacle or a commercial vehicle, these two scenarios are combined during the simulation. A summary of the simulation analysis and corresponding control parameters is provided in Table 6.

Table 6 Simulation control parameters

Parameter	Value
Simulation step (s)	0.04
Sampling frequency (Hz)	25
Desired speed (km/h)	108
Maximum limiting speed (km/h)	120
Decision time domain (s)	5
Intelligent vehicle information interaction and control system delay (s)	0.3
Safety margin, ε (m)	2
Lane-changing motivation threshold	6

1) Typical case 1: When the target vehicle reaches the desired speed and there is a static obstacle or commercial vehicle ahead.

The simulation schematic is presented in Fig. 7a. As shown in Fig. 7b, after 0.88 s, the target vehicle detects a commercial vehicle directly ahead at a relative distance of 148.9 m. The lane-changing motivation model outputs a motivation value of 6, which triggers lane-changing. Simultaneously, the lane cost function calculates the cost for each lane, and the left lane yields the lowest cost, indicating that a left lane-changing is optimal. The corresponding left steering signal is then sent to the control implementation module, which activates the turn signal light. Lane-changing decision-making instructions are also sent to the trajectory planning module to initiate trajectory generation. At this point, the target vehicle reaches the desired speed of approximately 107 km/h. By decoupling a fifth-degree polynomial, the optimal trajectory is generated within a 3-s time frame. As shown in Fig. 7c, the planned trajectory, speed, and acceleration remain within acceptable limits. Upon completion of lane-changing, the control module turns off the signal light, the motivation value is reset to zero, and the maneuver is concluded.

2) Typical case 2: When the target vehicle reaches the desired speed with a passenger vehicle ahead.

Under these conditions, the target vehicle reaches the desired speed, with an initial speed of 30 km/h. The speed of the vehicle in front on the left is 72 km/h, while the vehicle behind on the left is traveling at 79 km/h. The simulation schematic is presented in Fig. 8a.

From the simulation results in Fig. 8e, the relative distance between the target vehicle and the preceding vehicle is 62.69 m and decreases, which is below the minimum safe distance of 64.98 m. At this point, the lane-changing motivation value shown in Fig. 8c reaches 6, triggering the lane-changing decision. Simultaneously, the lane cost function identifies the third lane as

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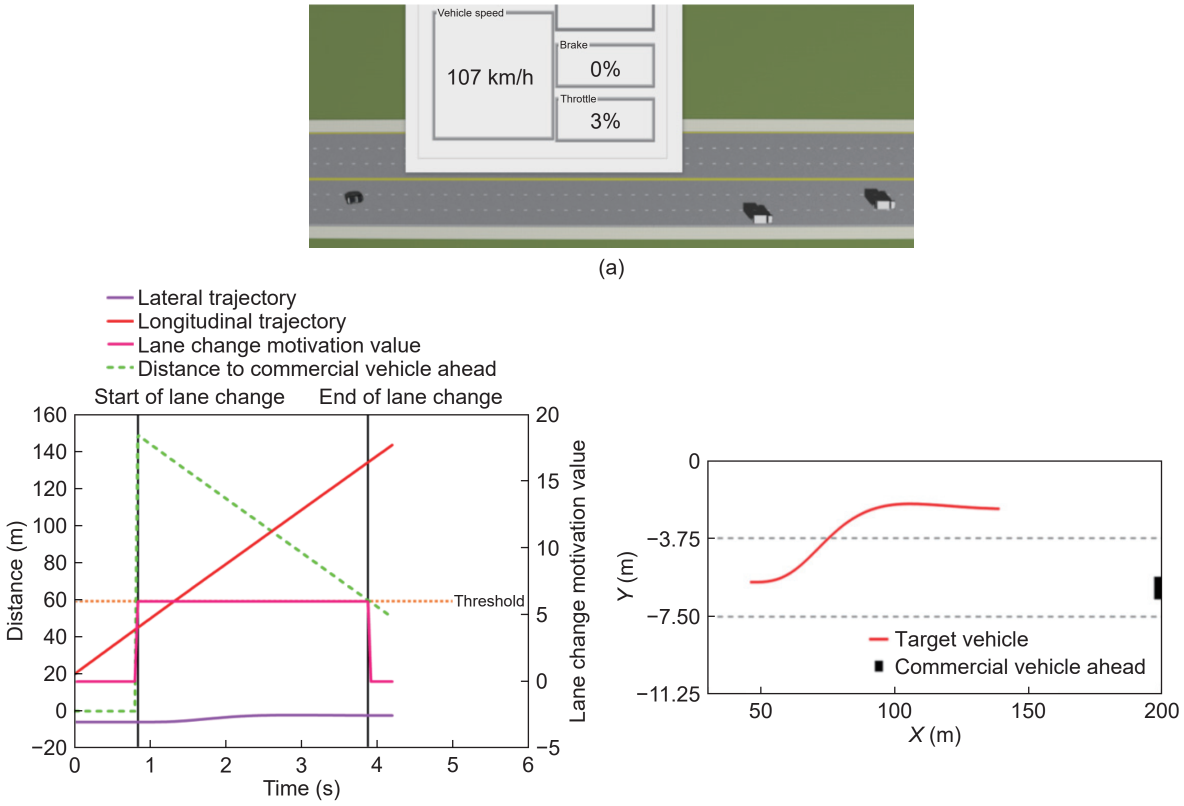

(a)

(b)

(c)

Fig. 7 Simulation results for typical case 1: (a) simulation schematic for typical case 1; (b) simulation results of lane-changing motivation values and trajectories; and (c) target vehicle trajectory planning result.

the optimal choice. The feasibility model evaluates the target lane using the relative distances to the vehicle ahead and behind—62.69 and 46.15 m, respectively—and confirms that safe lane-changing is feasible. According to the lane selection results in Fig. 8d, a lane-changing instruction is issued. Subsequently, trajectory planning begins. The vehicle speed at this moment is 106 km/h, which is close to the desired speed. The trajectory is generated by decoupling a fifth-degree polynomial, and lane-changing is completed within 3 s. The planned trajectory, speed, and acceleration all remain within the ideal range.

As shown in the lane-changing trajectory results in Fig. 8b, during the initial phase of the lane-changing—from 2.00 to 2.92 s—the center of mass of the target vehicle remains within lane 2. At this stage, the relative distance to the rear vehicle is 63.36 m, and the vehicle travels at a speed of 79 km/h. According to the risk evaluation model, the computed risk value is 0.67, which remains below the safety threshold of 1.0, indicating that the lane-changing maneuver can proceed safely. Once the target vehicle enters lane 3, the updated relative distance values indicate that the vehicle has entered the final phase of lane-changing. At 5 s, the lane-changing motivation value is reset to zero, signaling the completion of the maneuver.

3) Typical case 3: Target vehicle not reaching the desired speed, static obstacle, or commercial vehicle ahead.

The simulation diagram is presented in Fig. 9a.

As shown in Fig. 9b, at 1.24 s, the target vehicle detects a commercial vehicle directly ahead, with a relative distance of 149.17 m. The lane-changing motivation model outputs a value of 6, indicating a strong intention to change lanes. Among the available options, the left lane has the lowest cost, leading the vehicle to initiate a left lane-changing. The system activates the left turn signal and sends the corresponding command to the control implementation module, which manages the turn signal light. Simultaneously, the lane-changing decision is transmitted to the trajectory planning module. Although the vehicle has not yet reached its desired speed, the module begins generating a lane-changing trajectory using an improved RRT algorithm. The optimal trajectory is obtained when the lane-changing duration is set to 5 s. The resulting trajectory, speed, and acceleration all remain within the desired parameters. The planned trajectory is shown in Fig. 9c. The maneuver concludes at 6.24 s, at which point the control module turns off the turn signal, resets the lane-changing motivation value to zero, and finalizes the lane-changing.

4) Typical case 4: Target vehicle not at the desired speed, passenger car ahead.

In this scenario, the target vehicle has not yet reached its desired speed of 54 km/h. The vehicle ahead in the left lane is traveling at 72 km/h, offering a favorable opportunity for overtaking. Meanwhile, a commercial vehicle is present in the right lane ahead, limiting the possibility of a right-lane maneuver. The overall simulation setup for this situation is illustrated in Fig. 10a.

According to Fig. 10e, at 6.52 s, the target vehicle reaches a speed of 97 km/h. At this moment, the relative distance between the target vehicle and the vehicle directly ahead is 53.61 m and decreases, which is below the minimum safe following distance of 54.86 m. The corresponding lane-changing motivation value, as illustrated in Fig. 10c, reaches 6.14 at 7.56 s, prompting the system to issue a lane-changing instruction. Simultaneously, the lane cost calculation is performed, and the result—shown in Fig. 10d—identifies lane 1 as the optimal choice. A feasibility assessment confirms that the right lane is unoccupied, indicating a viable gap for lane-changing. Consequently, a lane-changing command is

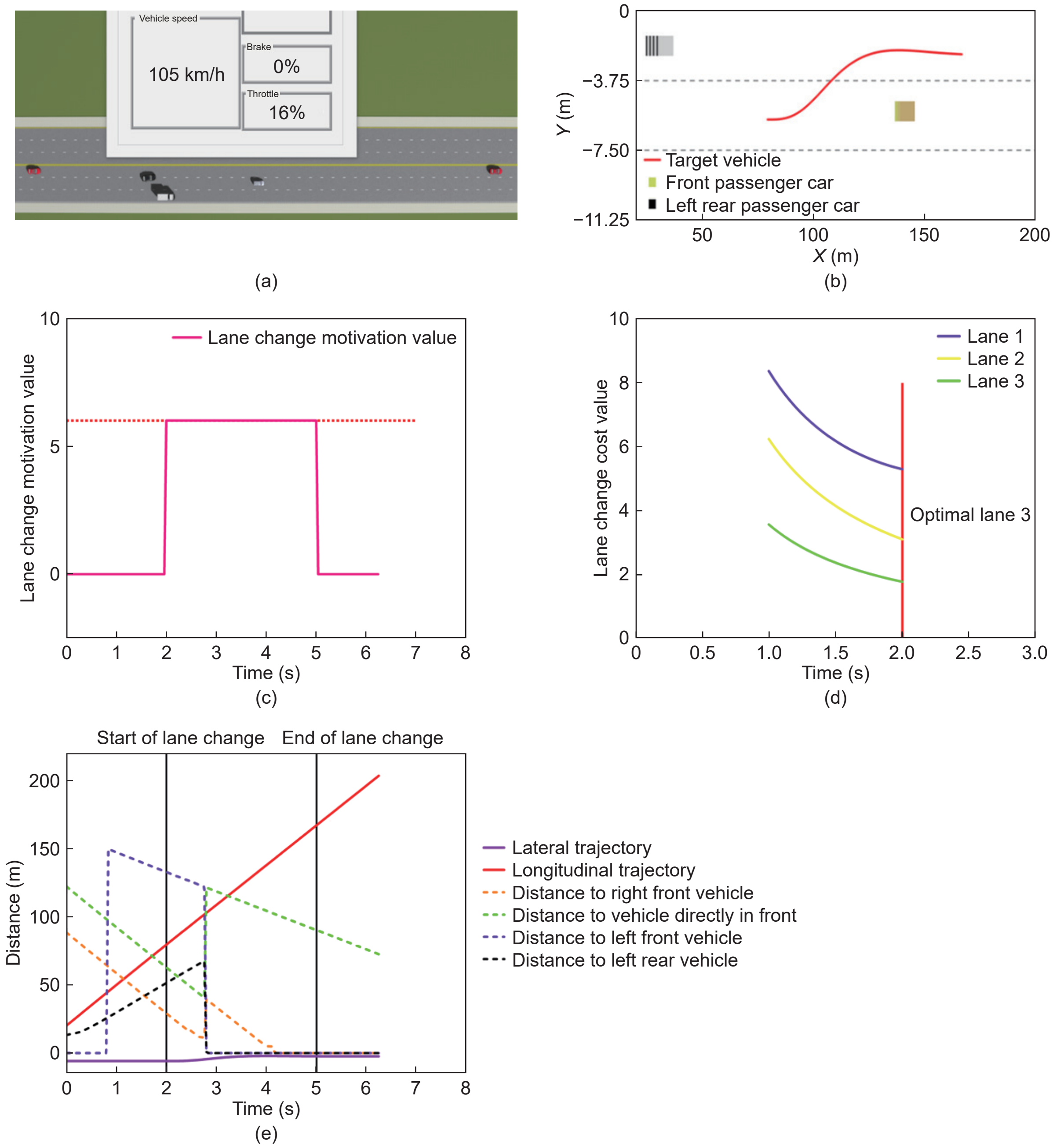

Fig. 8 Simulation results for typical case 2: (a) simulation schematic for typical case 2; (b) target vehicle trajectory planning result; (c) simulation result of lane-changing motivation value; (d) lane selection simulation result; and (e) switching to trajectory and relative distance simulation result.

generated and forwarded to the trajectory planning module. At this point, the target vehicle's speed is 98 km/h. Trajectory planning is carried out using the improved RRT-based algorithm, with the resulting lane-changing trajectory shown in Fig. 10b. The optimal trajectory is achieved with a lane-changing duration of 4 s. The planned trajectory, speed, and acceleration all fall within the ideal and safe operating parameters.

From the lane-changing trajectory depicted in Fig. 10b, it is observed that during the initial phase of lane-changing (7.6–8.96 s), the center of mass of the target vehicle remains within lane 2. At this stage, the relative distance between the target vehicle and the rear vehicle in the target lane is 95.11 m. Using the risk assessment model for lane-changing, the calculated risk value is 0.016, which is significantly below the threshold of 1, indicating a low-risk scenario and supporting the decision to proceed with lane-changing.

5 Conclusions

The results of this study offer significant support for the effectiveness of the proposed human cognition-driven lane-changing decision model for autonomous vehicles. The core innovation—integrating psychological constructs such as driver dissatisfaction with the current lane and the perceived attraction of a target lane—aligns well with the growing body of research that advocates for more human-centric and interpretable artificial intelligence in autonomous systems (Azadani et al., 2024; Yin et al., 2025). This approach moves beyond purely reactive or data-driven methods by embedding a plausible model of human reasoning into the decision-making loop (Xiang et al., 2024; Yang et al., 2024; Yoo et al., 2013).

The decision-making framework, by quantifying these psychological states, offers a distinct advantage in transparency

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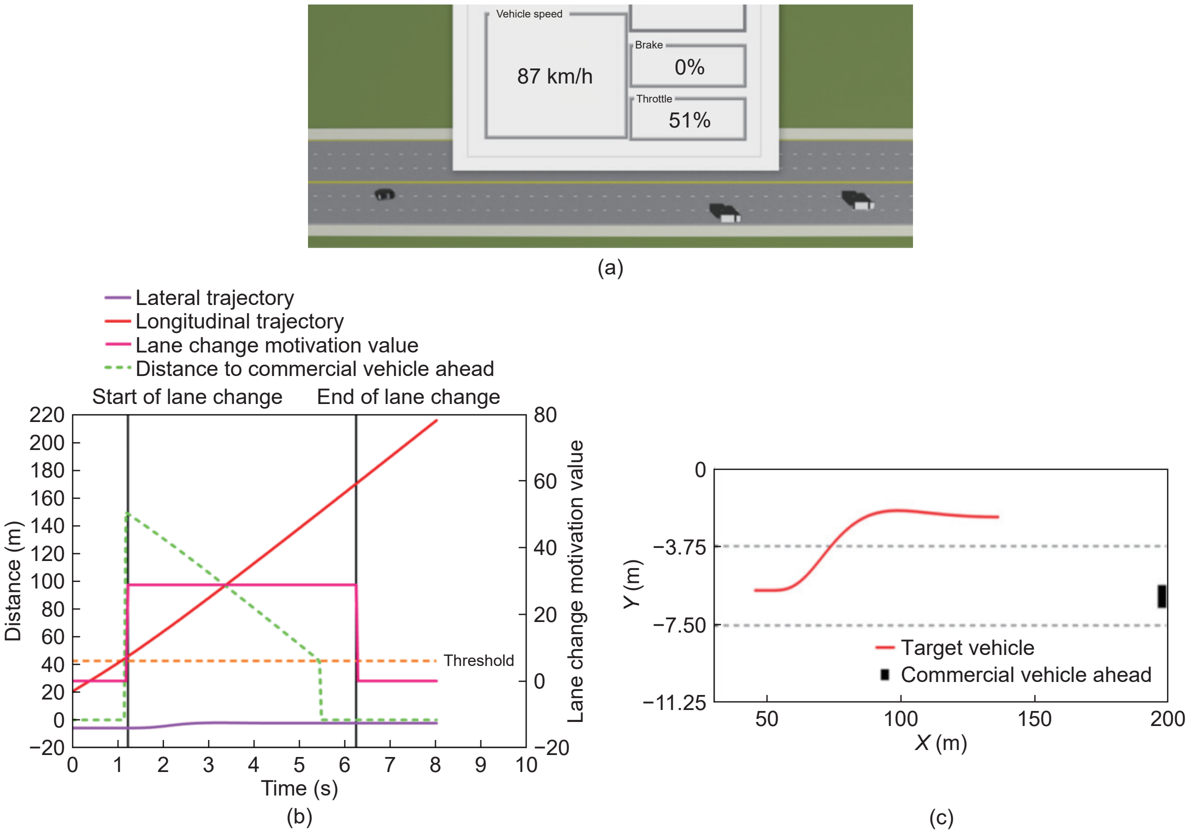

Fig. 9 Simulation results for typical case 3: (a) simulation schematic for typical case 3; (b) simulation results of lane-changing motivation values and trajectories; and (c) target vehicle trajectory planning result.

and predictability over opaque machine learning models. The successful execution of smooth and safe lane changes in challenging scenarios, including those with static obstacles and disruptive commercial vehicles, validates that this cognitive model can effectively translate abstract intentions into concrete, safe driving actions. This interpretability is not merely an academic exercise; it is crucial for verification, validation, and ultimately, for fostering public trust in autonomous technology, a point consistently emphasized in recent transportation studies (Yang et al., 2025).

The demonstrated ability of our model to produce more naturalistic and less aggressive maneuvers is of profound practical significance. This human-like behavior is critical for ensuring the harmonious integration of autonomous vehicles into mixed traffic flows, minimizing disruption to human drivers and enhancing overall traffic stability (Wen et al., 2025; Yu et al., 2023). For urban planners and traffic managers, a fleet of vehicles operating on such predictable and cooperative principles would allow for more accurate traffic flow modeling and potentially reduce the incidence of traffic oscillations caused by overly aggressive or hesitant automated driving.

To further advance the model's capabilities, future research should address several key areas. A primary direction is the development of an integrated decision and control framework, moving beyond the current decoupled approach to achieve global optimality in trajectory planning and execution. Furthermore, enhancing the model's robustness to sudden and unforeseen events, such as emergency braking by a lead vehicle or the unexpected appearance of pedestrians, is essential for real-world deployment. Investigating the use of advanced machine learning techniques to dynamically tune the parameters of the cognitive model based on real-time traffic data could also lead to a more adaptive and sophisticated decision-making system, ultimately contributing to the development of safer, more efficient, and socially acceptable autonomous vehicles.

6 Conclusions

To enhance the efficiency and safety of autonomous lane-changing in self-driving vehicles, this study focuses on developing a decision-making algorithm that reflects real driver behavior in highway scenarios. The research first explores drivers' motivations for lane changes and identifies six representative highway driving scenarios. A comprehensive decision-making framework is proposed, comprising environmental input processing, a lane-changing motivation model, a lane selection model, a feasibility assessment module, and a risk evaluation component. Additionally, an integrated system architecture is designed to unify the interactions between the lane-changing decision-making and trajectory planning modules. Experimental results obtained from the Prescan–Simulink simulation framework verify that the proposed algorithm performs stable and reliable lane changes under typical highway conditions, highlighting its potential for real-world deployment in autonomous driving systems.

Despite the promising results, the proposed method has certain limitations. The efficacy of our human-centric decision model is fundamentally dependent on the upstream perception-prediction modules and a downstream path tracking controller, which were treated as separate, simplified components in this work. In highly dynamic environments characterized by prediction errors or abrupt maneuvers from other agents, this decoupled architecture may limit the system's real-time adaptability and execution accuracy. Future work should therefore address these challenges by developing a more holistic framework that tightly integrates

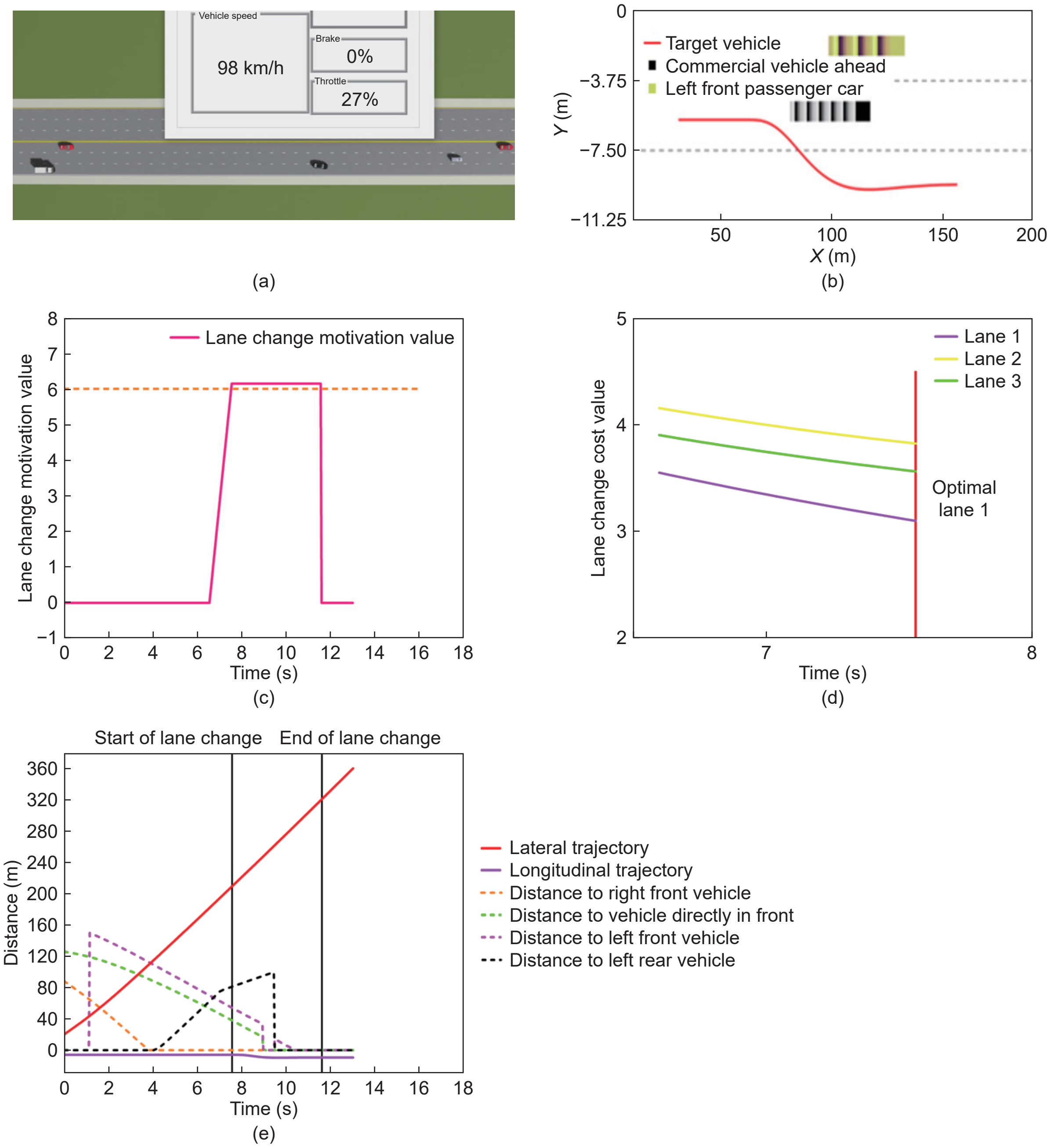

Fig. 10 Simulation results for typical case 4: (a) simulation schematic for typical case 4; (b) target vehicle trajectory planning result; (c) simulation result of lane-changing motivation value; (d) lane selection simulation result; and (e) switching to trajectory and relative distance simulation result.

prediction, decision-making, and control. This evolution will be crucial for enhancing the system's robustness and paving the way for validation in complex, real-world traffic scenarios.

Replication and data sharing

The datasets and code supporting this study are publicly available at https://ets-data.sciopen.com/ETSD.2025.9190055.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

Azadani, M. N., Boukerche, A., 2024. CAPHA: A novel context-aware behavior prediction system of heterogeneous agents for autonomous vehicles. *IEEE Trans Veh Technol*, **73**, 3065−3078.

Bevly, D., Cao, X., Gordon, M., Ozbilgin, G., Kari, D., Nelson, B., et al., 2016. Lane change and merge maneuvers for connected and automated vehicles: A survey. *IEEE Trans Intell Veh*, **1**, 105−120.

Balal, E., Cheu, R. L., Sarkodie-Gyan, T., 2016. A binary decision model for discretionary lane changing move based on fuzzy inference system. *Transp Res Part C Emerg Technol*, **67**, 47−61.

Bréhon-Grataloup, L., Kacimi, R., Beylot, A. L., 2023. Field trial for enhanced V2X multi-RAT handover in autonomous vehicle networks. In: 2023 IEEE 48th Conference on Local Computer Networks (LCN), 1–8.

Deng, J. H., Feng, H. H., 2019. A multilane cellular automaton multi-attribute lane-changing decision model. *Phys A Stat Mech Appl*, **529**, 121545.

Fan, J., Liang, J., Tula, A. K., 2022. A lane changing time point and path tracking framework for autonomous ground vehicle. *IET Intell Transp Syst*, **16**, 860–874.

Gao, Z., Jia, B., Xie, D., Wang, W., Wu, J., 2025. A discussion on the complexity and transit mechanisms of urban traffic systems. *Engineering*, **44**, 24–29.

Gipps, P. G., 1986. A model for the structure of lane-changing decisions. *Transp Res Part B Methodol*, **20**, 403–414.

Halati, A., Henry, L., Walker, S., 1997. CORSIM-corridor traffic simulation model. *Comput Sci*, **8**, 1–23.

Hao, H., Wang, Y., Chen, J., 2024. Empowering scenario planning with artificial intelligence: A perspective on building smart and resilient cities. *Engineering*, **43**, 272–283.

Hula, A., de Zwart, R., Mons, C., Weijermars, W., Boghani, H., Thomas, P., 2023. Using reaction times and accident statistics for safety impact prediction of automated vehicles on road safety of vulnerable road users. *Saf Sci*, **162**, 106091.

Hulse, L. M., Xie, H., Galea, E. R., 2018. Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. *Saf Sci*, **102**, 1–13.

Keyvan-Ekbatani, M., Knoop, V. L., Daamen, W., 2016. Categorization of the lane change decision process on freeways. *Transp Res Part C Emerg Technol*, **69**, 515–526.

Kuang, S., Liu, Y., Wang, X., Wu, X., Wei, Y., 2024. Harnessing multimodal large language models for traffic knowledge graph generation and decision-making. *Commun Transp Res*, **4**, 100146.

Li, H., Zhang, S., 2022. Lane change behavior with uncertainty and fuzziness for human driving vehicles and its simulation in mixed traffic. *Phys A Stat Mech Appl*, **606**, 128130.

Li, Q., Zhang, P., Yao, H., et al., 2024. Online learning-based model predictive trajectory control for connected and autonomous vehicles: Modeling and physical tests. *J Intel Connect Veh*, **7**, 86–96.

Li, Y., Bai, F., Lyu, C., Qu, X., Liu, Y., 2025. A systematic review of generative adversarial networks for traffic state prediction: Overview, taxonomy, and future prospects. *Inf Fusion*, **117**, 102915.

Lin, H., Liu, Y., Wang, L., Qu, X., 2025. A high-precision calibration and evaluation method based on binocular cameras and LiDAR for intelligent vehicles. *IEEE Trans Veh Technol*, **74**, 7404–7415.

Liu, Y., Wu, F., Liu, Z., Wang, K., Wang, F., Qu, X., 2023. Can language models be used for real-world urban-delivery route optimization? *Innovation*, **4**, 100520.

Ma, C., Li, D., 2023. A review of vehicle lane change research. *Phys A: Stat Mech Appl*, **626**, 129060.

Morris, B., Doshi, A., Trivedi, M., 2011. Lane change intent prediction for driver assistance: On-road design and evaluation. In: 2011 IEEE Intelligent Vehicles Symposium (IV), 895–901.

Pei, M., Zhu, H., Ling, J., Hu, Y., Yao, H., Zhong, L., 2023. Empowering highway network: Optimal deployment and strategy for dynamic wireless charging lanes. *Commun Transp Res*, **3**, 100106.

Peng, J. S., Wang, C. W., Fu, R., Yuan, W., 2020. Extraction of parameters for lane change intention based on driver's gaze transfer characteristics. *Saf Sci*, **126**, 104647.

Schmidt, E., Decke, R., Rasshofer, R., 2016. Correlation between subjective driver state measures and psychophysiological and vehicular data in simulated driving. In: 2016 IEEE Intelligent Vehicles Symposium (IV), 1380–1385.

Schwarting, W., Pierson, A., Alonso-Mora, J., Karaman, S., Rus, D., 2019. Social behavior for autonomous vehicles. *Pro Natl Acad Sci*, **116**, 24972–24978.

Selvi, V. T., Dhurgadevi, M., Prithiviraj, P., Jackulin, T., Baskaran, K., 2024. Extending the FSM Model for Critical Decision-Making and Safety Control in Autonomous Vehicles. *Int J Intell Syst Appl Eng*, **12**, 397–410.

Shao, Y., Deng, X., Song, J., Wu, H., 2022. Lane-changing model of intelligent connected vehicle considering the factor of turn signal. *J Adv Transp*, **2022**, 4357954.

Sheng, Z., Huang, Z., Chen, S., 2024. Traffic expertise meets residual RL: Knowledge-informed model-based residual reinforcement learning for CAV trajectory control. *Commun Transp Res*, **4**, 100142.

Sun, K., Zhao, X., Wu, X., 2021. A cooperative lane change model for connected and autonomous vehicles on two lanes highway by considering the traffic efficiency on both lanes. *Transp Res Interdiscip Perspect*, **9**, 100310.

Talebpour, A., Mahmassani, H. S., Hamdar, S. H., 2015. Modeling lane-changing behavior in a connected environment: A game theory approach. *Transp Res Procedia*, **7**, 420–440.

Takacs, A., Haidegger, T., 2024. A method for mapping V2X communication requirements to highly automated and autonomous vehicle functions. *Future Internet*, **16**, 108.

Wang, C., Li, Z., Fu, R., Zhang, M., Sun, Q., 2019. Lane change safety assessment of coaches in naturalistic driving state. *Saf Sci*, **119**, 126–132.

Wang, X. F., Chen, W. H., Jiang, J., Yan, Y., 2024. High-level decision-making for autonomous overtaking: An MPC-based switching control approach. *IET Intell Transp Syst*, **18**, 1259–1271.

Wen, J., Xu, Y., Dai, M., Lyu, N., 2025. Mathematical modeling and parameter estimation of lane-changing vehicle behavior decisions. *Mathematics*, **13**, 1014.

Weng, J., Meng, Q., 2012. Effects of environment, vehicle and driver characteristics on risky driving behavior at work zones. *Saf Sci*, **50**, 1034–1042.

Wu, P., Liu, X., Wang, S., Liu, T., Yao, X., Shang, T., et al., 2022. Research on intelligent vehicle speed planning algorithm based on the improved rapidly exploring random tree. In: International Conference on Green Intelligent Transportation System and Safety, 517–532.

Xiang, J., Wang, Z., Mi, Q., Wen, Q., Xu, Z., 2024. Cooperative lane-change control method for freeways considering dynamic intelligent connected dedicated lanes. *Electronics*, **13**, 16–25.

Xie, D. F., Fang, Z. Z., Jia, B., He, Z., 2019. A data-driven lane-changing model based on deep learning. *Transp Res Part C Emerg Technol*, **106**, 41–60.

Yoo, J.H., Langari, R., 2013. A Stackelberg game theoretic driver model for merging. In: Proceedings of the ASME 2013 Dynamic Systems and Control Conference, DSCC2013-3882, V002T30A003.

Yang, Q., Koutsopoulos, H. N., 1996. A Microscopic Traffic Simulator for evaluation of dynamic traffic management systems. *Transp Res Part C Emerg Technol*, **4**, 113–129.

Yang, Y., Zhan, J., Liu, Y., Qu, X., 2025. Policy-aware cross-city learning: A framework for sustainable urban governance. *Innovation*, **6**, 100986.

Yang, Z., Wu, Z., Wang, Y., Wu, H., 2024. Deep reinforcement learning lane-changing decision algorithm for intelligent vehicles combining LSTM trajectory prediction. *World Electr Veh J*, **15**, 173.

Yi, R., Yao, Y., Pu, F., Zhou, Y., Wang, X., 2024. Cooperative CAV mandatory lane-change control enabled by V2I. *Commun Transp Res*, **4**, 100126.

Yin, C., Yue, H., Shi, D., Wang, S., 2025. Dynamic gaming lane-changing decision-making for intelligent vehicles considering humanlike driving preferences. *J Transp Eng Part A Syst*, **151**, 04024087.

Yu, Y., Luo, X., Su, Q., Peng, W., 2023. A dynamic lane-changing decision and trajectory planning model of autonomous vehicles under mixed autonomous vehicle and human-driven vehicle environment. *Phys A Stat Mech Appl*, **609**, 128361.

Zhao, P., Wong, Y. D., Zhu, F., 2024. Modeling the clustering strength of connected autonomous vehicles and its impact on mixed traffic capacity. *Commun Transp Res*, **4**, 100151.

Zhao, Y., Chen, X., Liu, P., Nielsen, C. P., McElroy, M. B., 2025. Future ultrafast charging stations for electric vehicles in China: Charging patterns, grid impacts and solutions, and upgrade costs. *Engineering*, **48**, 309–322.

Zhang, G., Sun, D. H., Liu, W. N., 2015. Analysis of a new two-lane lattice hydrodynamic model with consideration of the global average flux. *Nonlinear Dyn*, **81**, 1623–1633.

Zhang, S., Deng, W., Zhao, Q., Sun, H., Litkouhi, B., 2013. Dynamic trajectory planning for vehicle autonomous driving. In: 2013 IEEE International Conference on Systems, Man, and Cybernetics, 4161–4166.

Zhang, T., Fu, M., Liu, T., Song, W., 2023. Spatio-temporal decision-making and trajectory planning framework with flexible constraints in closed-loop dynamic traffic. *IET Intell Transp Syst*, **17**, 704–715.

Zheng, Y., Pu, Z., Li, S., Han, Y., Xi, H., Ran, B., 2025. Measuring platooning performances of connected and automated vehicles in energy consumption, emission, and efficiency. *Energy*, **326**, 136172.

Zheng, Y., Xu, M., Wu, S., Wang, S., 2024. Maximum platoon size for platoon-based cooperative signal-free control at intersections. *IEEE Trans Intell Transp Syst*, **25**, 20854–20871.

Zheng, Y., Zhang, Y., Qu, X., Li, S., Ran, B., 2024. Developing platooning systems of connected and automated vehicles with guaranteed stability and robustness against degradation due to communication disruption. *Transp Res Part C Emerg Technol*, **168**, 104768.

Zhou, D., Ma, Z., Zhang, X., Sun, J., 2022. Autonomous vehicles' intended cooperative motion planning for unprotected turning at intersections. *IET Intell Transp Syst*, **16**, 1058–1073.

Zou, Q., Hou, Y., Wang, Z., 2019. Predicting vehicle lane-changing behavior with awareness of surrounding vehicles using LSTM network. In: 2019 IEEE 6th International Conference on Cloud Computing and Intelligence Systems (CCIS), 79–83.

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