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Research on Lane-Changing Behaviour Mechanisms and Collision Risks in Expressway Weaving Sections

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A handwritten signature in black ink, reading "Suyi Mao". The signature is written in a cursive, flowing style. Below the signature is a horizontal dotted line.

Suyi Mao
Turin, May 30, 2026

Summary

As a crucial node for the inflow and outflow of multiple traffic flows, weaving sections are characterised by complex vehicle interactions and high conflict potential. They may represent bottlenecks where crash risk is particularly prominent. Frequent and complex lane-changing behaviour primarily causes a decline in both traffic efficiency and safety. Nevertheless, weaving sections remain an indispensable element of road design. They provide essential merging, diverging, and lane-changing opportunities between closely spaced ramps and the mainline, thereby maintaining network continuity and access, while concentrating weaving manoeuvres within a defined segment to reduce unregulated lane changes along the mainline. In many cases, their use is further dictated by limited right-of-way, cost constraints, and the need to connect conflicting traffic streams. Systematically analysing lane-changing mechanisms and accurately predicting collision risk holds great theoretical value and practical significance for improving expressway safety. This thesis focuses on lane-changing behaviour and collision risk in expressway weaving sections, following a complete research chain from characteristics analysis to decision mechanism explanation, risk factors identification, and active risk prediction.

A driving simulation scenario was built based on drone-collected field data to ensure high fidelity to real-world conditions. The response surface centre composite design method was used to design experiments with recruited drivers. Efficiency and lane-changing behaviour metrics were selected as key characteristics. The two-sample Kolmogorov-Smirnov test comprehensively compared distribution characteristics between simulator and field data. Results show consistency alongside systematic differences driven by interactions among data collection methods, lane-changing types, and demographic characteristics.

Three key decision-making metrics were selected: lane-changing start position, accepted target lane lead gap, and accepted target lane lag gap. Hierarchical

Bayesian and double-hurdle extension models were established to capture unobserved heterogeneity by data type, lane-changing type, and lane-changing event level through random effects. Left lane changes require longer preparation distances than right ones. Surrounding vehicle size and type are key factors affecting position choice, while speed compression from following vehicles prompts more backward positioning. The double-hurdle model confirms two-stage decision independence, where binary gap acceptance and continuous gap size decisions are dominated by different factors, including relative motion characteristics and vehicle status.

The Lane Change Risk Assessment Index (LCRAI) was constructed by combining risk exposure and severity indexes through fault tree analysis. Enhanced K-means clustering divided events into extremely low, low, moderate, and high-risk levels. A random-parameter ordered Probit model considering heterogeneity of mean and variance was established after screening key variables. Results indicate that vehicle physical attributes, motion state, relative motion, decision results, and situational elements together constitute the key variable set. Dynamic motion and relative motion characteristics demonstrate higher influence intensity than static attributes.

Static and dynamic candidate feature sets were constructed using a feature engineering method combining spatial clustering enhancement and boundary cleaning sampling. An information fusion mechanism based on spatio-temporal representation decoupling was proposed with grade consistency maximisation as the objective function. A heterogeneous fusion framework combining XGBoost and GRU-KAN achieved optimal prediction performance at a 1-second warning window. SHAP interpretability analysis confirmed that kinematic characteristics dominate risk assessment and that lane-changing decisions causally relate to collision risk. Vehicle size and lane-changing motivation are important prerequisites. Three representative micro-dynamic evolution paths including sudden acceleration and deceleration alternation, forced lane changes, and consecutive lane changes were successfully extracted to concretise high-risk temporal evolution.

Main innovations of this thesis include four aspects. First, microscopic lane-changing characteristics were systematically validated to reveal systematic differences and complementary relationships between simulation and field data. Second, a hierarchical Bayesian lognormal double-hurdle modelling framework was proposed to analyse two-stage decision mechanisms and expand theoretical categories. Third, a comprehensive quantitative LCRAI was constructed based on risk exposure and severity indexes, and a heterogeneity-aware cause analysis model

identified key risk factors and their influence mechanisms. Fourth, a heterogeneous fusion risk prediction framework with grade consistency optimisation was developed to reveal characteristic mechanisms and temporal evolution patterns of high risk, providing technical support for real-time warning and differentiated intervention in Advanced Driver Assistance Systems (ADAS).

Type of Dissertation and Related Publications

This dissertation is presented in the form of a monograph, a single, comprehensive manuscript presenting a unified piece of original research. However, portions of the research contained herein have been disseminated through peer-reviewed publications. The following papers have been produced during this doctoral study, and the corresponding sections of this manuscript are indicated for each:

- (1) Gao, D., Lee, J. J., & **Mao, S.** (2026). Systematic review of weaving area safety: Assessment, behavior, and countermeasures. *Accident Analysis & Prevention*, 230, 108470. <https://doi.org/10.1016/j.aap.2026.108470>. (Published)

This work corresponds to Chapter 1 of this dissertation.

- (2) **Mao, S.**, Lee, J. J., Karimi, A., Lioi, A., & Bassani, M. (2025). Validation of lane-changing behaviour in a weaving section using a driving simulator experiment. *Transportation Research Part F: Traffic Psychology and Behaviour*, 115, 103364. <https://doi.org/10.1016/j.trf.2025.103364>. (Published)

This work corresponds to Chapters 2 and 3 of this dissertation.

These publications have been integrated into the present monograph to form a coherent and continuous dissertation. The list above is provided for transparency and does not change the monograph nature of this dissertation.

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Professor Jaeyoung Lee accepted me as his doctoral student at Central South University and introduced me to the world of academic research. Professor Marco Bassani accepted me as a doctoral student at Politecnico di Torino and taught me the rigour, dedication, and perseverance that true research demands.

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Chapter 1

1. Introduction

1.1 Research background

Road traffic safety has long been recognised as a critical global public health priority. According to the Global Status Report on Road Safety 2023 published by the World Health Organization, approximately 1.19 million people die from road traffic crashes annually, which equals more than 3,200 fatalities per day. Road traffic injuries remain the leading cause of death for children and young adults aged 5–29 years, and over 90% of these fatalities occur in low- and middle-income countries (WHO, 2023). With the continuous acceleration of global motorisation and urbanisation, traffic conflicts and network-level congestion have intensified, posing long-term sustained threats to public safety and socioeconomic development. In response, the United Nations 2030 Agenda for Sustainable Development has set an explicit target to reduce global road traffic deaths and injuries by 50% by 2030. The subsequent Decade of Action for Road Safety 2021–2030 further operationalises this goal via a Global Plan organised around five core pillars: road safety management, safer roads and vehicles, safe road users, post-crash care, and speed management (WHO, 2021).

Expressways pose unique safety challenges due to high operating speeds, controlled access, and prolonged emergency response times. Within expressway networks, weaving sections are critical bottlenecks where traffic conflicts are concentrated. Figure 1.1 shows a schematic diagram of a typical expressway weaving section. The performance of a weaving section is influenced by several geometric factors, including weaving length, number of lanes, weaving configuration, ramp spacing, shoulder width, and presence of an auxiliary lane. These factors affect both capacity and safety by shaping the intensity, location, and complexity of mandatory and discretionary lane-changing manoeuvres.

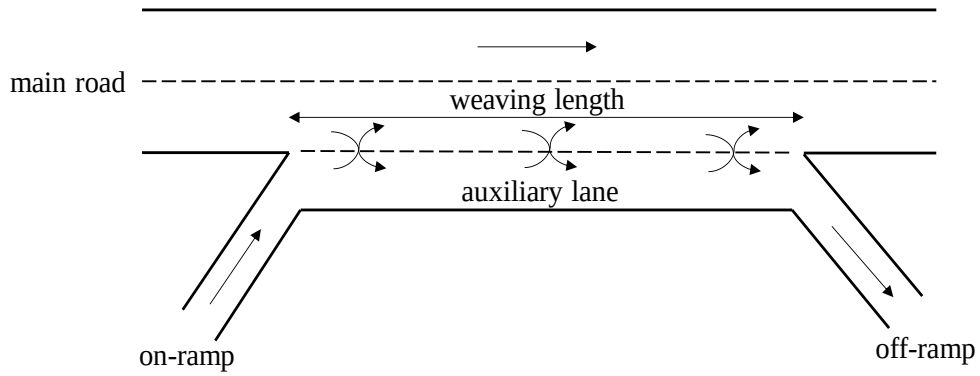


Figure 1.1 Schematic diagram of a typical expressway weaving section.

Weaving sections accommodate frequent merging and diverging manoeuvres under high traffic density with complex vehicle interactions, leading to substantially higher crash risks compared to basic expressway segments. The geometric design and highly dynamic operational environment of weaving sections impose significant cognitive demands on drivers, and driver misjudgement can easily result in rear-end or sideswipe collisions that often lead to severe consequences. A defining feature of weaving sections is the prevalence of mandatory lane-changing manoeuvres driven by fixed route requirements. Drivers must complete path transitions within restricted spatial boundaries, which gives rise to frequent non-cooperative or forced lane changes. These manoeuvres disrupt traffic flow stability, exacerbate congestion, and act as direct triggers for traffic crashes. Statistics from the National Highway Traffic Safety Administration show that lane-change-related crashes account for 240,000 to 610,000 incidents annually in the United States alone, resulting in at least 60,000 injuries (Fitch et al., 2009). Extant literature further confirms the critical role of lane-changing behaviour in crash occurrence (Kretschmer et al., 2005; Amin et al., 2014; Bax et al., 2014). Therefore, to effectively mitigate operational bottlenecks and improve overall network safety, it is necessary to develop a thorough understanding of traffic dynamics in expressway weaving sections, particularly the decision-making logic and risk generation mechanisms underlying lane-changing behaviour, and establish robust frameworks for crash risk identification.

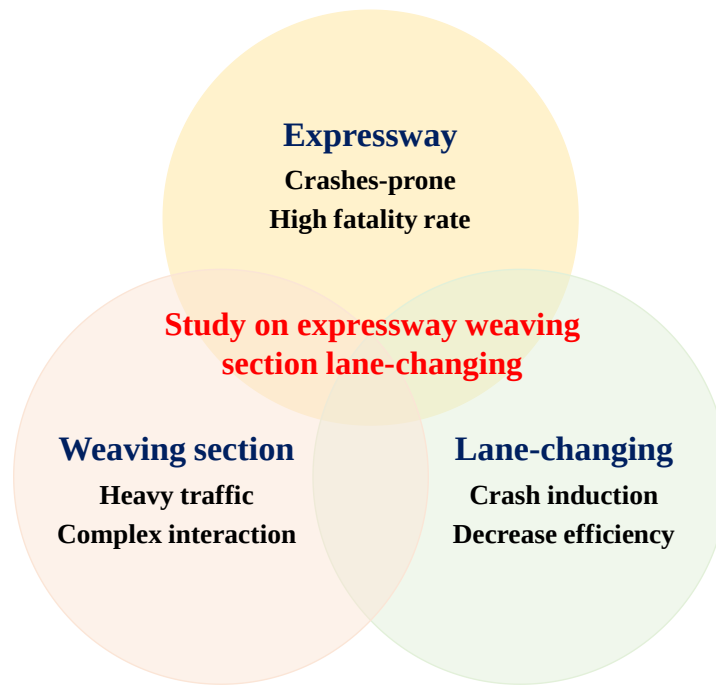


Figure 1.2 Study on lane-changing behaviour in expressway weaving section: the key coupling domain of multiple safety risks.

1.2 Research significance

With the sustained growth in motor vehicle ownership and the rapid expansion of expressway networks, road traffic safety, particularly the safe operation of expressway systems, is facing increasingly severe challenges. As critical nodes where merging and diverging traffic streams interact, expressway weaving sections feature unique characteristics including high traffic density, complex vehicle interactions, and elevated conflict potential. This makes them typical bottleneck segments with disproportionately high crash risks. Frequent and intricate lane-changing manoeuvres within weaving section are a primary contributor to traffic flow instability, reduced throughput, and crash occurrence, which constitutes a core challenge for precision-oriented expressway safety management. Accordingly, a systematic and in-depth investigation of lane-changing behaviour in expressway weaving sections carries both significant theoretical value and urgent practical relevance. Focusing on lane-changing behaviour in expressway weaving section, this thesis addresses two key research questions: 1) mechanism analysis and decision modelling of lane-changing behaviour, and 2) risk factor identification and precise prediction of crash risk. Through the integrated application of multi-source data fusion, hierarchical decision modelling, heterogeneous risk factor analysis, and accurate crash risk prediction, this research generates contributions at both the theoretical and practical levels. At the theoretical level, this thesis advances the field in four principal dimensions:

(1) Enriching the analytical framework for lane-changing behaviour mechanisms in weaving sections. Addressing the limitation of overreliance on single data sources in existing research, this study integrates drone-captured vehicle

trajectory data and driving simulator experimental data to systematically compare the similarities and differences of lane-changing behavioural characteristics across data sources, providing empirical support for a more robust analytical framework.

(2) Refining the decision-making logic of lane-changing behaviour in weaving sections. To address the insufficient attention paid to mandatory lane changes in existing models, this study introduces a hierarchical modelling framework that examines decision logic across different lane-change types including mandatory manoeuvres, and identifies key microscopic risk factors, advancing the understanding of complex lane-changing decision mechanisms.

(3) Extending methodological approaches for crash risk factor analysis of lane-changing in weaving sections. This study quantifies the crash risk of individual lane-changing manoeuvres along two dimensions: risk exposure duration and expected collision severity. It then develops heterogeneity-aware statistical models to improve the granularity and reliability of risk factor analysis.

(4) Exploring novel pathways for precise crash risk prediction of lane-changing in weaving sections. This study establishes a heterogeneous data fusion framework that takes prediction grade consistency as the primary optimisation objective, and incorporates interpretability analysis and temporal evolution mechanisms to elucidate the formation mechanisms of elevated crash risk.

At the practical level, the findings of this thesis provide decision-support evidence for geometric design optimisation and refined traffic management of expressway weaving sections; offer reference parameters for lane-change planning algorithms in Advanced Driver Assistance Systems (ADAS) and connected and automated vehicles (CAVs); and enable real-time risk warning and intervention grounded in microscopic behavioural mechanisms, thereby providing essential technical support for improving the overall safety and operation efficiency of expressway weaving sections.

1.3 Literature review

Focusing on lane-changing behaviour mechanisms and crash risk in expressway weaving sections, this chapter systematically reviews four core research domains: lane-changing behavioural characteristics, lane-changing decision modelling, lane-changing crash risk assessment, and lane-changing crash risk prediction.

1.3.1 Lane-changing behavioural characteristics

Lane-changing refers to the manoeuvre where a vehicle transitions from its current lane to an adjacent lane travelling in the same direction, categorised as either discretionary or mandatory, to achieve a specific driving objective (Chauhan et al., 2022). As a core topic in microscopic traffic flow theory, lane-changing behaviour on basic expressway segments has been extensively investigated, with a mature methodological framework established to date. Researchers utilising observational data have thoroughly examined key dimensions of lane-changing, including: lane-changing intention recognition (Deng et al., 2019; Xing et al., 2020), timing and

positioning selection (Ali et al., 2018; Jokhio et al., 2023), acceptable gap thresholds (Gurupackiam & Jones, 2011; Sun & Elefteriadou, 2012; St-Aubin et al., 2013; Ali et al., 2018; Yang et al., 2019), execution dynamics (Antin et al., 2020; Duan et al., 2022) and execution duration (Toledo & Zohar, 2007; Ali et al., 2018; Wang et al., 2019; Yang et al., 2019), as well as the spatiotemporal evolution of kinematic features including vehicle speed (Thiemann et al., 2008; St-Aubin et al., 2013; Balal et al., 2014; Wang et al., 2019; Duan et al., 2022) and headway/gap distance (Thiemann et al., 2008; Wang et al., 2019). Concurrently, the influences of multidimensional factors on lane-changing decisions have been comprehensively validated, including road geometry, weather, and lighting conditions (Shi & Liu, 2019; Das & Ahmed, 2021; Chen et al., 2023), traffic density and car-following state (Moridpour et al., 2010; Lv et al., 2013; Li et al., 2018), driver demographics (Yang et al., 2006), driving style (Zhou et al., 2017), and vehicle type and performance (Moridpour et al., 2010; Chen et al., 2023). Collectively, existing studies demonstrate that lane-changing is a highly heterogeneous decision-making process shaped by the coupling effects of multiple influencing factors, which has promoted the theoretical evolution from rule-based descriptions to discrete choice models and game-theoretic behavioural mechanism models.

However, transferring this existing knowledge base to weaving sections encounters fundamental barriers to applicability. As specialised road segments characterised by intensive merging and diverging demands, weaving sections reshape lane-changing logic in three critical respects: first, strong goal-oriented attributes drive predominantly mandatory lane-changing manoeuvres under severe spatiotemporal pressure, leading to more aggressive gap acceptance behaviour; second, dramatically intensified vehicle interactions require frequent, uncertain dynamic negotiations between lane-changing vehicles and surrounding traffic, generating greater disruptive effects on traffic flow stability; third, heterogeneous traffic compositions introduce significant heterogeneity in drivers' decision preferences and lane-changing execution strategies. Directly applying classical models or parameter thresholds calibrated for basic road segments cannot capture the high-risk, highly dynamic operational characteristics of weaving sections. Therefore, dedicated investigation into diverse lane-changing mechanisms under tight spatiotemporal constraints is both a necessary step for theoretical refinement and a fundamental prerequisite to address bottleneck safety challenges in freeway operations.

To address these limitations, high-resolution trajectory extraction and image processing technologies have been widely adopted in transportation engineering research. Contemporary data acquisition systems primarily consist of three categories: (1) drone-based trajectory datasets (Guo et al., 2024; Zheng et al., 2024), which directly capture spatiotemporal and kinematic indicators including lane-change duration, travel distance, and gap acceptance; (2) instrumented naturalistic driving systems (Das & Ahmed, 2022a; 2022b), which provide complementary micro-level observational perspectives and are particularly suited for extracting behavioural parameters under adverse weather conditions; and (3) driving simulators (Cai et al., 2018; Yuan et al., 2019; Wang et al., 2020; Zheng et al.,

2021), which enable high controllability of experimental variables, allowing for safe replication of complex conflict scenarios, systematic evaluation of roadway geometric design parameters, and quantification of individual driver heterogeneity. Existing synthesis of empirical evidence indicates that lane-changing decisions in weaving sections emerge from the complex coupling interactions among roadway geometry, real-time traffic environment, and driver characteristics under spatiotemporal constraints. Only by clarifying the heterogeneous patterns generated by the interplay of driving styles, demographic attributes, and driver mental workload can microscopic traffic flow models achieve improved simulation fidelity and stronger causal explanatory power.

1.3.2 Lane-changing decision modelling

Decision modelling acts as a bridge connecting observable behavioural manifestations to their underlying decision mechanisms. Gap acceptance theory provides the classical foundational framework for this domain; early research focused primarily on calibrating acceptable gap thresholds, while later-developed probabilistic models have more effectively captured the stochasticity and heterogeneity of decision-making processes. Building on this foundation, existing research in this field can be categorised into four primary streams:

(1) Rule-based lane-changing models

Gipps (1986) pioneered the integration of gap acceptance theory with lane-change motivation and safety thresholds. Yang and Koutsopoulos (1996) decomposed the lane-changing process into four sequential stages and established the classic discretionary/mandatory binary taxonomy. Hidas (2005) extended this established framework to incorporate cooperative and forced lane-change mechanisms. The widely adopted MOBIL model uses individual vehicle acceleration as the criterion for optimal lane-changing strategy selection (Kesting et al., 2007). While these models are logically transparent and computationally efficient, they rely on overly rigid predefined rules, which struggle to capture driver adaptivity and heterogeneity under the high-frequency vehicle interaction conditions characteristic of highway weaving sections.

(2) Discrete-choice lane-changing models rooted in random utility theory

Early research established a dynamic three-stage framework (Ahmed et al., 1996), which was later extended to integrate gap acceptance rules into mandatory or discretionary lane-changing decision structures (Toledo et al., 2007). To address the limitations of fixed parameters and the independence of irrelevant alternatives assumption, researchers developed random-parameter models to capture unobserved heterogeneous preferences at the individual level, latent class models to partition samples into homogeneous subgroups, and nested logit models to accommodate the nested structure of multi-stage lane-changing decisions. However, all these models are still focused on modelling discrete lane-changing outcomes, and provide only limited characterisation of continuous decision variables such as execution timing, lateral displacement, and the size of the accepted gap.

(3) Game-theoretic lane-changing models

Game-theoretic lane-changing models abstract lane-changing vehicles and surrounding traffic participants as players in a game-theoretic interaction. Early formulations modelled ramp merging and mainline through movements as non-cooperative games (Kita, 1999), and subsequent empirical studies incorporated conflict avoidance mechanisms into utility function evaluation (Arbis & Dixit, 2019). In the CAVs era, deep reinforcement learning and multi-agent game frameworks have been integrated for autonomous driving decision-making tasks (Talebpour et al., 2015; Ji & Levinson, 2020; Lopez et al., 2022). However, most existing game-theoretic lane-changing models predominantly assume complete driver rationality and complete information availability, and thus cannot adequately capture bounded rationality, incomplete information, and heterogeneous driver preferences. Furthermore, the high complexity of equilibrium solutions and substantial computational requirements limit the real-time applicability of these models.

(4) Data-driven lane-changing models

In the machine learning paradigm, Hunt and Lyons (1994) pioneered the application of neural networks to lane-changing modelling, while Hou et al. (2015) integrated random forests with the AdaBoost algorithm to achieve high-accuracy lane-changing prediction. In the deep learning domain, Xie et al. (2019) used deep belief networks cascaded with Long Short-Term Memory (LSTM) to reconstruct the temporal process of lane-changing behaviour. Zhang et al. (2019) leveraged LSTM networks to realise joint prediction of car-following and lane-changing behaviours. Although these data-driven models achieve substantially higher predictive accuracy than traditional model-driven approaches, they still rely heavily on the quality and scale of training data. Meanwhile, their inherent black-box property limits their applicability to behavioural mechanism analysis and policy evaluation.

1.3.3 Lane-changing crash risk assessment

The core of driving risk assessment lies in quantifying the mapping relationship between lane-changing operations and potential crash outcomes. Early research predominantly relied on surrogate safety measures, among which Time-to-Collision (TTC) is the most widely applied (Das & Ahmed, 2022a; 2022b). However, its limitations in handling non-linear conflict contexts have promoted the development of Extended Time-to-Collision (ETTC) (Zhao et al., 2023; Hu et al., 2024). Zhao et al. (2023) realised automated instantaneous risk grading for lane-changing conflicts. Hu et al. (2024) calibrated a 1.25 second safety threshold for ETTC. Zhang et al. (2023) proposed Generalized Time-to-Collision (GTTC) that incorporates the physical dimensions of vehicles. Other additional safety metrics include Deceleration Rate to Avoid a Crash (DRAC) (Jiang et al., 2023; Yuan et al., 2025), Stopping Distance Index (SDI) (Onelcin & Alver, 2023), etc. Das and Ahmed (2022a; 2022b) jointly applied TTC, Post-Encroachment Time (PET), and

DRAC in their study, and found that conflict frequency increases significantly under adverse weather conditions.

Recognising the limitations of single-indicator assessment, researchers have developed various composite risk metrics. Park et al. (2018) proposed the Lane Change Risk Index (LCRI), which was later extended to the Lane Change Risk Level at Weaving Segments (LCRIws) that incorporates the influence of weaving section length (Onelcin & Alver, 2023). Zhang et al. (2023) introduced the Lane Change Risk Assessment Index (LCRAI) that integrates risk exposure duration and expected collision severity. Zhao et al. (2025) developed the Integrated Risk Index (IRI) that accounts for potential conflicts with four adjacent vehicles. Recently, risk field theory has provided new perspectives for lane-changing risk assessment. Ma et al. (2023) constructed a multi-vehicle interaction risk potential field for real-time assessment in CAVs scenarios. These models overcome the limitation of traditional surrogate parameters that can only capture pairwise vehicle interactions, but their high computational complexity and stringent data requirements mean further research is required before they can be deployed in practical engineering applications.

1.3.4 Lane-changing crash risk prediction

The essence of risk prediction is to enable effective preventive intervention. Two temporal research paradigms exist in existing literature: the first treats risk prediction as an extension of trajectory prediction, which falls into the category of real-time forecasting. Joo et al. (2021) employed a multivariate Bayesian structural time series model to predict the trajectories of adjacent vehicles and quantify corresponding driving risks. Hao et al. (2020a) integrated driving state recognition, Monte Carlo simulation, and importance sampling to calculate collision probability. Wang et al. (2022) proposed a two-stage multimodal trajectory prediction method that defines collision risk as the product of manoeuvre mode probability, collision probability, and expected crash severity. The second paradigm directly predicts risk during manoeuvre execution using pre-manoeuve or early-stage observation data, which is categorised as advance forecasting. Li et al. (2020) trained Support Vector Machine (SVM) classifiers on the NGSIM dataset and achieved a prediction accuracy of 72.81%. Chen et al. (2020) proposed a machine learning classifier based on spatial sequence features. Shangguan et al. (2022) first applied LSTM networks for driving intent recognition, then used lightweight gradient boosting trees for subsequent risk prediction. Zhang et al. (2023) constructed a proactive risk prediction framework that incorporates driving style factors and analysed the influence mechanisms of different risk factors.

Existing risk prediction studies predominantly rely on single baseline models, and overlook the incompleteness of feature information caused by inconsistent underlying data requirements across different models. Furthermore, most studies ignore the inherent class imbalance problem in risk datasets and only use prediction accuracy as the sole evaluation metric. Finally, existing research mainly focuses on improving prediction accuracy while paying insufficient attention to the risk

formation mechanisms implicitly captured by model outputs. These research limitations constitute the core entry points for this thesis, which focuses on heterogeneous data fusion, grade consistency optimisation, and interpretability analysis of risk prediction.

1.4 Research objectives and framework

1.4.1 Research objectives

Focusing on lane-changing behaviour mechanisms and crash risk in expressway weaving sections, this thesis addresses two core scientific questions, mechanism analysis and decision modelling, and risk factor identification and accurate prediction, via a systematic investigation structured along four dimensions. The specific research objectives are as follows:

(1) Mechanism analysis of lane-changing behaviour in weaving sections

A multi-source dataset integrating on-site video trajectory data and driving simulator data is constructed. Comprehensive comparative validation of lane-changing behavioural characteristics across data sources is conducted from both the macroscopic perspective of traffic efficiency and the microscopic perspective of driving behaviour. And in-depth analysis of behavioural heterogeneity and its underlying mechanisms is performed from multiple dimensions including data collection mode, lane-changing type, and driver characteristics.

(2) Decision modelling of lane-changing behaviour in weaving sections

Leveraging multi-source data and the hierarchical nested structure of lane-changing decisions, this thesis integrates continuous decision variables (lane-changing position, accepted gap) with multi-level influencing factors (data source, lane-changing type) into a unified analytical framework; develops a lane-changing decision model that can capture individual heterogeneity and behavioural type differentiation; and clarifies the heterogeneity of lane-changing decision mechanisms in weaving sections and their formation processes.

(3) Crash risk factor analysis for lane-changing in weaving sections

The risk level of each individual lane-changing event is quantified along two dimensions: risk exposure duration and expected collision severity. Scientifically sound risk classification is achieved via clustering analysis; the formation mechanism of crash risk is analysed from a heterogeneity perspective. And key risk factors and their causal pathways are systematically identified.

(4) Accurate crash risk prediction for lane-changing in weaving sections

Considering the complementary advantages of different data representation methods, this study establishes a heterogeneous information fusion framework. It takes prediction class consistency as the primary optimisation objective to construct a crash risk prediction model with minimum cross-class misclassification; and uses interpretability analysis to clarify the intrinsic relationship between elevated lane-changing crash risk and microscopic vehicle kinematic features, providing theoretical support and technical reference for proactive risk intervention in ADAS.

1.4.2 Research framework

Focusing on the lane-changing behaviour mechanisms and crash risk in expressway weaving sections, this thesis conducts a systematic investigation across four dimensions corresponding to four core research components, whose interrelationships are illustrated in Figure 1.3. These components follow a logical progression of “characteristics analysis → decision mechanisms → risk factors → risk prediction”, forming a complete research chain extending from surface-level observation to in-depth mechanism mining, and from risk factor identification to proactive warning and management.

(1) Research on lane-changing behaviour mechanisms in weaving sections corresponds to Research Objectives 1 and 2. Objective 1 addresses the limitation of single-source data by combining field observation with driving simulation to construct a multi-source database, systematically comparing the commonalities and differences of lane-changing behavioural characteristics across data sources, revealing heterogeneity patterns and their underlying regularities. Objective 2 addresses two key gaps in existing models: insufficient attention to mandatory lane changes, and limited characterisation of continuous decision variables. By integrating continuous decision variables and multi-level influencing factors into a unified framework, this study develops a decision model that can capture individual heterogeneity and behavioural type differentiation, to achieve refined characterisation and theoretical interpretation of lane-changing decision regularities.

(2) Research on lane-changing crash risk in weaving sections corresponds to Research Objectives 3 and 4. Objective 3 addresses the limitations of single-metric risk assessment and subjective crash risk level classification by constructing an integrated quantification framework that combines risk exposure duration and expected collision severity. This study achieves data-driven scientific classification of crash risk levels, explores unobserved heterogeneity, and establishes quantitative linkages between lane-changing decision behaviour and safety outcomes. Objective 4 addresses three key drawbacks of existing prediction models: incomplete feature extraction, unreasonable evaluation mechanisms, and insufficient model interpretability. By establishing a heterogeneous fusion framework, this study constructs a prediction model with grade consistency as the core optimisation objective, and adopts interpretability analysis to elucidate risk formation mechanisms and temporal evolution patterns. This approach ultimately forms a closed-loop technical pathway from risk identification to predictive early warning.

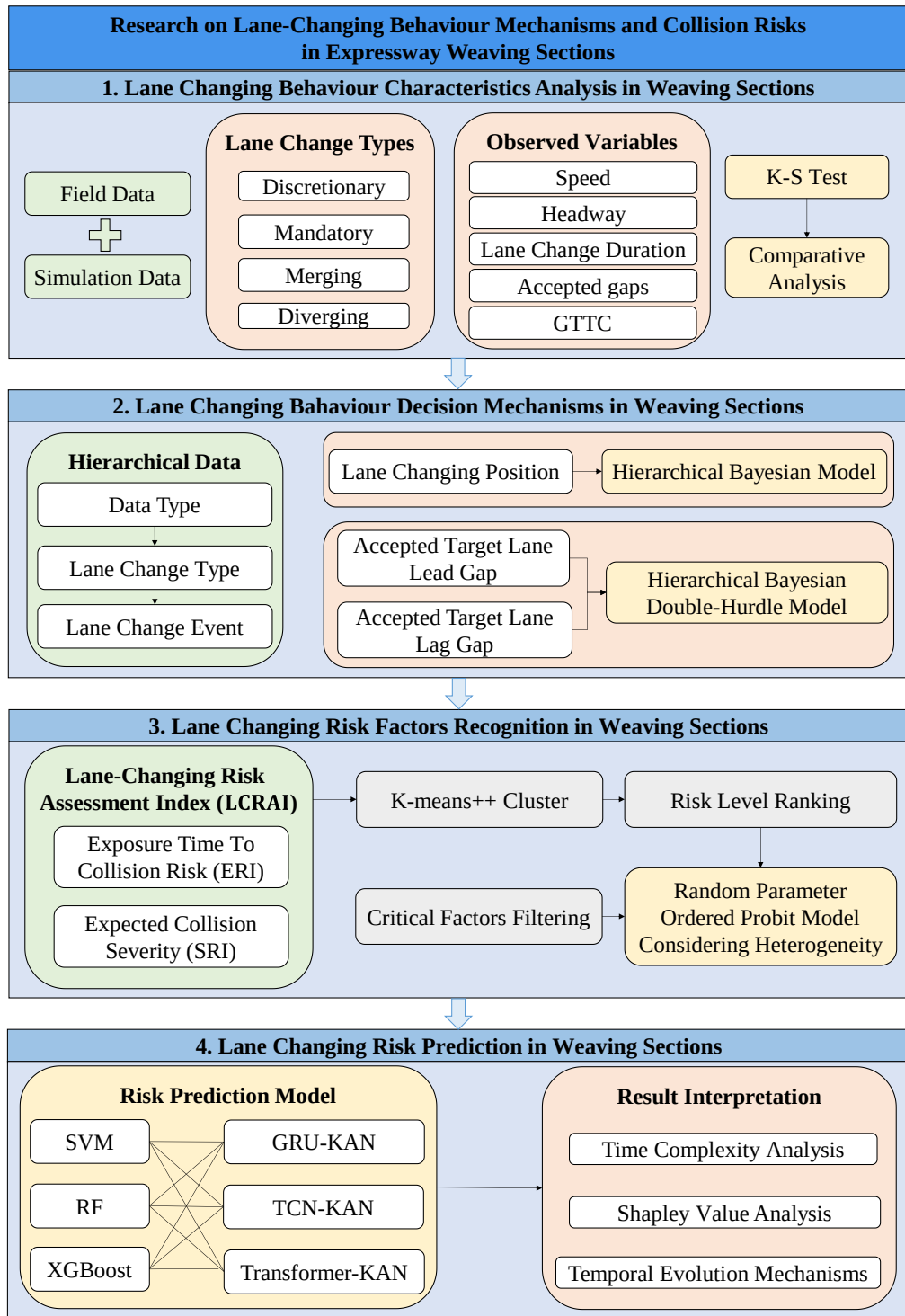


Figure 1.3 Research framework of this thesis.

Chapter 2

2. Theoretical framework and data preparation

2.1 Background

As the theoretical foundation and data preparation chapter of this thesis, this section provides a detailed elaboration of the core concepts, operational characteristics, trajectory extraction procedures, and underlying theoretical framework required for the study of lane-changing behaviour in weaving sections. Focusing on this specific road facility, this chapter sequentially analyses its conceptual definition, geometric configuration, traffic flow characteristics, and potential safety hazards, thereby clearly defining the physical attributes and theoretical scope of the core research object. In terms of methodology and empirical data construction, this chapter systematically reviews the existing traffic conflict theory system, and centres on discussing how to effectively identify and measure traffic conflicts using high-precision vehicle trajectories, which establishes a logical foundation for the subsequent in-depth quantitative risk assessment and cause analysis; on the other hand, this chapter provides a detailed description of the field video collection method for weaving sections, and documents the complete technical workflow from vehicle trajectory extraction, data cleaning to outlier removal, forming a standardised closed loop for data acquisition and processing. Subsequently, this chapter further clarifies the specific quantitative indicators and extraction methods for lane-changing behaviour characteristics. Relying on these key indicators, this chapter conducts a preliminary analysis of the microscopic traffic flow state, conflict distribution characteristics, and lane-changing behaviour patterns contained in the collected trajectory data, to phenomenally reveal how drivers cope with complex high-pressure driving scenarios in weaving sections, as well as the characteristics of their decision-making game logic and behavioural adaptation mechanisms. Overall, this chapter not only provides systematic methodological support for the study of lane-changing behaviour in weaving sections, but also lays a high-quality data foundation for the in-depth analysis in subsequent chapters.

2.2 Fundamental characteristics of weaving sections

An accurate understanding of the basic traffic characteristics of weaving sections is the primary prerequisite for investigating lane-changing mechanisms and micro-level collision risks. Accordingly, this section builds on the core theoretical framework of weaving sections defined in the Highway Capacity Manual (HCM) published by the United States (HCM, 2000), and systematically elaborates the fundamental characteristics of weaving sections along different dimensions: definition, geometric configuration, traffic flow operation characteristics, and safety influencing factors. This structure is designed to lay a solid theoretical foundation for the subsequent quantitative modelling.

2.2.1 Definition and geometric configuration of weaving sections

A weaving section is a specialised traffic facility within expressway systems, defined as a specific segment where multiple same-direction traffic streams merge and diverge via lane intersections in the absence of traffic signal control. This segment is typically composed of an on-ramp and a downstream adjacent off-ramp connected by an auxiliary lane, forming a continuous weaving traffic flow pattern. According to the definition specified in the HCM, weaving influence extends approximately 152 metres (500 feet) both upstream and downstream of the ramp nose. When the distance between the merge area and diverge area exceeds 914 metres (3,000 feet), the two sections are classified as independent segments, with no significant interaction between adjacent ramps.

In terms of geometric configuration characteristics, weaving sections can be categorised into single weaving sections and multiple weaving sections based on the number of configured ramps. A single weaving section comprises one consecutive on-ramp and one adjacent off-ramp, and exhibits a relatively straightforward traffic flow pattern. A multiple weaving section consists of multiple consecutive on-ramps and off-ramps, resulting in more complex traffic flow interactions. For the classification of single weaving sections, the Type A, Type B, and Type C classification framework is widely adopted in existing research (HCM, 2000). This classification is defined based on the minimum number of lane changes required for weaving vehicles to traverse the weaving section. Three typical geometric configurations of weaving sections and their corresponding traffic flow trajectories are illustrated in Figures 2.1 to 2.3.

The geometric configuration and traffic flow organisation characteristics of a typical Type A weaving section are presented in Figure 2.1. In this type of weaving section, all vehicles merging into the mainline from the on-ramp and all vehicles diverging from the mainline to the off-ramp must complete at least one mandatory lane change. Based on differences in traffic flow organisation, Type A weaving sections can be subdivided into two subclasses: A1 and A2. Type A1 is classified as ramp weave, and its core structural feature is that the on-ramp is connected to the downstream off-ramp via an auxiliary lane. In contrast, Type A2 is a more complex weaving system composed of multi-lane entrances and exits. From the

perspective of lane resource allocation, Type A weaving sections exhibit significant spatial constraint characteristics: all lane-changing behaviours of weaving vehicles are restricted to the range of two adjacent lanes, and this area must also accommodate through traffic on the mainline. This resource allocation pattern forces weaving vehicles and non-weaving vehicles to share limited road space, which easily generates multiple traffic conflict points under high traffic volume and negatively impacts traffic efficiency. Type A weaving sections are the most common type of weaving section in China's road network, with Type A1 ramp weave sections being particularly prevalent. The typical lane-changing behaviour characteristics and traffic conflict patterns of this weaving section type make it an ideal research object for investigating the traffic flow characteristics and safety assessment of weaving sections.

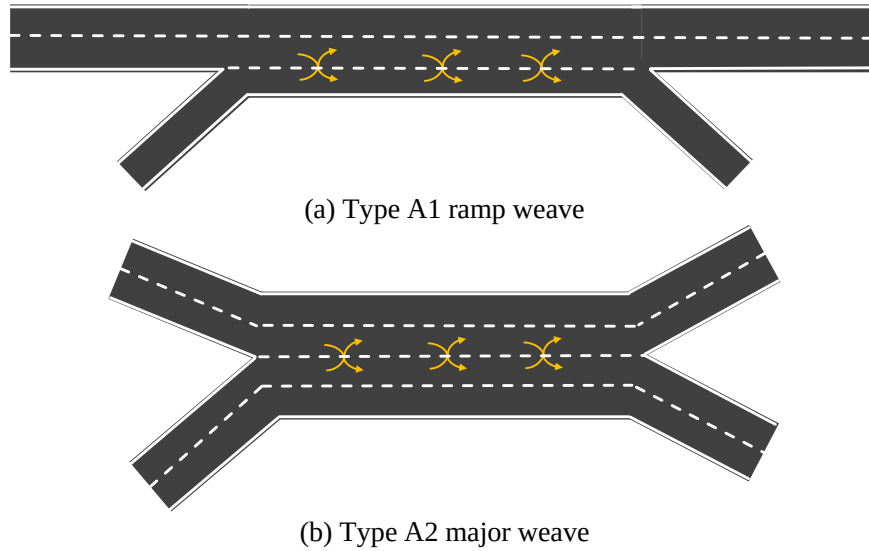
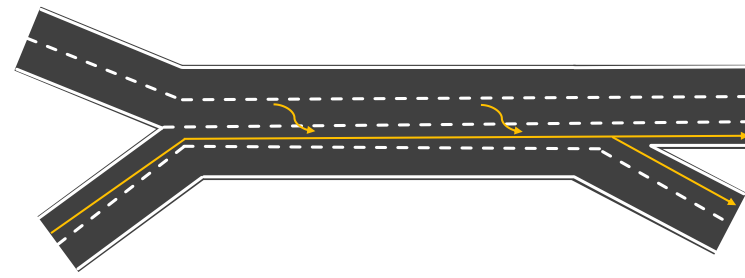
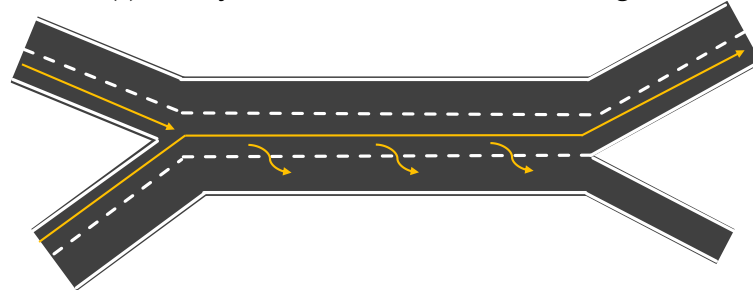


Figure 2.1 Type A weaving section.

The three typical configurations of Type B weaving sections are illustrated in Figure 2.2. Such configurations are commonly observed at large interchange hubs with three to four entrance and exit lanes. In Type B weaving sections, a portion of weaving vehicles do not require any lane change to complete route shifting, while the remaining weaving vehicles need at most one lane change to fulfil travel requirements. From the perspective of geometric design, Type B weaving sections are configured with multi-lane on-ramps and off-ramps, which significantly reduces the demand for mandatory lane changes and enables some vehicles to access their target routes directly via the original lane. In terms of lane resource utilisation, Type B weaving sections also exhibit high flexibility: weaving vehicles can not only use dedicated weaving lanes and their adjacent lanes, but can also utilise outer general lanes to share road space with non-weaving vehicles under specific conditions. Compared with Type A weaving sections, the geometric design of Type B weaving sections endows them with a distinct advantage in mitigating spatial constraints. By reducing the number of required lane changes, this design effectively lowers the probability of traffic conflicts, and consequently improves the overall traffic efficiency and safety performance of weaving sections.



(a) B1 major weave with lane balance at exit gore



(b) B2 major weave with merge at entry gore



(c) B3 major weave with merge at entry gore and lane balance at exit gore

Figure 2.2 Type B weaving section.

The two typical structural configurations of Type C weaving sections are presented in Figure 2.3. In terms of geometric layout, Type C weaving sections share certain similarities with Type B weaving sections: both can provide direct through paths for partial weaving traffic flows without requiring lane changes. However, the two structures differ in traffic organisation, primarily in the number of required lane changes. Within Type C weaving sections, some vehicles can adjust their travel routes directly via exclusive lanes without executing any lane-changing manoeuvres. The remaining vehicles face more complex travel demands, and must complete two or more consecutive lane changes to reach their target routes. This differentiated traffic demand endows Type C weaving sections with a distinctive traffic flow pattern: they retain the accessibility of direct through travel, while integrating the complexity of multiple lane-changing operations. Accordingly, the operational characteristics of Type C weaving sections exhibit unique transitional properties. The traffic flow complexity of Type C weaving sections is higher than that of Type B weaving sections with a uniform lane-changing pattern, but lower than that of Type A weaving sections where all vehicles are required to perform lane changes.

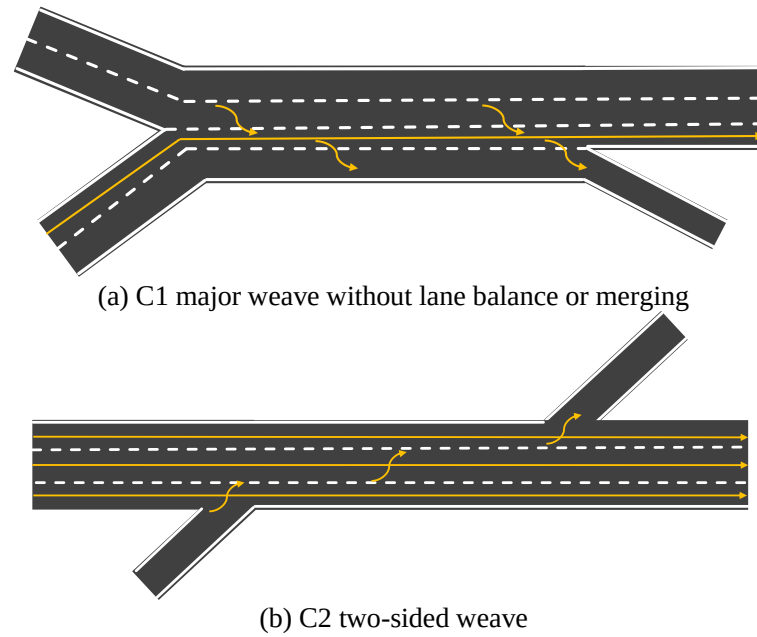


Figure 2.3 Type C weaving section.

The structural configuration of weaving sections directly determines the operational characteristics of traffic flow, and different weaving section types exhibit significant differences in lane utilisation patterns, lane-changing demand intensity, traffic operational efficiency, and traffic conflict patterns. Among these configurations, Type A weaving sections are the most prevalent in roadway networks. Due to attributes such as rigid lane-changing requirements and constrained lane resources, Type A weaving sections are particularly prone to becoming traffic bottlenecks. Given the extensive distribution of Type A1 weaving sections in roadway networks and their critical impacts on the operational efficiency and safety level of transportation systems, this thesis focuses on Type A1 weaving sections, takes lane-changing behaviour as the research object, and systematically conducts research on three key topics: lane-changing behaviour characteristic and mechanism analysis, conflict cause analysis, and conflict risk prediction.

2.2.2 Operational characteristics of traffic flow in weaving sections

Traffic flow in a weaving section can be categorised into two types: weaving flow and non-weaving flow. Under low-density traffic conditions, weaving vehicles can complete lane-changing manoeuvres more smoothly, and the disturbance of lane-changing behaviour on the overall traffic flow is relatively limited. However, under high-density traffic conditions, as inter-vehicle headway decreases, weaving vehicles often need to adopt strategies such as deceleration or even temporary stopping to identify an acceptable lane-changing gap. These processes typically trigger a two-fold negative chain reaction. On one hand, vehicles waiting to change lanes lower local road space utilisation, which directly reduces the overall traffic efficiency of the section. On the other hand, after a weaving vehicle successfully merges into the target lane, the following vehicle originally travelling normally in that lane must decelerate to maintain a safe following distance. This deceleration is

highly likely to induce the propagation of perturbations within the traffic flow, further degrading the already constrained traffic capacity of the weaving section.

Overall, traffic flow in weaving sections exhibits six primary characteristics. First, weaving sections accommodate multi-directional merging traffic flows. The complex weaving of movements within the area forces drivers to perform frequent lane changes and speed adjustments over very short time horizons, increasing drivers' cognitive burden and impeding their decision-making processes. Second, high travel speed and high traffic density coexist. Weaving sections typically accommodate high-speed traffic while also gathering dense flow volumes, forming a spatially compact traffic distribution pattern. Third, weaving sections are characterised by intensive lane-changing demand. When multiple alternative paths converge, vehicles must conduct frequent lane changes to identify and reach their optimal travel route. Fourth, weaving sections adopt a composite traffic control configuration. Ramp signal control, lane guidance signs and other control facilities are typically installed in weaving sections, which requires drivers to quickly and accurately interpret guidance information and make appropriate driving responses in a timely manner. Fifth, weaving sections involve multimodal traffic participants. On urban road weaving sections, motor vehicles, non-motor vehicles and pedestrians often interact and interweave with each other, jointly forming a complex mixed-traffic environment. Sixth, high-risk traffic conflicts occur at high frequency. Dense weaving of vehicles travelling in different directions can easily induce typical collisions such as side scrapes and rear-end crashes in the area, which also places stringent requirements on drivers' risk prediction ability and active collision avoidance skills.

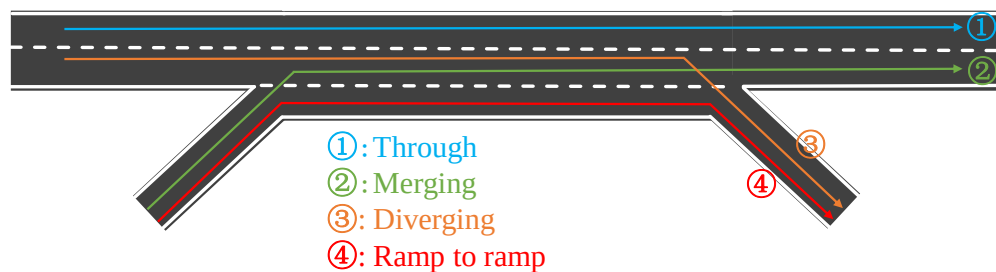


Figure 2.4 Traffic flow composition in Type A1 weaving sections.

2.2.3 Factors influencing operational safety in weaving sections

As a complex transportation operation system, the safety performance of a weaving section is determined by the interactive interplay of multi-dimensional factors. Core variables governing the system's safety level include: physical characteristics such as weaving length and lane width, traffic flow attributes including volume and weaving ratio, and micro-level driver behaviour.

Among physical characteristics, the primary influence of weaving length on safety is well established. Per the HCM specification, this indicator is measured from the merge gore point where the right edge of the freeway shoulder lane and the left edge of the merging lane are 0.6 m apart, to the diverge gore point where

the two edges are 3.7 m apart. An excessively short weaving length directly reduces available lane-changing space, forcing drivers to adopt more aggressive manoeuvres and increasing conflict probability. Conversely, an overly long weaving section not only induces many unnecessary redundant lane changes, but also imposes sustained high cognitive load on drivers navigating complex road conditions. In addition, lateral lane width also regulates the safety margin of the weaving section. Overly narrow lanes increase lateral pressure between adjacent vehicles; especially under high-speed and heavy-flow conditions, the risk of side collisions grows exponentially. This insufficient lateral space also imposes additional psychological burden on drivers, reducing their operational stability during lane-changing (Li et al., 2016). A moderately set lane width, by contrast, can provide a valuable lateral buffer to accommodate the complex dynamic interactions between vehicles.

At the traffic flow operation level, traffic volume is a key indicator affecting the operational status of weaving sections. When traffic volume remains moderate, weaving sections can maintain smooth operation. Once the overall load exceeds the capacity threshold, the interaction frequency between vehicles rises sharply and headways are severely compressed. When traffic volume exceeds the critical value, traffic flow rapidly becomes unstable, and the risk of rear-end and side collisions also increases dramatically. Beyond overall traffic volume, the composition of traffic flow also affects operational safety. The weaving ratio, defined as the proportion of weaving traffic relative to total mainline traffic, intuitively reflects the operational load intensity of the section. When the weaving ratio becomes excessively high, it disrupts the orderly organisation of traffic flow and increases the crash risk. Existing studies have confirmed that when the weaving ratio exceeds a reasonable threshold, traffic conflicts increase significantly due to the higher frequency of vehicle trajectory crossings (Mallipaddi & Anderson, 2020).

Driver behaviour in weaving sections is mainly manifested in three aspects: lane-changing behaviour, car-following characteristics, and speed selection. Unsafe lane changes, such as forced lane changes and emergency lane changes, can significantly increase the probability of traffic conflicts. Studies have confirmed that increased on-ramp traffic will further amplify the crash risk associated with these unsafe behaviours. Close car-following also sharply reduces the available safety buffer space, especially in exit areas. Speeding increases crash risk by extending braking distance and reducing vehicle handling stability (Wu et al., 2018; Mallipaddi & Anderson, 2020).

2.3 Analysis of conflict characteristics in weaving sections

Traffic crashes are inherently characterised by randomness and low probability of occurrence, making it challenging to collect enough crash samples within a short timeframe for empirical traffic safety analysis. Furthermore, key microscopic traffic flow state data preceding collisions are typically missing from official crash datasets. To address these limitations, traffic conflict techniques have been developed. The core logic of this approach is to quantify the potential risky

interactions between road users, thereby overcoming the technical limitations of traditional crash-based statistics, including small sample sizes, long data collection cycles, and the absence of microscopic traffic information. Under this theoretical framework, researchers have developed surrogate safety measures (SSMs) to conduct accurate, quantitative evaluations of road traffic safety conditions (Tarko et al., 2009).

Compared with traditional crash-based analysis methods, SSMs offer several distinct advantages. First, SSMs enable proactive hazard identification and early intervention before actual collisions occur, endowing safety assessment systems with forward-looking warning capabilities. Second, SSMs can integrate multi-source risk data to produce a more comprehensive and multi-dimensional characterisation of system-level safety. Additionally, this approach eliminates the dependence on historical crash data, reduces the cost of underlying data collection, and guarantees high repeatability of assessment results, thereby effectively alleviating the data bias issue that is unavoidable in traditional statistical methods (Wu & Jovanis, 2012). In recent years, driven by continuous iterations of high-precision traffic sensing devices and advanced data mining algorithms, surrogate safety analysis has become an essential component of the modern traffic risk assessment system. This thesis will adopt SSMs to identify and quantify traffic conflicts, with the aim of revealing the micro-scale evolutionary mechanism of operational risks in freeway weaving sections.

2.3.1 Traffic conflict techniques

The origin of the traffic conflict technique can be traced back to the mid-20th century. After Klebelsberg first conceptualised it as dangerous interactive traffic behaviour in 1964 (Klebelsberg, 1964), the technique has evolved into one of the most representative methods for surrogate safety analysis through decades of theoretical development and methodological refinement. From diverse theoretical perspectives, researchers have defined traffic conflicts across multiple dimensions. Among these frameworks, the two most influential are the proximity criterion and the avoidance behaviour criterion (Hyden, 1977; Zheng & Sayed, 2020). The proximity criterion focuses on the proximity of road users' spatiotemporal trajectories: if multiple road users maintain their existing movement trends, and the physical distance or TTC between them falls below a predefined critical threshold, a conflict is identified. This approach facilitates efficient quantitative conflict identification using SSMs, but the lack of universally accepted measurement indicators often significantly impairs the objectivity and accuracy of final judgement. An alternative perspective centres on avoidance behaviour, positing that the essence of a traffic conflict lies in the avoid actions taken by drivers, such as emergency braking or steering, after perceiving potential collision risks. While this definition effectively captures the explicit behavioural characteristics of traffic conflicts, in engineering practice its extreme reliance on subjective judgement during the identification process and the absence of a unified quantitative standard make it difficult to integrate into real-time dynamic analysis scenarios. Overall,

both frameworks lean heavily on qualitative description and do not establish clear quantitative boundaries for interaction intensity.

To address the theoretical limitations of the conventional separation of qualitative and quantitative analyses, researchers have attempted to integrate the two approaches and proposed that the so-called traffic conflict is essentially a dynamic risk-bearing interaction that occurs between road users on intersecting collision trajectories (Laureshyn et al., 2010). Figure 2.5 illustrates three typical road network scenarios based on the interaction patterns of vehicle trajectories. Figure 2.5(a) depicts an inevitable collision scenario where the trajectories overlap completely in both spatial and temporal dimensions. In contrast, the trajectories in Figure 2.5(b) intersect physically but are deliberately staggered in the temporal dimension. For Figure 2.5(c), the trajectories are completely separated with no substantial interaction between them. This definitional framework not only dissects the mechanism of traffic conflict at its root, but also lays the foundation for the subsequent automated identification of traffic conflicts.

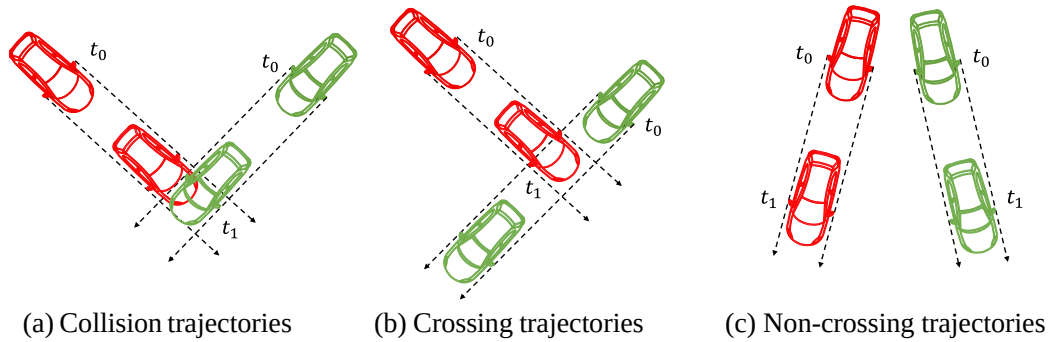


Figure 2.5 Schematic diagram of vehicle trajectory classification.

Traffic conflicts can be categorised into multiple types according to different classification criteria. Based on the conflicting participants, traffic conflicts are divided into motor vehicle-motor vehicle conflicts, motor vehicle-non-motor vehicle conflicts, motor vehicle-pedestrian conflicts, non-motor vehicle-non-motor vehicle conflicts, and non-motor vehicle-pedestrian conflicts. When classified by conflict severity, a three-level evaluation system can be established, ranging from minor conflicts to moderate conflicts, then to severe conflicts. Minor conflicts refer to low-risk interactions that can be resolved via simple evasive manoeuvres. Moderate conflicts require distinct evasive actions and are associated with observable crash risk. Severe conflicts are high-risk scenarios that require emergency evasive measures. According to their spatial distribution characteristics, traffic conflicts can be grouped into two primary categories: intersection conflicts and roadway segment conflicts. Based on vehicle movement trajectories, intersection conflicts can be further subdivided into left-turn conflicts, right-turn conflicts, and through-movement conflicts. Roadway segment conflicts are categorised into rear-end conflicts, crossing conflicts and head-on conflicts according to the relative movement direction of vehicles.

Specifically, by introducing collision angle θ as a quantifiable indicator, a classification standard based on geometric characteristics can be established: when

$\theta \in [0^\circ, 45^\circ]$, the conflict is a rear-end conflict, which represents longitudinal interaction risk between vehicles travelling in the same direction, as shown in Figure 2.6(a); when $\theta \in (45^\circ, 135^\circ]$, the conflict is a crossing conflict, which refers to crossing risk caused by vehicles cutting laterally into the path of other road users, as shown in Figure 2.6(b); when $\theta \in (135^\circ, 180^\circ]$, the conflict is a head-on conflict, which represents frontal collision risk between oncoming vehicles, as shown in Figure 2.6(c).

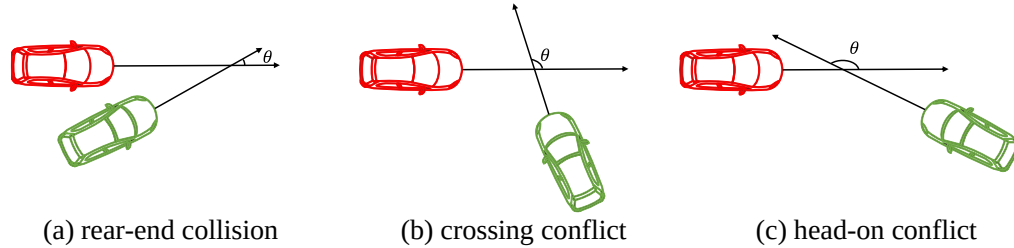
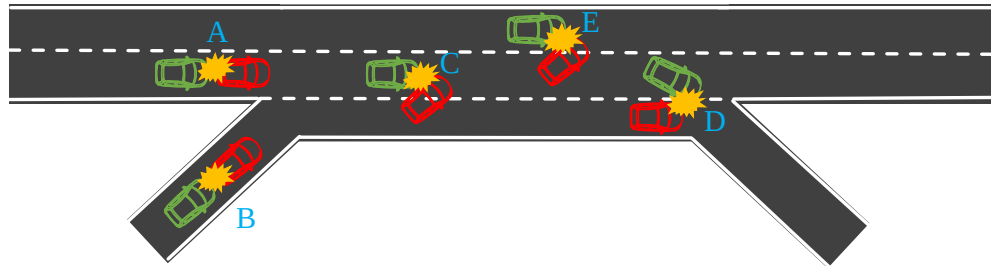


Figure 2.6 Classification of traffic conflicts based on collision angle.

In the road weaving operating environment, vehicles need to complete lane-changing manoeuvres to achieve merging or diverging. This change in spatial position disrupts the stability of existing traffic flow, causes crossing and overlapping of vehicle trajectories, and thus induces various traffic conflicts. Based on existing systematic analyses of traffic flow characteristics in weaving sections and established conflict classification criteria, typical traffic conflicts in weaving sections can be categorised into the following five types (as shown in Figure 2.7).



- A:** Rear-end conflicts caused by main road vehicles decelerating before entering the weaving section
- B:** Rear-end conflicts caused by deceleration of ramp vehicles before entering the weaving section
- C:** Crossing conflicts arising from the interaction between main road vehicles and ramp vehicles
- D:** Crossing conflicts caused by main road vehicles forcibly entering the ramp before the weaving section exit
- E:** Crossing conflicts between vehicles in the outer lane and those in the inner lane, caused by vehicles in the outer lane attempting to avoid weaving traffic.

Figure 2.7 Different types of traffic conflicts in weaving sections.

The triggering mechanisms of Class A and Class B traffic conflicts are generally concentrated in two representative scenarios. In the first scenario, when the leading vehicle on the main road is forced to brake abruptly due to forward road conditions, and the following vehicle fails to decelerate in response, a rear-end

collision threat arises from insufficient braking distance. The second scenario typically occurs during vehicle merging, when the merging driver detects insufficient safe gap and chooses to decelerate and wait for an acceptable gap, if the following vehicle fails to anticipate the leading vehicle's manoeuvre in time, a rear-end conflict is also highly likely to occur. Class C and Class D conflicts are both categorised as crossing weaving risks. Among them, Class C conflicts occur most frequently in weaving sections, and their root cause is the complex trajectory interaction of multiple vehicle flows. When vehicles travelling in different directions change lanes synchronously within limited time and space, and their trajectories overlap, a crossing conflict will be triggered once the physical distance between vehicles falls below the minimum safety threshold. In contrast, the spatial distribution of Class D conflicts is more concentrated, and they tend to cluster in exit diversion areas. If mainline vehicles miss the optimal window to change lanes to the off-ramp, they often perform abrupt deceleration or even stop to wait for an exiting opportunity, which will inevitably trigger a chain braking reaction in the following traffic. If a driver attempts to force an unsafe lane change at this stage, the collision risk for the entire traffic stream will increase rapidly. Class E conflicts are mostly triggered by interactions among non-weaving vehicles. To avoid interference from outer-lane weaving traffic, some non-weaving vehicles will proactively conduct a defensive lane change to inner lanes. In this process, if the driver misestimates the speed and gap of vehicles in the target lane, unplanned trajectory crossing will occur.

2.3.2 SSMs

SSMs primarily adopt risk quantification models to characterise potential hazards in vehicle interactions, which eliminates the dependence on crash data and enables indirect measurement and advance prediction of road risks. With the continuous advancement of related theories, researchers have developed a set of differentiated indicator systems adapted to complex traffic scenarios and conflict patterns. After systematically reviewing the existing literature, Mahmud et al. divided the indicator systems into three core categories: temporal proximity, spatial proximity, and deceleration characteristics (Mahmud et al., 2017). This classification clarified the existing research landscape and laid a theoretical foundation for the subsequent targeted selection of applicable indicators for different traffic scenarios.

Among existing evaluation frameworks, SSMs based on temporal proximity are the most widely adopted category. Their core theoretical premise is that once the spatial distance between traffic participants decreases below a specific critical threshold, the potential collision risk will rise significantly. By analysing the relative motion relationships among road users, these indicators establish a risk assessment method that integrates spatiotemporal parameters. This approach effectively incorporates the interaction between spatial distance and motion velocity, thereby dynamically capturing the potential of traffic participants to avoid collisions. By calculating the time difference between traffic participants arriving at potential collision points, combined with dynamic parameters such as movement

speed and heading angle, these indicators can quantitatively measure the evolution process and severity of traffic conflicts. One of the most representative indicators is the Time-to-Collision (TTC) metric proposed by Hydén (1996). TTC is defined as the time required for two road users to reach a collision point from their current positions while maintaining their existing motion states, and it is calculated via a piecewise function as follows:

$$TTC_i(t) = \begin{cases} \frac{X_L(t) - X_F(t) - L_L}{v_F(t) - v_L(t)}, & v_F(t) > v_L(t) \\ \infty, & v_F(t) \leq v_L(t) \end{cases} \quad (\text{Eq2.1})$$

where, $X_F(t)$ and $X_L(t)$ denote the front position coordinates of the following vehicle and the leading vehicle at time t , respectively. $v_F(t)$ and $v_L(t)$ represent the instantaneous speed of the corresponding two vehicles, respectively. And L_L is the length of the leading vehicle. When the speed of the following vehicle is higher than that of the leading vehicle, TTC is positive, indicating potential collision risk, in the opposite case, TTC approaches infinity, indicating no collision risk.

In practice, the TTC threshold needs to be calibrated based on specific traffic conditions to define conflict risk levels. Extant research has proposed threshold values ranging from 1 to 5 seconds for different application scenarios: Van der Horst suggested a 1.5-second threshold for intersection scenarios (Van der Horst, 1990). The conflict classification system developed by Sayed et al. adopts 2 s and 0.9 s as the criteria for distinguishing minor conflicts and severe conflicts respectively (Sayed et al., 1994). Meng and Qu recommend a 4-second threshold for urban tunnel environments (Meng & Qu, 2012).

Based on the analysis of traffic conflict patterns in the weaving section presented in Figure 2.7, this study finds that traffic conflicts in this area primarily take two typical forms: crossing conflicts and rear-end collisions. As shown in Equation (2.1), the traditional TTC index requires pre-set collision angles for application, and its theoretical foundation is premised on independent calculation after classifying traffic conflicts by fixed angles. However, in the dynamic operating environment of weaving sections, when vehicles perform lane-changing manoeuvres, they will form multi-angle conflict scenarios with surrounding vehicles. Because traffic participants ahead of and behind the target vehicle can all execute lane-changing behaviour according to their respective trajectory demands, this leads to a diversified distribution of conflict angles between vehicles. The core theoretical limitation of traditional TTC indicators lies in their failure to fully account for the vector characteristics of vehicle movement directions. Traditional TTC constructs its calculation model based on the simplified assumption of same-direction driving. However, the spatial differences in relative position vectors and velocity directions between vehicles during actual lane-changing manoeuvres make it difficult for traditional TTC to accurately characterise the risk nature of vehicle lane-changing behaviour in weaving sections.

To address these limitations, researchers have proposed the indicator of Generalized Time-to-Collision (GTTC) (Ward et al., 2015; Zhang et al., 2023). By

incorporating vector parameters of vehicle movement directions, GTTC enables the construction of a risk assessment method for multi-angle conflict scenarios, and can accurately characterise the dynamic evolution of collision risk during lane-changing manoeuvres in weaving sections. Given the inherent complexity of traffic flow in weaving sections, this thesis adopts the GTTC indicator to capture conflict characteristics of vehicle interactions in this facility. Compared with the conventional TTC indicator, GTTC can effectively describe traffic conflicts that are not restricted by vehicle movement direction and interaction angle.

Since road vehicles have distinct geometric shapes rather than being point particles, specific contact locations must first be identified for potential collision analysis. The closest point between two vehicles Veh_i and Veh_j is defined as the potential collision point, and the mathematical expression for the shortest distance $D_{i,j}$ between any two points on the surfaces of the two vehicles is given as follows:

$$D_{i,j} = \min \{d_{m,n} | m \in Veh_i, n \in Veh_j\} \quad (\text{Eq2.2})$$

The positions of the two points on the vehicle are defined as p_m and p_n respectively, and the velocities of the two points are defined as v_m and v_n respectively. This thesis assumes that the two vehicles are approaching each other at a constant speed, which means the acceleration of both vehicles is zero. Accordingly, the distance $d_{m,n}$ between the two points can be derived from the following equation (Ward et al., 2015; Zhang et al., 2023).

$$d_{m,n}^2 = \|p_m - p_n\|^2 = (p_m - p_n)^T (p_m - p_n) \quad (\text{Eq2.3})$$

Differentiating both sides of Equation (2.3) yields the rate of change of the distance $\dot{d}_{m,n}$:

$$d_{m,n} \dot{d}_{m,n} = (p_m - p_n)^T (v_m - v_n) \quad (\text{Eq2.4})$$

The distance $d_{m,n}$ between any two points on Veh_i and Veh_j , as well as its first derivative $\dot{d}_{m,n}$, can be calculated using Equations (2.5) and (2.6), respectively.

$$d_{m,n} = \sqrt{(p_m - p_n)^T (p_m - p_n)} \quad (\text{Eq2.5})$$

$$\dot{d}_{m,n} = \frac{(p_m - p_n)^T (v_m - v_n)}{d_{m,n}} \quad (\text{Eq2.6})$$

The distance $D_{i,j}$ between Veh_i and Veh_j is calculated using the Equation (2.2) to obtain the minimum distance between Veh_i and Veh_j . The relative approach speed of the two vehicles is the first derivative $\dot{D}_{i,j}$ of the distance $D_{i,j}$ between these two points.

Based on the conventional definition of TTC, the GTTC is defined as the time gap that elapses before a collision between two moving vehicles occurs, assuming

that both vehicles maintain their current speeds and travel directions. When the inter-vehicle distance at the expected collision moment equals zero, GTTC can be derived by solving Equation (2.7), and the piecewise function expression given in Equation (2.8) is finally obtained.

$$D_{i,j} + \dot{D}_{i,j} \times GTTC = 0 \quad (\text{Eq2.7})$$

$$GTTC = \begin{cases} \frac{-D_{i,j}}{\dot{D}_{i,j}}, & \dot{D}_{i,j} < 0 \\ +\infty, & \dot{D}_{i,j} \geq 0 \end{cases} \quad (\text{Eq2.8})$$

This definition has a clear physical interpretation: when relative motion reduces the distance between the two vehicles ($\dot{D}_{i,j} < 0$), GTTC represents the expected time to collision; when the distance between the two vehicles remains unchanged or increases ($\dot{D}_{i,j} \geq 0$), no collision risk is identified, and GTTC is defined as infinite.

2.4 Drone video data collection and processing for the weaving section

2.4.1 Data acquisition and geospatial calibration

In recent years, drones have been widely applied to traffic data collection, owing to their technical advantages including flexible deployment and high-altitude bird's-eye perspective. The overhead shooting angle of drones can effectively avoid ground obstructions, yielding high-quality video data for vehicle trajectory extraction. As indicated in existing research, the Type A1 weaving section exhibits typical lane-changing behaviour characteristics and distinct traffic conflict patterns, making it an ideal research object for investigating traffic behaviour in weaving sections.

This thesis selects the most representative Type A1 weaving section in China's highway network as the research object. Through systematic comparison and screening of multiple candidate sites, the Yuhua hub segment of the Changsha Airport Expressway is finally determined as the research site. The total length of the weaving section is approximately 650 metres. Due to the limited observation coverage of drones, the actual data collection area covers a 400-metre section. The weaving section adopts a six-lane layout in both directions, with one on-ramp in the eastbound direction, and one on-ramp and one off-ramp in the westbound direction. The three lanes of the mainline have widths of 3.75 m, 3.75 m, and 5 m respectively, while the ramp width is 5 m. The maximum speed limit of the mainline is 100 km/h, the minimum speed limit is 60 km/h, and the speed limit of the ramp is 5 km/h. As illustrated in Figure 2.8, field data collection was conducted using a multi-drone cooperative operation mode. Between 15:00 and 15:25 on May 31, 2021, 25 minutes of continuous video data was captured via aerial photography by three drones operating at an altitude of 120 m, with a video sampling frame rate of 30

Hz. Video stitching technology was applied to integrate multi-perspective footage to construct a complete observation area covering the entire weaving section, and vehicle trajectory data was subsequently extracted based on the integrated footage.

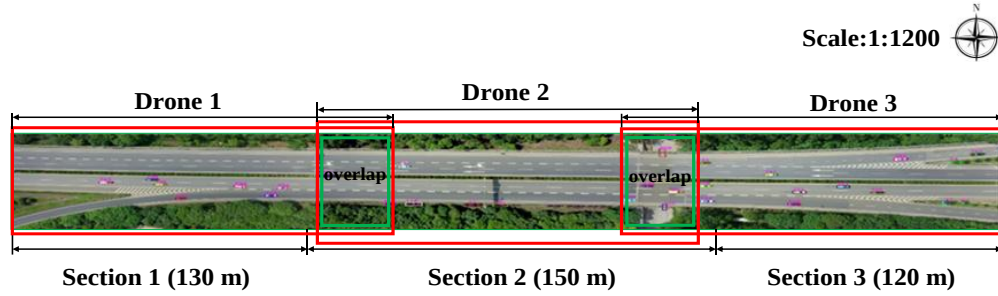


Figure 2.8 Aerial perspective of the weaving section of Changsha Airport Expressway.

To achieve accurate mapping of drone video data from the image coordinate system to the geodetic coordinate system, this thesis adopts a geographic registration method based on ground control points. The proposed method converts pixel coordinates of video frames into absolute geographic coordinates by constructing coordinate transformation relationships between two sets of control points. As illustrated in Figure 2.9, eight ground control points are arranged at key locations (e.g., the endpoints of diverging lines, lane markings) according to the spatial geometric characteristics of the weaving section. This layout guarantees that the control points are uniformly distributed across the entire image frame, and can effectively cover the main activity areas of vehicle trajectories. The longitude and latitude coordinates of each ground control point were collected in field surveys using a high-precision GPS measuring instrument, and the entire geographic registration procedure was implemented in ArcGIS.

A frame with minimal traffic flow, sharp imagery and no significant distortion was selected from the drone video sequence as the base map, to minimise the interference of moving vehicles on reference point identification. To improve the accuracy and robustness of the coordinate transformation model, this thesis uses all 8 ground control points to construct the transformation model. In ArcGIS, the pixel positions of the 8 reference points on the base map are sequentially and precisely located, and their image coordinates (x, y) are recorded. The longitude and latitude coordinates measured through field surveys are used as the ground truth geographic coordinates of the reference points, and are input into the system in one-to-one correspondence with the pixel coordinates obtained above. The mapping relationship between pixel coordinates and geographic coordinates is established using a first-order polynomial transformation (affine transformation) algorithm, which can effectively compensate for image rotation, scaling and translation distortion caused by oblique drone camera angles.



Figure 2.9 Location of the ground reference point for georeferencing.

2.4.2 Trajectory data extraction

This thesis adopts a technical approach that combines deep learning-based detection with discriminative model tracking to precisely extract vehicle movement trajectories. Specifically, the Mask R-CNN (Mask Region-based Convolutional Neural Network) model is applied to perform instance segmentation of vehicles in individual video frames, and the CSRT (Channel and Spatial Reliability Tracking) algorithm is adopted to achieve stable vehicle tracking across consecutive frames, which guarantees the continuity and integrity of the extracted trajectories (Zheng, 2019). The Mask R-CNN model is built on the classic Faster R-CNN (Faster Region-based Convolutional Neural Network) architecture by adding an additional parallel branch to predict the segmentation mask for each detected target. Conventional detectors typically output only an axis-aligned bounding box for each target, while Mask R-CNN generates a high-quality binary mask in addition to the target category label and confidence score. As illustrated by the green area in Figure 2.10, this mask achieves pixel-level precise alignment, which accurately depicts the complete contour of the target vehicle. Based on this fine-grained segmentation result, the absolute position of the vehicle can be stably locked at the pixel scale. Next, based on the predicted segmentation mask, the algorithm further calculates the minimum-area rotated bounding box that can fully enclose the mask, which corresponds to the red rectangle marked in Figure 2.10. Compared with a standard axis-aligned bounding box, this derived rotated bounding box fits the vehicle geometry far better. As can be observed from the yellow region in Figure 2.10, traditional axis-aligned bounding boxes easily include large areas of invalid background pixels when processing vehicles that frequently turn or travel diagonally in weaving sections, which introduces measurement errors in the estimated target size and position. In contrast, the rotated bounding box effectively mitigates this limitation. The accurate vehicle orientation and geometric dimensions obtained from the rotated bounding box serve as prerequisites for the subsequent precise calculation of vehicle heading angle, centre point coordinates, and three-dimensional position coordinates.

After completing frame-by-frame vehicle detection, this thesis introduces the CSRT algorithm to conduct vehicle tracking, so as to connect discrete detection results into smooth and continuous trajectories. This algorithm effectively integrates a spatial reliability map into the correlation filter framework, enabling high positioning accuracy, but it also incurs corresponding increases in computational cost. In weaving sections, vehicles are prone to mutual occlusion. When combined with interference from abrupt light changes and overlapping shadows, target tracking drift and loss has long been a major technical bottleneck in trajectory extraction. Moreover, the coherence of tracking trajectories directly determines the calculation quality of subsequent feature indicators for lane-changing behaviour in weaving sections. To address this problem, this thesis designs a tailored target re-identification mechanism that combines static target detection with Intersection of Union (IoU) logic, following the approach proposed

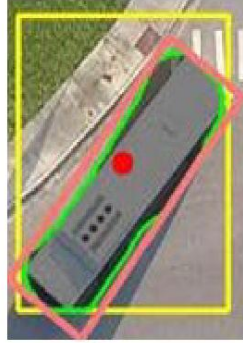
by Zheng (2019). The specific implementation steps of this mechanism are as follows:

Step 1, Stationary frame identification. When the system detects that the tracking speed of a target vehicle drops to 0, the current frame is recorded as $frame_j$.

Step 2, Vehicle detection and IOU calculation. Full inference of vehicle detection is conducted on $frame_j$ via the Mask R-CNN model. For each lost tracking target, then the IOU between its last tracked bounding box ($DetectionResult$) and all detected bounding boxes ($GroundTruth$) in the current frame is calculated, as defined in Equation (2.9):

$$IOU = \frac{DetectionResult \cap GroundTruth}{DetectionResult \cup GroundTruth} \quad (Eq2.9)$$

Step 3, Target re-association judgement. If the calculated IOU of a region pair exceeds a predefined threshold (this work adopts an empirical value of 0.5), the lost target is judged to be re-identified, and the CSRT tracking process is immediately reinitialised with the corresponding new detection bounding box as the initial state. This approach effectively alleviates the identity switching problem that commonly occurs after long-term occlusion or severe interference, thereby ensuring the long-term trajectory integrity of vehicle tracking.



— Mask — Straight Bounding — Rotated Bounding

Figure 2.10 Differences between mask, straight bounding box, and rotated bounding box.

To objectively evaluate the performance of the proposed detection algorithm, this thesis establishes the following quantitative evaluation metrics across three dimensions: correctness, completeness, and quality. The first metric is Correctness (COR), which quantitatively reflects the proportion of valid vehicle samples among all targets detected by the algorithm, and its calculation equation is given in Equation (2.10):

$$COR = \frac{TP}{TP + FP} \quad (Eq2.10)$$

The second metric is the Completeness (COP), which quantifies an algorithm's ability to correctly identify all truly existing vehicles. Its calculation equation is provided below:

$$COP = \frac{TP}{TP + FN} \quad (\text{Eq2.11})$$

The third metric is the Quality (QUA), which is introduced because relying on a single indicator alone tends to introduce evaluation bias. This metric enables a comprehensive assessment of both the accuracy and coverage of test results, and its calculation logic is presented in Equation (2.12):

$$QUA = \frac{TP}{TP + FP + FN} \quad (\text{Eq2.12})$$

where, TP denotes the number of correctly detected vehicles, FP denotes the number of incorrectly detected vehicles, and FN denotes the number of missed vehicles. Missed vehicles are defined as vehicle targets lost during tracking, resulting from complex environmental factors including shadow interference, abrupt illumination changes, and vehicle occlusion.

To verify the performance of the proposed algorithm, 200 vehicle images were randomly selected from 1,000 total samples to construct the test set. Experimental results indicate that the detection algorithm achieved a COR of 98%, a COP of 77%, and a QUA of 76% on the constructed test set. Notably, the algorithm is expected to yield better performance than the reported single-frame test results when applied to real-world video sequences, as it can further improve detection performance via multi-frame information fusion and trajectory smoothing during continuous video processing. Figure 2.11 illustrates the detection performance of the algorithm in a typical test scenario, demonstrating that the proposed method can effectively identify the majority of vehicle targets.



Figure 2.11 The detection performance of the proposed algorithm.

2.4.3 Data smoothing and outlier handling

Original vehicle trajectories extracted via object detection and tracking algorithms inevitably contain noise caused by multiple factors, including sensor errors, video jitter, illumination variations, and occlusions in complex traffic scenes. This noise introduces fluctuations to trajectory coordinate sequences and increases data uncertainty. If raw noisy trajectories are directly applied to microscopic driving

behaviour analysis, it will likely lead to inaccurate calculations of key motion parameters such as vehicle speed and acceleration. Therefore, further data processing is required after extracting original trajectories to improve overall data quality. This thesis adopts a trajectory data processing framework that integrates data smoothing and outlier handling. Specifically, the moving average method is first applied to smooth trajectory coordinate sequences to suppress high-frequency noise. Then, instantaneous vehicle speed and acceleration are calculated based on the smoothed trajectories. Finally, thresholds are set according to physical constraints to identify and eliminate abnormal data points that deviate significantly from normal driving behaviour.

(1) Data smoothing

The moving average method is a time series smoothing technique whose core principle is to suppress random fluctuations and highlight the long-term trend of a sequence by computing the average of data within a fixed sliding window. In this thesis, a centred simple moving average is applied to smooth the planar coordinates (X_t, Y_t) of the target vehicle across consecutive frames, with the sliding window size set as $n = 5$. Specifically, the smoothed coordinate of the current frame is calculated as the arithmetic mean of five position points: the current frame and two adjacent frames before and after it. The computational equations are given as follows:

$$X'_t = \frac{X_{t-2} + X_{t-1} + X_t + X_{t+1} + X_{t+2}}{5} \quad (\text{Eq2.13})$$

$$Y'_t = \frac{Y_{t-2} + Y_{t-1} + Y_t + Y_{t+1} + Y_{t+2}}{5} \quad (\text{Eq2.14})$$

where, (X_t, Y_t) denotes the raw coordinates of frame t , (X'_t, Y'_t) denotes the smoothed coordinates.

The method cannot be applied to the start and end points of the trajectory due to insufficient sliding window data. To guarantee the continuity of the complete trajectory, this study adopts a data-filling smoothing strategy for both ends of the trajectory. Specifically, for the initial segment of the trajectory (i.e., when the vehicle just enters the detection area), the average of the first five valid frame coordinates is calculated and assigned to the first three data points.

$$X'_1 = X'_2 = X'_3 = \frac{X_1 + X_2 + X_3 + X_4 + X_5}{5} \quad (\text{Eq2.15})$$

$$Y'_1 = Y'_2 = Y'_3 = \frac{Y_1 + Y_2 + Y_3 + Y_4 + Y_5}{5} \quad (\text{Eq2.16})$$

For the terminal segment of the trajectory (when the vehicle is approaching the boundary of the detection area), we take the average of the coordinates from the last 5 valid frames and assign the averaged value to the final 3 data points:

$$X'_T = X'_{T-1} = X'_{T-2} = \frac{X_{T-4} + X_{T-3} + X_{T-2} + X_{T-1} + X_T}{5} \quad (\text{Eq2.17})$$

$$Y'_T = Y'_{T-1} = Y'_{T-2} = \frac{Y_{T-4} + Y_{T-3} + Y_{T-2} + Y_{T-1} + Y_T}{5} \quad (\text{Eq2.18})$$

where T denotes the total number of consecutive frames for which the vehicle is successfully detected. This approach effectively smooths the trajectory data while maximally retaining the original inherent features of the trajectory, which provides a high-quality data foundation for subsequent analyses.

(2) Outlier handling

Although high-frequency noise has been removed from the smoothed trajectory data, outliers may remain due to tracking algorithm failure or interference from real-world scenarios. These outliers distort the interpretation of vehicles' microscopic driving behaviours, so it is necessary to develop an effective outlier processing mechanism for trajectory data. Based on the basic characteristics of the collected trajectory data in weaving sections, outlier processing in this study is divided into three main categories: trajectory stagnation outliers, speed anomaly outliers, and excessively short trajectory duration outliers.

① Identification and elimination of trajectory stagnation

In weaving section traffic scenes, severe inter-vehicle occlusion, abrupt illumination changes, or transient target presence can lead to temporary tracking failure of the CSRT tracker. In such scenarios, the algorithm typically retains the vehicle position at the coordinates of the last frame before tracking loss, which causes trajectory stagnation. In the collected dataset, these stagnated trajectories present as continuous coordinate sequences with fixed position, which contradicts the physical fact that vehicles are in continuous motion. To remove the invalid data caused by trajectory stagnation, we define that tracking loss occurs at the current time step if the planar coordinates of a target vehicle (X_t, Y_t) remain unchanged for five consecutive frames. During post-processing, the system automatically identifies the starting frame of tracking stagnation t_s , and deletes all trajectory data of the target vehicle from t_s to the end of the trajectory T in the dataset.

② Identification and elimination of speed outliers

The motion state of the vehicle must conform to the physical properties of the road and the constraints of traffic regulations. The maximum speed limit of the weaving section from which the trajectory data analysed in this study was collected is 100 km/h. However, in raw trajectory data, due to noise originating from factors such as detection frame jitter and instantaneous coordinate jumps, calculated instantaneous speeds obtained via differencing may violate physically plausible ranges. To ensure the physical plausibility of speed data, a loose but reasonable upper speed threshold should be defined. In this work, the threshold is set to 1.5 times the road's maximum speed limit, namely 150 km/h. For any time step t in a trajectory, if the calculated instantaneous speed exceeds this threshold, the data at time t is classified as a speed outlier, and the corresponding trajectory point at outlier time t is directly removed.

③ Identification and elimination of trails with excessively short

A subset of trajectories in the collected dataset is characterised by overly short duration, which is primarily caused by systematic boundary effects during the data acquisition process. This issue can be categorised into two specific scenarios:

1. Boundary truncation at the start of recording: some vehicles are already approaching the end of the detection area and are about to exit the frame when the video recording begins.

2. Boundary truncation at the end of recording: some vehicles only enter the detection area immediately before the video recording terminates.

Since these short trajectories contain limited motion information, they cannot support statistically reliable micro-behaviour analysis. Therefore, this thesis establishes a trajectory screening criterion: all trajectories with a total duration of less than 1 second are excluded from the analysis in this study.

Due to the spatiotemporal constraints of video recording, these short trajectories account for a very small proportion of the entire trajectory dataset. Excluding such boundary-fragmented trajectories will not alter the macroscopic statistical distribution of the traffic flow, nor will it introduce systematic bias into the subsequent analysis.

After data smoothing and outlier removal, the original trajectory dataset was effectively cleaned, and data quality was significantly improved. Considering the constraints of the drone aerial field of view and flight altitude, and to ensure that the study sample can fully cover the core phase of vehicle interaction, all subsequent analyses in this thesis are restricted to the weaving section located in the lower half of the video frame. To clearly illustrate vehicle operational behaviour in the weaving section, spatiotemporal trajectory plots (see Figure 2.12) were generated, where each continuous curve represents the actual spatiotemporal displacement of an individual vehicle within the weaving section.

As observed from the trajectory patterns in Figure 2.12, low-speed states (represented by warm-coloured lines) appear in both the weaving section and the mainline area upstream of the on-ramp. This spatial distribution is highly consistent with the typical operational characteristics of weaving sections: intensive lane-changing conflicts and vehicle-vehicle interactions force traffic to decelerate, and this deceleration disturbance propagates upstream. It is worth noting that significant longitudinal coordinate oscillations occur at the 100 m and 250 m positions. This phenomenon does not reflect the actual physical motion of vehicles, but is an artifact introduced by the collaborative data collection of three drones: the two positions mentioned above are located exactly at the stitching gap between the fields of view of different drones. When a vehicle crosses the stitching boundary, minor pixel misalignment in image registration causes an instantaneous step jump in its longitudinal coordinate. Although a moving average method was applied for denoising and smoothing, linear low-pass filters are primarily designed to suppress high-frequency random white noise. For the strong impulse step error at stitching seams, extreme values are only distributed to adjacent frames, making complete elimination of the error difficult. Since these oscillations have a short duration, they have negligible impact on the statistical distribution of the full dataset.

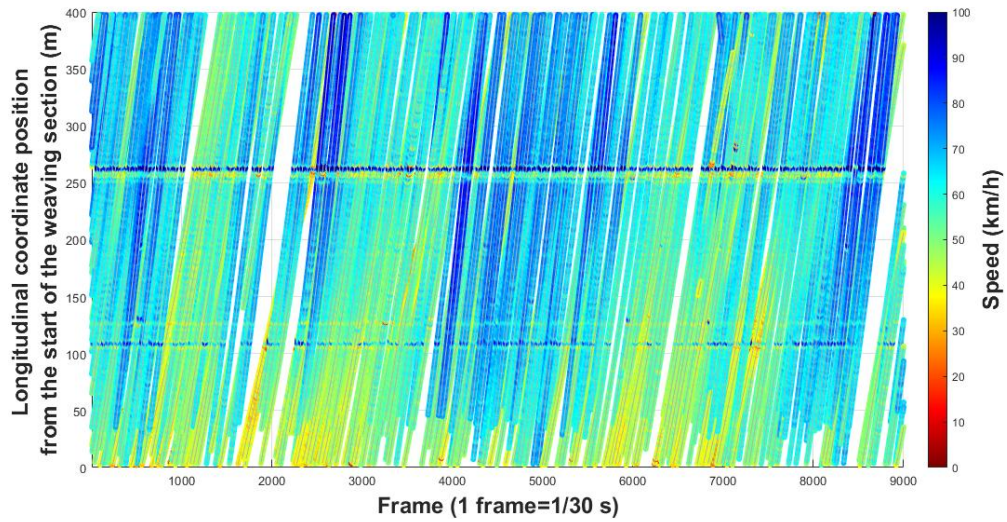


Figure 2.12 Spatio-temporal variation in longitudinal coordinates of sampled vehicles in the weaving section (within the first 5 minutes).

2.4.4 Lane marking

To further investigate the characteristics of vehicle lane-changing behaviour in weaving sections, fine-grained lane-level calibration of vehicle trajectories is required. First, the geocoordinate data of georegistered vehicle trajectories is imported into the ArcGIS software platform under a unified coordinate system, which ensures all trajectory data is aligned with the high-precision road base map in the same georeference frame, laying a solid foundation for subsequent spatial overlay analysis. Second, within the ArcGIS environment, each lane's polygonal boundary is delineated one by one against the registered aerial base map, based on clearly distinguishable lane markings, to construct independent lane vector layers. Finally, the built-in “Intersection” spatial analysis tool of the ArcGIS platform is invoked. Following the principle of geometric intersection operation, this tool can automatically identify and extract spatial overlaps between input features. In this study, each lane polygon layer and all vehicle trajectory point layers are input as features for intersection analysis. This process automatically assigns lane number attributes to trajectory points falling within the boundary of each lane, enabling accurate identification of the vehicle's occupied lane at each timestamp. Through the above workflow, the original vehicle trajectory data is effectively integrated with lane-level road network information, and accurate lane labelling is completed for all vehicle trajectory points.

2.4.5 Features of trajectory data

The quality and information completeness of the raw trajectory dataset were improved via preprocessing steps including data smoothing, outlier detection and removal, and lane-level calibration. After preprocessing, complete high-quality trajectory data from 1,669 vehicles were retained to construct the fundamental dataset for subsequent analysis, and the descriptions of its main fields are presented in Table 2.1.

Table 2.1. Specification of vehicle trajectory data attributes.

Field Symbols	Definitions
FrameNum	The frame number of videos.
CarID	The ID number of the vehicle.
Len_Car	The length of the vehicle (m).
Wid_Car	The width of the vehicle (m).
Xsmooth	The X-axis coordinates of the smoothed processed vehicle trajectory.
Ysmooth	The Y-axis coordinates of the smoothed processed vehicle trajectory.
LaneID	The lane ID number of the vehicle is currently occupying.
V	The instantaneous speed of the vehicle (m/s).
Alpha	The driving direction angle of the vehicle (°).
Dcentre	The distance (m) from the Centre of Gravity (CoG) of the vehicle to the lane line.
Acc	The instantaneous acceleration of vehicle movement (m/s ²).
CLVID	The leading vehicle ID number in the current lane.
CFVID	The following vehicle ID number in the current lane.
TLVID	The leading vehicle ID number in the target lane.
TFVID	The following vehicle ID number in the target lane.
dCLV	The distance (m) between the vehicle changing lanes and the leading vehicle in the current lane.
dCFV	The distance (m) between the vehicle changing lanes and the following vehicle in the current lane.
dTLV	The distance (m) between the vehicle changing lanes and the leading vehicle in the target lane.
dTFV	The distance (m) between the vehicle changing lanes and the following vehicle in the target lane.

This thesis adopts the sliding window differential averaging method to calculate key motion parameters, with the objective of effectively suppressing numerical noise induced by minor coordinate fluctuations. Given that the video sampling frequency is 30 Hz, directly solving for instantaneous velocity via coordinate differencing between adjacent frames yields excessive errors originating from the short time interval. To calculate velocity at a specific time point, this thesis extracts the coordinate of the target time point along with the coordinate data from the preceding three frames, and takes the average velocity within the window as the instantaneous speed estimate at that time point. Correspondingly, the calculation of acceleration is derived from the obtained velocity sequence: the velocity data from the 30 frames preceding the current time point is selected, and the average rate of change of velocity is adopted as the instantaneous acceleration at that time point. This approach suppresses high-frequency noise while retaining sufficient temporal resolution, thereby improving the robustness of motion parameter calculation.

2.5 Feature extraction of lane-changing behaviour in weaving sections

When a vehicle performs a lane change, it engages in complex dynamic interactions with surrounding vehicles, whose trajectories and operational states constrain the execution efficiency of the driver's decision-making and ultimately affect the resulting traffic safety. This section first defines the core elements constituting the lane-changing scenario, then establishes the recognition mechanism for lane-changing behaviour and constructs the corresponding characteristic index system.

2.5.1 Definition of lane-changing scenarios

Since lane-changing manoeuvres induce spatial game interactions between road vehicles, they exert substantial impacts on the overall traffic efficiency and safety of the target road segment (Sun et al., 2014; Pang et al., 2020). To accurately characterise this interactive process, this thesis identifies four vehicles that directly interact with the lane-changing vehicle throughout the entire manoeuvre, and defines them as key lane-changing participants. As illustrated in Figure 2.13, the green-highlighted vehicle is the lane-changing vehicle, denoted as LCV (Lane-Changing Vehicle). The vehicles interacting with the LCV are defined as follows: Current Lane Leading Vehicle (CLV), Current Lane Following Vehicle (CFV), Target Lane Leading Vehicle (TLV) and Target Lane Following Vehicle (TFV).

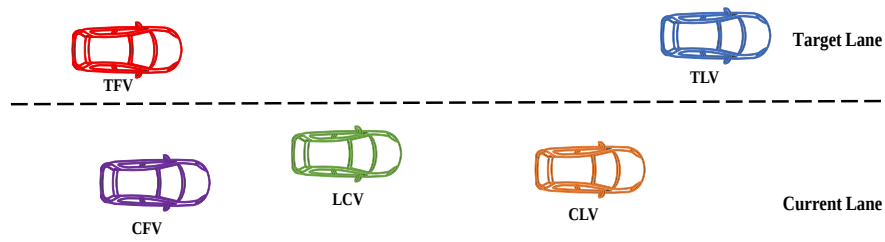


Figure 2.13 Schematic diagram of lane-changing vehicles and key lane-changing participants during the lane-changing process.

2.5.2 Definition of lane-changing types

Based on the underlying motivations of lane-changing behaviour, lane-changing can be categorised into two fundamental types: mandatory lane-changing and discretionary lane-changing. Specifically, mandatory lane-changing refers to lane-changing manoeuvres that vehicles must complete under constraints from objective traffic conditions, which are generally triggered by external environmental factors, such as following a pre-planned driving route, avoiding road construction or obstacles, and so on. The decision to perform this type of lane change is not based entirely on drivers' subjective preferences; rather, it is a necessary operation conducted under the constraints of specific traffic rules or road geometry. In contrast, discretionary lane-changing is primarily initiated by drivers' personal intentions, with the objectives of increasing travel speed, optimising car-following

status, or pursuing a more comfortable driving environment, featuring distinct subjective selectivity. When focusing on weaving scenarios, vehicles' merging or diverging manoeuvres for switching driving paths are conventionally classified as route-based mandatory lane changes. However, in practical traffic scenarios, merging and diverging usually occur at the junctions between ramps and main roads, and are often accompanied by intense acceleration and deceleration interactions. This gives them essential differences from mandatory lane changes on straight sections of regular main roads, in terms of both the spatial environment and the underlying dynamic feedback of vehicles.

It is precisely due to this heterogeneity that generalising conclusions across all non-discretionary lane-changing behaviours leads to reduced analytical accuracy. Accordingly, this thesis differentiates merging and diverging manoeuvres from the traditional definition of mandatory lane-changing. For the Type A1 weaving sections investigated in this study, the mandatory lane-changing occurring on the mainline straight segment is defined with a clearer physical boundary: it specifically refers to the transitional manoeuvre where a vehicle gradually changes lanes from the left lane to the right lane prior to executing the final diverging movement.

Overall, this section reorganises and develops a set of classification criteria illustrated in Figure 2.14, which incorporates the dynamic attributes and underlying motivation of vehicles in the study area. Based on this classification scheme, lane-changing patterns in the entire weaving section are subdivided into four fundamental types: discretionary lane-changing, mandatory lane-changing (restricted exclusively to the straight segments of the main carriageway), merging, and diverging. Furthermore, to accurately characterise the microscopic properties of each individual lane-changing behaviour, this study discretises consecutive lane-changing operations into individual events: specifically, when a vehicle completes two consecutive lane-changing manoeuvres, the two operations are defined as two independent lane-changing behaviours respectively.

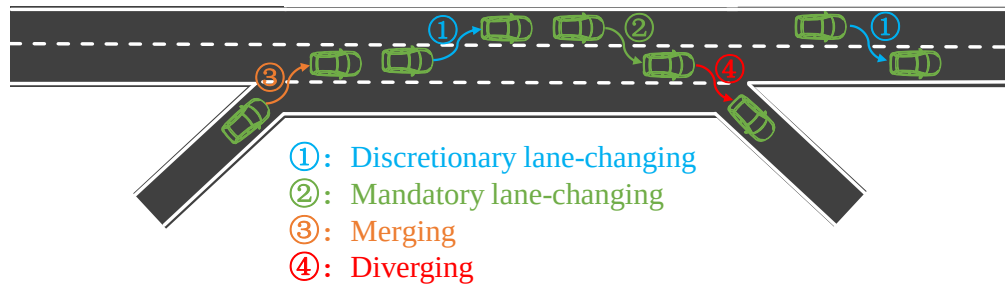


Figure 2.14 Schematic diagram of the definition of four lane-changing types in Type A1 weaving section.

2.5.3 Identification of lane-changing moments

Lane-changing is fundamentally characterised by the continuous lateral displacement of a vehicle away from the centreline of its current lane. To intuitively quantify the magnitude of this dynamic deviation, the lane offset is commonly adopted as the evaluation metric in existing research. Based on the specific

geometric configuration presented in Figure 2.15, this metric quantifies the perpendicular distance between the vehicle's Centre of Gravity (CoG) and the centreline of the lane it occupies. For definition: when the CoG deviates to the left of the lane centreline, the offset is assigned a positive value; when it deviates to the right, the offset is assigned a negative value. Lane-changing is not an instantaneous manoeuvre but a continuous, coherent spatial displacement process. To fully decompose the manoeuvre along the timeline, this thesis defines three key time nodes: the start of the lane change, the insertion of the lane change, and the end of the lane change, which accurately demarcate and reconstruct the entire sequence of lane-changing actions (Ali et al., 2018; Yang et al., 2019).

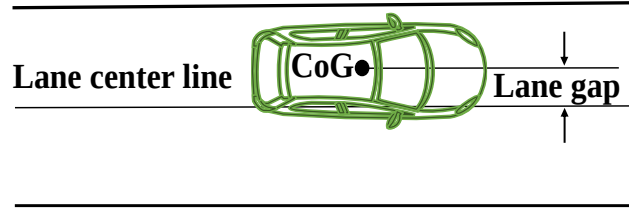


Figure 2.15 Definition of lane gap.

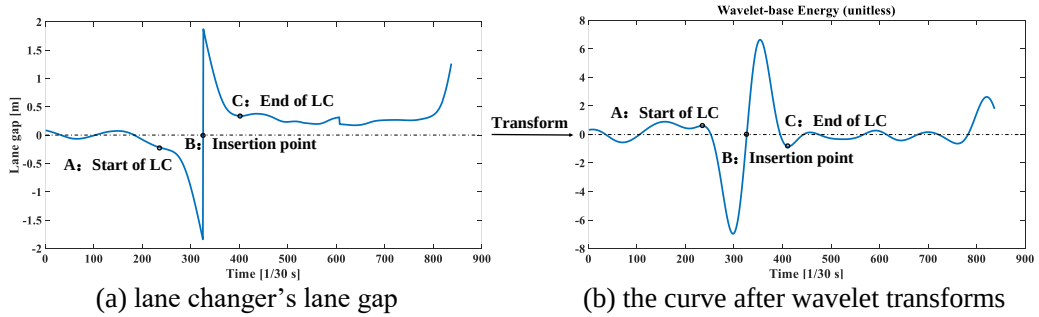


Figure 2.16 Identification of three crucial time points during lane-changing.

(1) Start of lane change: Point “A” in Figure 2.16(a) denotes the start of a lane change, corresponding to the moment the subject vehicle initiates lateral movement within its current lane. For example, during a right lane change, the lane gap gradually decreases, whereas the lane gap gradually increases during a left lane change.

(2) Lane change insertion point: Point “B” in Figure 2.16(a) denotes the lane change insertion moment, defined as the instant when the vehicle's CoG crosses the boundary of the target lane. Mathematically, this moment is characterised by an abrupt sign change in the lane gap. For a right lane change, the lane gap transitions from negative to positive at this instant.

(3) End of lane change: Point “C” in Figure 2.16(a) denotes the end of a lane change. The lane change process is marked as complete when the vehicle finishes lateral movement and maintains stable travel in the target lane.

In this thesis, a transformation method based on the Mexican Hat Wavelet is adopted to extract the three key time points of the lane-changing process accurately. This is achieved by transforming the lane lateral spacing sequence into a wavelet coefficient curve, as illustrated in Figure 2.16(b). This method exhibits distinct

advantages for feature extraction from time series data and can effectively identify singularities and trend variations in signals (Zheng et al., 2011; Ali et al., 2018; Yang et al., 2019; Ali et al., 2020).

2.5.4 Definition of lane-changing duration

The lane-change duration is defined as the time interval from the initiation of a lane-changing manoeuvre to the restoration of a stable driving state in the target lane, as illustrated in Figure 2.17. Based on the wavelet transform-based lane-changing moment identification method proposed in Section 2.5.3, the start and end timestamps of the entire lane-changing process can be accurately determined, and the lane change duration is obtained by calculating the time difference between these two timestamps. To characterise the core stages of a vehicle's actual lane-changing process more precisely, this study further defines the "effective lane-changing process" to distinguish it from the complete lane-changing cycle, which incorporates the pre-lane-change lateral preparation and post-lane-change stabilisation recovery stages. Specifically, the effective lane-changing process refers to the critical phase during which the vehicle physically crosses the lane boundary. The start of an effective lane change is marked by the vehicle's first contact with the target lane line, while its end is defined by the vehicle's last contact with the original lane line. By focusing on the core stage where the vehicle completes substantial lateral displacement between adjacent lanes, this definition facilitates more accurate evaluation of the dynamic characteristics and safety performance of the lane-changing execution phase in subsequent analyses.

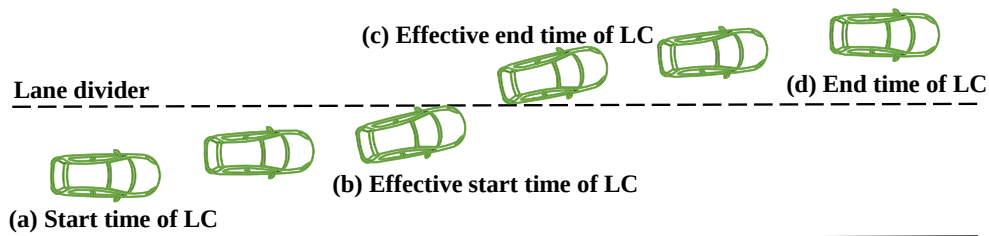


Figure 2.17 The process of lane-changing.

2.5.5 Definition of accepted target lane lead and lag gap

As illustrated in Figure 2.18, this thesis focuses on two accepted gap metrics for lane-changing: the accepted target lane lead gap (AG_TLead), defined as the time gap between the LCV and the TLV at the initiation of the lane change; the accepted target lane lag gap (AG_TLag) is defined as the time gap between the LCV and the TFV at the initiation of the lane change. To obtain the numerical values of these two indicators, the spatial gap between the LCV and the TLV (or TFV) is first calculated, then divided by the relative speed between the LCV and the TLV (or TFV). The sign (positive or negative) of the accepted target lane gap reflects the vehicle interaction pattern. A positive result indicates that the longitudinal trajectories of the LCV and the target lane vehicle do not overlap at the time of lane

change initiation. This typically corresponds to a discretionary lane change initiated by the driver when road conditions are favourable, often achieved through cooperation with other surrounding vehicles. Conversely, a negative gap indicates a longitudinal spatial overlap between the two vehicles. This phenomenon corresponds to a forced lane change manoeuvre into the target lane performed by the driver under constrained traffic conditions, which is commonly observed in high-risk lane-changing scenarios and forced lane-changing game studies.

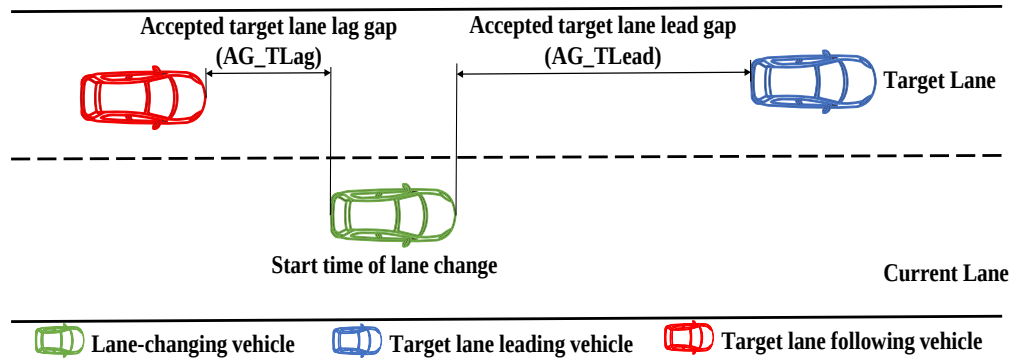


Figure 2.18 Definition of accepted target lane lead and lag gaps.

2.6 Analysis of traffic operational characteristics of trajectory data in the weaving section

2.6.1 Traffic operation status

Speed and headway are two core parameters reflecting the operational status of traffic flow. Based on collected vehicle trajectory data, this study analyses the distribution characteristics and fitting patterns of speed and headway in the weaving section. As shown in Figure 2.19, the empirical data achieved a satisfactory goodness of fit and passed the Kolmogorov-Smirnov (K-S) test, confirming that vehicle speed in this area approximately follows a normal distribution with a mean of 55.9 km/h and a standard deviation of 11.3 km/h. It should be noted that the statistical sample covers the instantaneous speeds of all vehicles in the weaving section, including both through-traffic vehicles and lane-changing vehicles. A clear observation is that although the posted speed limit of this segment is 100 km/h, the overall observed average vehicle speed decreased significantly. This can be attributed to the frequent merging and diverging manoeuvres at both ends of the ramp, which trigger intense interactive behaviours within the traffic stream, disrupt the original steady state of traffic flow, and ultimately lead to an overall reduction in the traffic efficiency of the segment. Further analysis of the directional traffic flow proportion indicates that the weaving ratio of this segment exceeds 30%. This high weaving intensity provides robust empirical evidence for the observed lower average speed. In fact, this speed reduction pattern is consistent with general academic consensus. Numerous empirical studies have documented that the average speed of traffic flow in weaving sections generally ranges from 50 km/h to 70 km/h (Yang et al., 2012; Sulejic et al., 2017; Yuan et al., 2019).

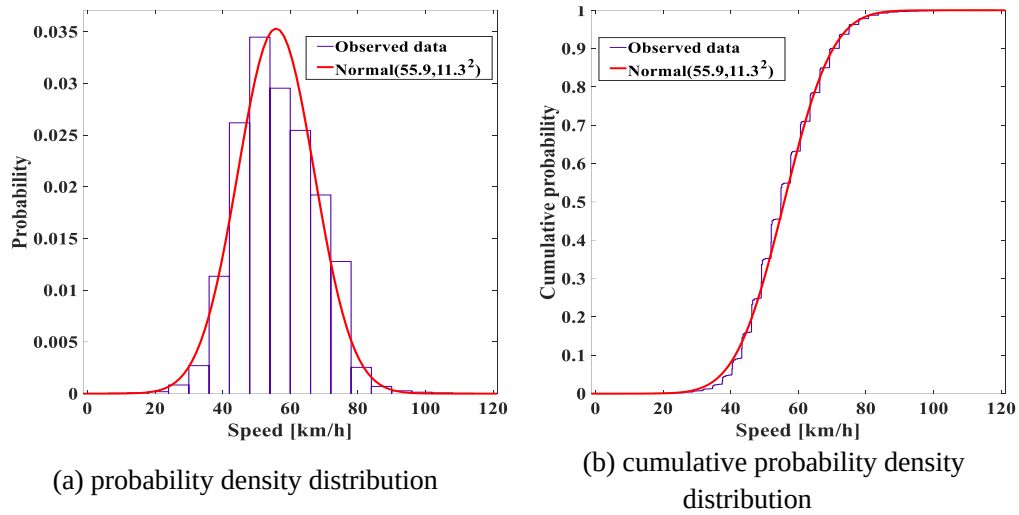


Figure 2.19 Distribution of vehicle speed in the weaving section.

To explore differences in speed distribution across lanes, this study plots the speed probability density curves for each lane, as presented in Figure 2.20. The results indicate that the left lane of the main roadway maintains the highest average speed, followed by the right lane of the main roadway at an intermediate level, while the auxiliary lane has the lowest average speed, forming a distinct stepped gradient across the three lane types. This spatial distribution pattern is closely associated with the operational mechanism of traffic flow in weaving sections: as connecting corridors between ramps and the main roadway, auxiliary lanes undertake the core functions of merging and diverging, with extremely frequent vehicle lane-changing behaviour, dense conflict points, and significant traffic disturbances, resulting in the lowest average speed; the left lane of the main roadway is farthest from the weaving conflict zone and is least affected by vehicle interactions, so traffic flow operates more stably and can maintain a higher speed; the right lane of the main roadway acts as a transition zone, with an average speed falling between the other two, which demonstrates the continuous variation characteristic of speed distribution in weaving sections.

The fitting results of the headway probability density distribution for each lane in the weaving section are presented in Figure 2.21. Consistent with the observed velocity distribution characteristics, the headway distribution also exhibits clear gradient characteristics: the main road left lane has the largest average headway, followed by the main road right lane, while the auxiliary lane has the smallest headway. Exponential distribution, gamma distribution, and lognormal distribution have been widely adopted in existing research to model vehicle headways (Cowan, 1975; May, 1990; Saha et al., 2019). Through comparing the goodness-of-fit of different distribution models, this study finds that the exponential distribution provides the most accurate description of the headway characteristics in the study area. Considering that the probability density of field observation data is concentrated within the 2–8 second interval, this thesis adopts a truncated exponential distribution to constrain the distribution range to 2–8 seconds. This approach not only conforms to fundamental traffic flow theory but also accurately reflects the characteristics of actual observed data.

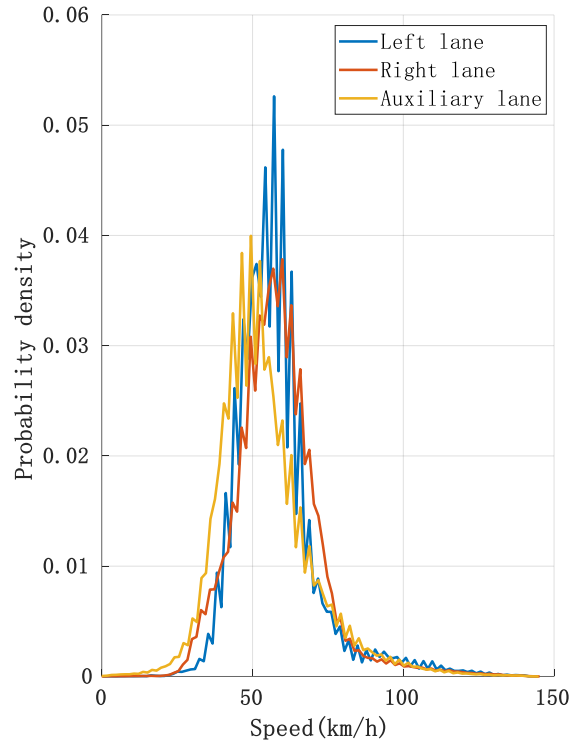


Figure 2.20 Speed distribution of each lane in the weaving section.

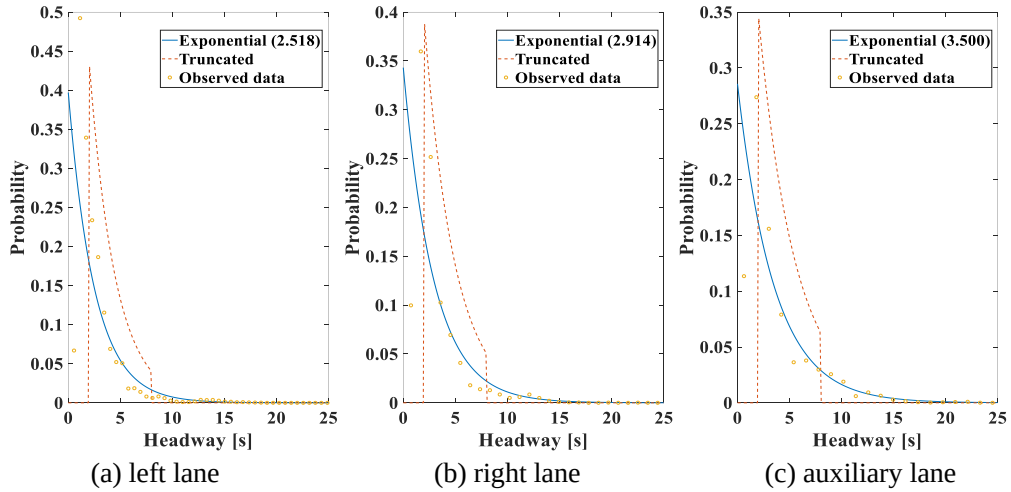


Figure 2.21 Headway distribution of each lane in the weaving section.

2.6.2 Characteristics of traffic conflicts

Based on the definition of lane-changing scenarios, the criteria for classifying lane-changing types, the method for identifying lane-changing moments, and the feature index system established in Section 2.5, the vehicle trajectory data were processed, and a total of 1,666 valid lane-changing behaviours were extracted. Among them, 660 were discretionary lane changes, 343 were mandatory lane changes, 102 were merging lane changes and 561 were diverging lane changes. Non-discretionary lane changes account for 60% of all extracted lane-changing events, indicating that the high density of mandatory lane changes in weaving sections is a critical source of traffic conflict risk.

To explore the characteristics of traffic conflicts in the collected video trajectory data, spatial distribution heat maps of traffic conflicts between LCV and key lane-changing participants (Figure 2.22) and probability distribution plots of GTTC values under different lane-changing types (Figure 2.23) were generated based on the GTTC defined in Section 2.3.2. From the conflict distribution patterns between LCV and the CLV and TLV, it can be observed that these two types of conflicts exhibit a high degree of consistency in spatial distribution, and their main concentration areas are all located upstream of the weaving sections of the left and right lanes of the main line. This is because intensive lane-changing operations within weaving sections cause severe lateral disturbances to the traffic flow, reducing the overall speed in the local area. At the same time, vehicles changing lanes in the upstream area often maintain a higher initial speed, and this significant speed drop increases the collision probability between lane-changing vehicles and leading vehicles.

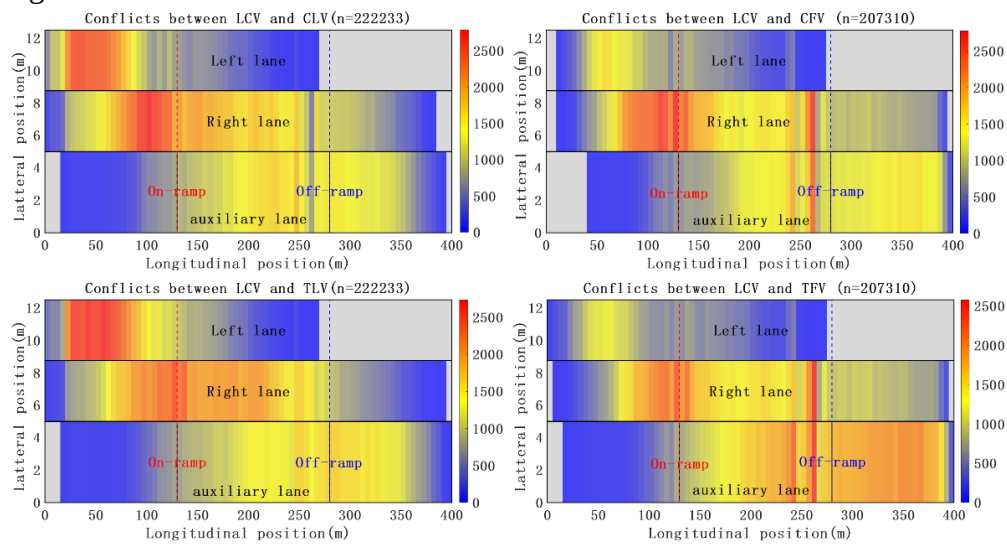


Figure 2.22 A heat map of the spatial distribution of traffic conflicts between LCV and key lane-changing participants.

In addition, the interaction risk between LCV and the CFV and TFV also shows similar spatial clustering characteristics. The areas adjacent to the on-ramp on the right side of the main line and the junction between the right off-ramp of the main line and the auxiliary lane are high-risk conflict zones. It is particularly noteworthy that conflicts between LCV and TFV are especially frequent in the downstream section of the auxiliary lane. Combined with actual traffic operation conditions, this pattern is most likely triggered by the sudden braking of the leading vehicle during the lane-changing process. If the following driver does not have sufficient reaction time, a conflict is highly likely to occur. Further analysis of the GTTC probability distribution under different lane-changing types in Figure 2.23 shows that, in terms of the overall trend, the GTTC values between LCV and TLV/TFV are generally lower than those between LCV and CLV/CFV, indicating that traffic conflicts between LCV and vehicles in the target lane have higher severity.

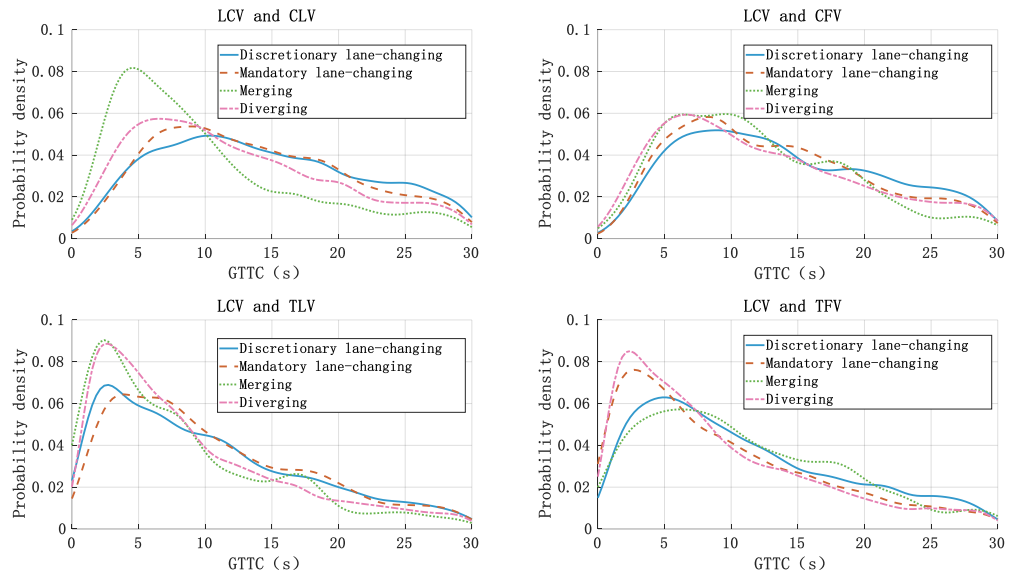
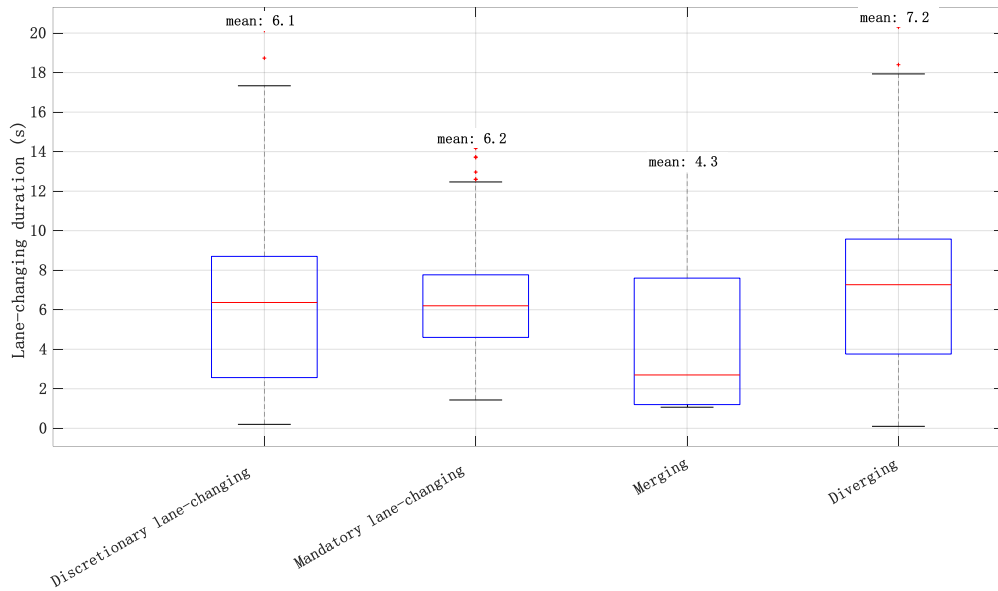


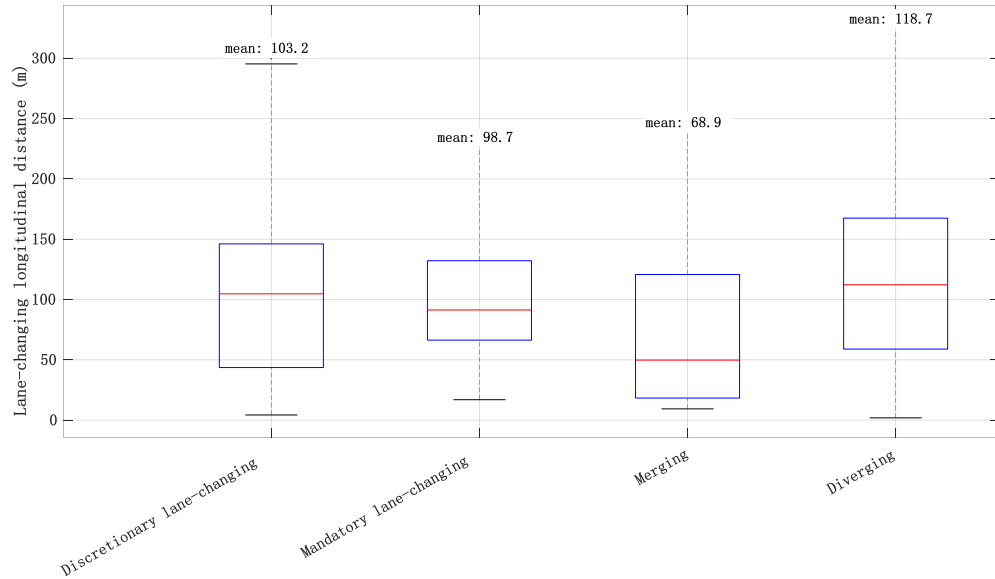
Figure 2.23 Probability distribution of GTTC between LCV and key lane-changing participants under different lane-changing types.

2.6.3 Characteristics of lane-changing behaviour

The key behavioural characteristics of lane-changing events were extracted, and the distribution patterns of different types of lane-changing behaviours in terms of lane-changing duration and longitudinal distance are illustrated in Figure 2.24. Analysis of the figure indicates that the four categories of lane-changing behaviours exhibit distinct differences in the distributions of lane-changing duration and longitudinal distance. Merging manoeuvres present the most compact spatiotemporal characteristics, with the shortest average lane-changing duration and the smallest average longitudinal lane-changing distance. In contrast, diverging manoeuvres have the loosest spatiotemporal characteristics, with the longest average lane-changing duration and the largest average longitudinal lane-changing distance. This discrepancy may be associated with the significant difference in sample sizes between merging and diverging manoeuvres during data collection, which reflects the inherent traffic characteristic that diverging traffic demand is substantially higher than merging traffic demand within the weaving section. Discretionary lane-changing and mandatory lane-changing have relatively similar distribution patterns of lane-changing duration and longitudinal distance, which implies that the two types of lane-changing manoeuvres executed on the mainline straight segment of a weaving section generally share consistent spatiotemporal characteristics.



(a) distribution of lane-changing duration



(b) distribution of the longitudinal distance during lane-changing

Figure 2.24 Distribution of lane-changing duration and longitudinal distance across different lane-changing types.

To explore the spatial evolution patterns of these four types of lane-changing manoeuvres, this thesis processed the cleaned trajectory data and generated spatial distribution heat maps for the start and end positions of lane-changing manoeuvres (the start positions are shown in Figure 2.25, and the end positions are shown in Figure 2.26). Analysis of the heat map results reveals that various lane-changing behaviours exhibit significant spatial distribution regularity, and these regularities are closely correlated with the geometric characteristics of the weaving section and the attributes of traffic operations.

Observing the lane-changing start positions in Figure 2.25, discretionary lane-changing is largely concentrated in the weaving section and its upstream area, which reflects drivers' anticipatory driving behaviour. To avoid involvement in complex interactive interactions within the weaving section, drivers tend to

complete lane-changing in advance. Similarly, the start positions of mandatory lane-changing are mainly distributed at the front end of the weaving section and its further upstream, which essentially reflects those drivers prepare in advance for the subsequent exit from the mainline. In contrast, the start points of merging manoeuvres are subject to extremely strong physical space constraints and are largely compressed within the weaving section. Two high-density distribution peaks form at the on-ramp and the middle section of the weaving section, which accurately reflects the urgent demand of on-ramp traffic to merge into the mainline. The starting range of diverging manoeuvres is much wider, with heat coverage extending from the upstream area all the way into the interior of the weaving section, indicating that many drivers initiate lane-changing preparations when they are still far from the off-ramp.

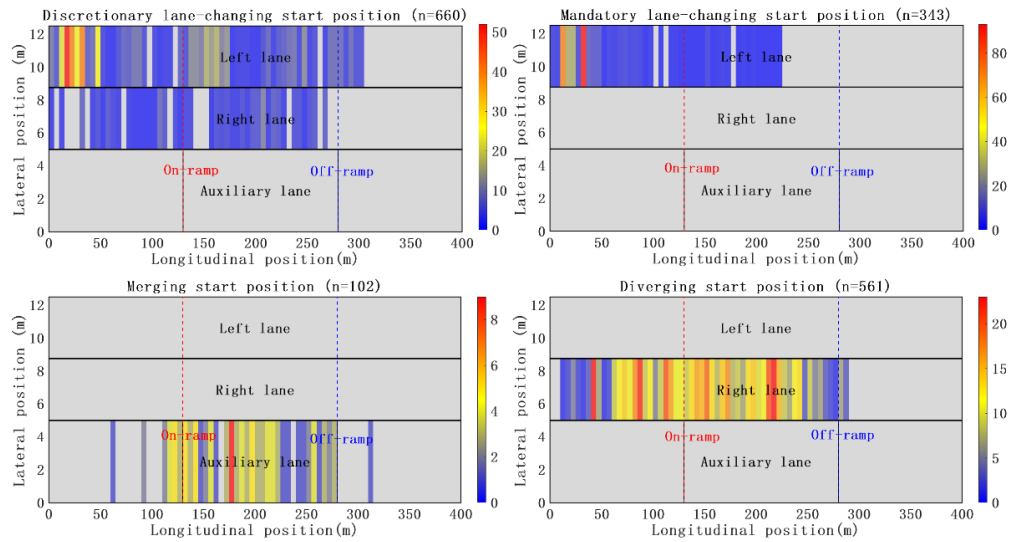


Figure 2.25 Heat map of the spatial distribution of lane-changing start positions for different lane-changing types.

Further combined with the heat map of lane-changing end positions in Figure 2.26, the spatial differentiation among the four types becomes more pronounced. Discretionary lane-changing exhibits high flexibility in end position selection, with an overall large-area discrete distribution. The end positions of mandatory lane-changing are concentrated in the weaving section and its upstream area, and this spatial distribution characteristic can effectively avoid head-on conflicts with incoming traffic from the ramp. For the other two types of lane-changing with explicit end targets, the end positions of merging lane-changing are distributed across the weaving section and its downstream areas, while the end positions of diverging lane-changing are highly concentrated near the weaving section and off-ramp, highlighting its unique exit-oriented feature.

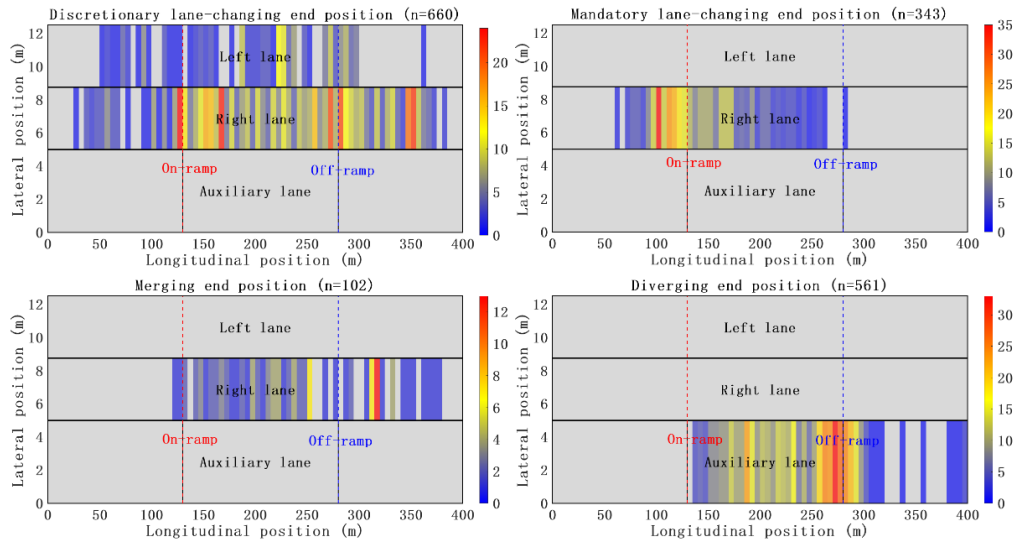


Figure 2.26 Heat map of the spatial distribution of lane-changing end positions for different lane-changing types.

2.7 Conclusions

As the theoretical foundation for this entire thesis, the primary objective of this chapter is to organise the theoretical context and complete the preparation of underlying research data. Specifically, this chapter analyses the definition, geometric features, traffic flow operational characteristics, and safety influencing factors of weaving sections sequentially, thereby defining the scope of the research object in terms of boundary attributes and problem categories. Regarding safety assessment, this chapter introduces a traffic conflict identification mechanism based on vehicle micro-trajectories, with a focus on the specific application of time-adjacent surrogate safety indicators, thus establishing a logical connection between drivers' micro-operations and the macro-level risks of the road network, and clarifying the analytical framework for subsequent risk assessment and root cause analysis. From the perspective of empirical data support, this chapter presents a scheme for obtaining field observation data via drone aerial photography. A closed-loop data processing pipeline is formed from pre-processing of raw video footage, target detection, and continuous tracking, to the final output of trajectory coordinates, supplemented by customised outlier cleaning rules, which guarantees the high reliability of the resulting vehicle trajectory dataset.

Based on the cleaned high-precision vehicle trajectory data, this study constructs a parametric characterisation system for lane-changing behaviour characteristics, and provides clear definitions and calculation rules for core variables including the definition of lane-changing scenarios, type classification, precise identification of the start and end time of lane-changing, statistics of lane-changing duration, and acceptable target lane gaps. Meanwhile, with the aid of intuitive visualisation, this chapter conducts preliminary descriptive statistical analysis on the traffic flow conditions, spatial distribution of conflicts, and various lane-changing features contained in the field observation data. These objectively

presented patterns reflect the underlying decision-making logic and adaptive behaviour of drivers in high-density weaving environments. Overall, the full-chain framework covering theoretical introduction, data collection, cleaning and processing, and feature extraction constructed in this chapter lays a solid theoretical foundation and provides methodological support for the in-depth research conducted in subsequent chapters.

Chapter 3

3. Analysis of lane-changing behaviour in the weaving section based on field observation and driving simulation

3.1 Background

At present, research related to weaving sections mainly relies on three types of data acquisition methods: field observation, simulation modelling, and driving simulation experiments. Constrained by the complexity of road geometry and the limitations of video processing technology, there are still significant challenges in obtaining high-quality vehicle trajectory data from real traffic scenarios. The data generated by simulation models often lacks sufficient reality validation, especially in the reality of driving behaviour. In an operating environment where complex traffic flows weaving, it is particularly difficult to accurately simulate the lane-changing decisions of human drivers, and the influence of different demographic characteristics on driving behaviour is often overlooked. Driving simulators, as an effective tool capable of capturing microscopic driving behaviour, provide controllable and repeatable experimental conditions for studying lane-changing behaviour in weaving sections. Although driving simulators have been widely used in traffic behaviour research in recent years, the credibility and validity of their data output remain a core issue of continuous concern in the academic field (Mullen et al., 2011; Wynne et al., 2019; Zhang et al., 2024). Several studies have verified the effectiveness of driving simulators for different driving scenarios and road conditions (Godley et al., 2002; Bella, 2005; Underwood et al., 2011; Meuleners & Fraser, 2015; Branzi et al., 2017; Bassani et al., 2018; Catani & Bassani, 2019; Karimi et al., 2020; Faschina et al., 2021; Olsson, 2023; Chen et al., 2025). However, most of these studies have focused on relatively simple road configurations such as straight or curved sections, and paid relatively less attention

to complex road configurations. In addition, most studies have relied mainly on macroscopic behavioural metrics such as speed and lane position, and have not delved into the potential differences in the characteristics of lane-changing behaviour at the microscopic level. To date, most studies on lane-changing behaviour in weaving sections have relied on a single data source, and this single paradigm makes it difficult to achieve multi-angle characterisation and cross-validation of complex lane-changing behaviour. No studies have specifically conducted systematic comparative validation of microscopic lane-changing behaviour characteristics in complex road configurations such as weaving sections between simulated and real environments based on driving simulation and field observation data.

To deeply analyse the intrinsic characteristics of lane-changing behaviour in weaving sections, explore the similarities and differences in behavioural characteristics under different data sources, and provide a reliable basis for future testing of lane-changing decision-making in weaving sections of intelligent connected vehicles based on virtual simulation platforms, this study collected field observations and simulation data to conduct a systematic comparative analysis of lane-changing behaviour characteristics in a weaving section. To this end, this chapter presents a framework for comparative study of lane-changing behaviour characteristics in weaving sections based on driving simulation experiments and field video trajectory data, systematically conducting comparative analysis of the behavioural characteristics of four types of lane-changing behaviours. First, based on the video trajectory data of the weaving section processed in Chapter 2, construct the driving simulation physical simulation environment and traffic simulation scenarios; Secondly, the driving simulation experiment scheme is planned using the response surface central composite design method, and data collection is carried out according to the experimental process; Finally, select and extract the key lane-changing behaviour characteristic metrics defined in Chapter 2, and compare and analyse the behaviour metrics under the two types of data sources using two-sample Kolmogorov–Smirnov (K-S) test. By comparing the results, the differences in lane change behaviour characteristics in weaving sections are revealed from both field observation and simulation dimensions, laying the foundation for a deeper understanding of the mechanism of lane change behaviour in weaving sections and promoting the construction of related models and simulation validation.

3.2 Driving simulation experiment

The data collection of the weaving section driving simulation experiment is based on a high degree of reproduction of the real traffic environment in the weaving section. For this purpose, based on the field investigation data (video trajectories and road environment) in Chapter 2, this study constructs simulation scenarios from both static and dynamic dimensions: one is to establish static physical simulation scenarios consistent with the field geometric conditions, and the other is to generate dynamic traffic simulation scenarios reflecting the characteristics of real traffic flow.

3.2.1 Driving simulation experiment scenario

(1) Driving simulator equipment

The simulation study was conducted using the fixed base driving simulator of the Road Safety and Driving Simulation Laboratory (RSDS) at Politecnico di Torino (Italy). The simulator was equipped with three 32-inch monitors (resolution: 1920×1080 pixels, frequency: 60 Hz, field of view: $130^\circ \times 20^\circ$), a fully outfitted driving position that included a seat, instrument panel, force feedback steering wheel, pedals, manual transmission, and vibration pads to simulate road roughness, wheel roll, and impacts. During the experiments, the cockpit images displayed on the screens enabled drivers to visualise the vehicle's width, adding realism to the simulation. A Dolby Surround 5.1 sound system provided an authentic reproduction of the car engine, nearby traffic, and the surrounding environment. SCANeR Studio® simulation software was utilised to build the driving scenarios, run the simulation, and collect the driving data. The driving simulator was validated for longitudinal and transversal behaviour, and the passing manoeuvre (Bassani et al., 2018; Catani & Bassani, 2019; Karimi et al., 2020).



Figure 3.1 Driving simulator equipment.

(2) Static physical simulation scenario

To ensure the accuracy and validity of the driving simulation experiment results, the construction of static physical simulation scenarios needs to maintain a high degree of consistency with the actual road conditions in terms of road geometry and surrounding environmental elements. This study systematically restored the road alignment, section composition and surrounding environment based on the data of the weaving section collected in Chapter 2. The road terrain

data as shown in Figure 3.2 was extracted by processing the Shape file of the geographical elements of the area (including geometric position and attribute information). The weaving section was designed to be 650 metres in total length. Due to the limitations of the drone shooting range, the actual modelling range in this study was 400 metres of continuous sections within it. The extracted terrain data covered the length and curvature parameters of linear elements such as straight segments, circular curves, and circumferential curves.

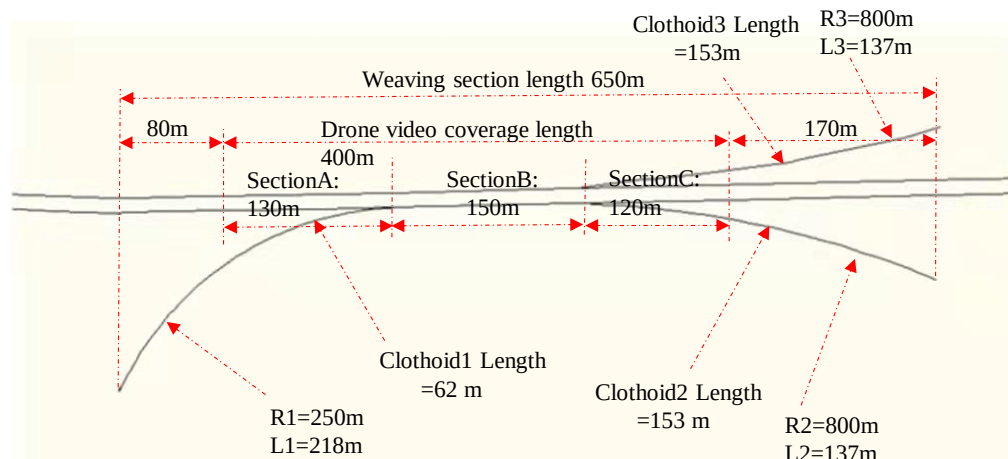


Figure 3.2 Geographical data of weaving section.

2 m	0.375 m	3.75 m	3.75 m	5 m	3m
median strip	marginal strip	left lane	right lane	auxiliary lane	hard shoulder

Figure 3.3 Section information of pavement in the weaving section.

Also, in combination with the cross-sectional information shown in Figure 3.3, the widths of the three lanes on the main road were determined to be 3.75 metres, 3.75 metres and 5 metres respectively; The ramps and auxiliary lanes are both 5 metres wide, and the hard shoulder is 3 metres wide. The study focused on the lower half of the weaving section within video coverage, which is separated from the opposite lane by a 2-metre-wide median strip and a 0.365-metre-wide marginal strip. All the above geometric data serve as the core basis for the construction of the static scenario. Based on the road terrain modelling, in order to enhance the realism of the actual driving scenario, this study further integrated satellite images and field survey data to construct a complete three-dimensional virtual scenario including road facilities such as roadbeds and pavements, traffic signs, guardrails, street lamps, as well as environmental elements such as vegetation and buildings. Figure 3.4 shows the terrain information of the weaving section constructed in the SCANer Studio® software for simulation modelling, and Figure 3.5 shows the comparison between the satellite image of the actual weaving section and the three-dimensional model of the constructed driving simulation scenario. The established

physical simulation scenario achieves high-precision reproduction of the weaving section in terms of road geometry and environmental layout.

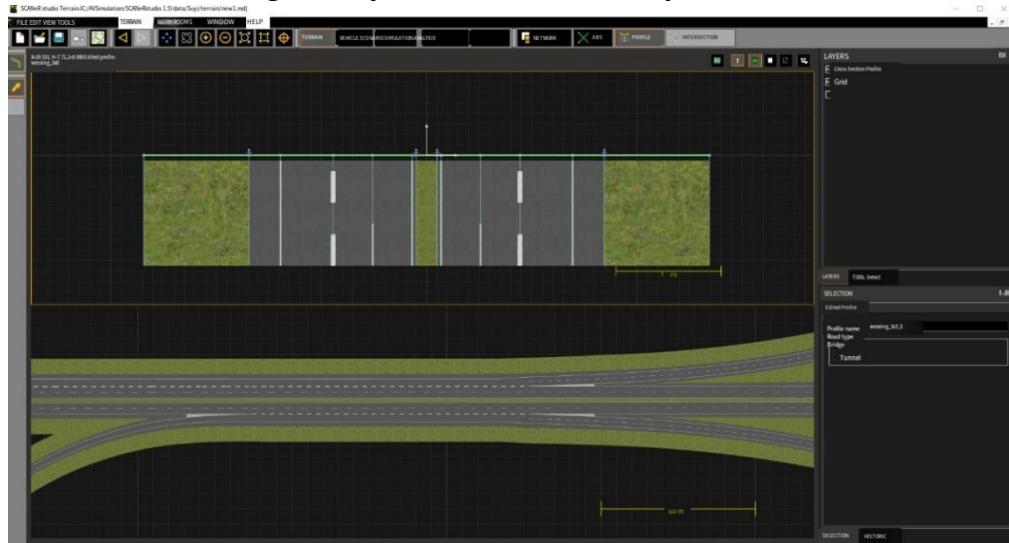


Figure 3.4 Terrain information of the weaving section in SCANr Studio®.

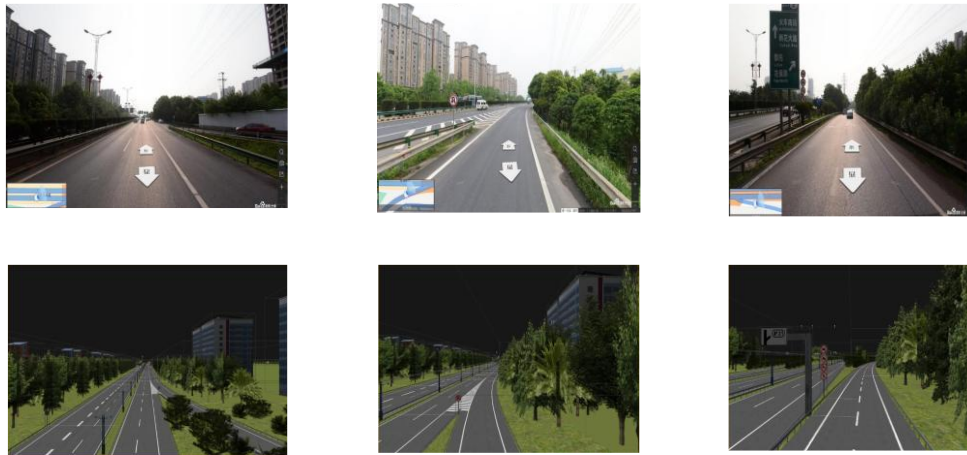


Figure 3.5 Comparison between the field satellite imagery and the simulated model.

(3) Dynamic traffic simulation scenarios

Based on completing the construction of the static physical simulation scenario, a dynamic traffic simulation scenario needs to be further built to accurately reproduce the actual traffic operation state in the weaving section. The construction of dynamic traffic simulation scenarios mainly involves the import of physical models of traffic participants and the setting of motion behaviour parameters. The core objective is to make the simulation environment consistent with the real scenario at the level of traffic dynamic behaviour through reasonable configuration of traffic flow parameters.

To achieve an effective reproduction of the actual traffic flow, this study set the number of vehicles in each lane and their corresponding driving trajectory ratios for the driving simulation experiment based on the traffic flow features obtained from video trajectory data processing in Chapter 2. Specifically covering four typical driving trajectories: through, merging, diverging, and ramp to ramp, the proportions

of each type of trajectory were determined strictly in accordance with the field observation results. In terms of vehicle speed control, the speed normal distribution parameters based on field data fitting in Figure 2.19 of Chapter 2 are used as the basis for vehicle speed setting in the simulation environment to ensure the authenticity of the speed distribution characteristics. Vehicle following behaviour is controlled by the headway. The headway in the simulation experiment is randomly generated, and its probability distribution follows the truncated headway function established based on the field data (Figure 2.21). In terms of vehicle type composition, field observations indicated that the traffic composition was dominated by passenger cars and included a small number of vans. To accurately reflect this feature, the proportions of various vehicle types in the simulation environment were set in accordance with the field statistics. It should be noted that since this study mainly focused on the lane-changing behaviour characteristics of passenger cars, all drivers participating in the driving simulation experiment operated the same type of passenger car to eliminate the potential impact of differences in vehicle dynamic characteristics on driving behaviour.

In addition, in order to maintain consistency in scenario conditions, all driving simulation experiments were uniformly set to daytime, good weather traffic operation scenarios in reference to the environmental conditions during the field investigation. Through the fine-tuned configuration of the above parameters, the dynamic traffic simulation scenarios constructed in this study achieved a high degree of reproduction of the weaving section in terms of traffic composition, operational status, and behavioural characteristics, thus providing a real and reliable experimental environment for the subsequent comparative analysis of driving behaviour.

3.2.2 Driving simulation experiment design

(1) Experimental route design

Based on the completion of the construction of static and dynamic simulation scenarios, systematic design of the experimental route and process is required to ensure the validity and reliability of the driving behaviour data. Due to the limitations of the drone shooting range in Chapter 2, the effective video data coverage length of the weaving section collected on-site is 400 metres. In order to realistically reproduce the driving behaviour in the weaving section in the simulation environment and ensure the comparability of the experimental data, the drivers participating in the experiment need to go through a basic section of adaptive driving before entering the target weaving section to gradually establish a stable driving rhythm and scenario perception. To further control potential interference factors during the experiment, this study fully considers the psychological and physiological responses of drivers in the process design. To avoid fatigue and learning effects caused by repeated exposure to the same scenario, buffer sections and time intervals of sufficient length were set after each passing through the weaving section to ensure that the driver was in a natural, unadopted driving state when re-entering the weaving section. At the same time, the total

duration of the simulation experiment was strictly controlled to reduce the possible motion sickness caused by prolonged simulated driving, thereby ensuring the authenticity and stability of the behavioural data.

To obtain enough high-quality samples of lane-changing behaviour in the weaving section within the limited experimental time, a well-structured closed-loop experimental route was designed. The route was arranged in an upside-down symmetrical layout, and the two weaving sections were strictly consistent with the field data in terms of road alignment, cross-sectional structure, and geometric parameters. The two weaving sections are smoothly connected by straight sections, circular curves, and transition curves, providing drivers with transitional space for behavioural and psychological adaptation and effectively optimising the overall operational efficiency of the experimental route. The experimental route was based on the SCANeR Studio[®] simulation platform for terrain modelling and path configuration, and the final generated route model is shown in Figure 3.6. The overall design, based on accurately reproducing the road environment in the weaving section, considers the executability of the experimental operation and the systematisms of the data collection, laying a solid experimental foundation for the subsequent extraction and comparative analysis of lane-changing behaviour characteristics in the weaving section.

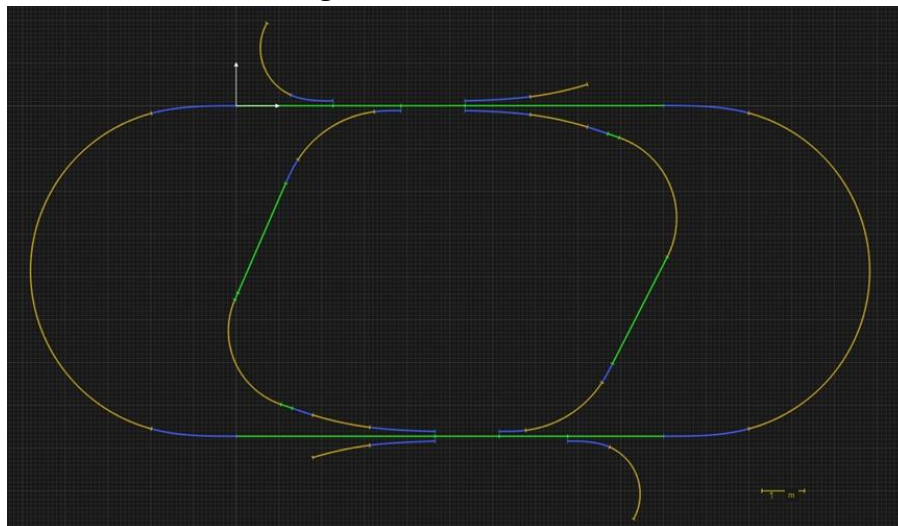


Figure 3.6 Experimental test route constructed in SCANeR Studio[®].

Based on the experimental test route shown in Figure 3.6, and in relation to the analysis objective of the lane-changing behaviour characteristics in the weaving section in this study, combined with the distribution ratio of various types of driving trajectories observed in the weaving section in Chapter 2, this study systematically planned a representative experimental driving route scheme for each subject, as shown in Figure 3.7. The red arrows in the figure indicate the expected driving trajectory of the vehicle within the weaving section, and the green line segments indicate the driving path in the non-weaving section of the main line.

To fully collect lane-changing data under different driving path patterns, each driver was required to complete a total of 11 weaving section driving tasks in the simulated environment. The task structure was scientifically configured based on

the frequency and sequence of various driving trajectories observed in the field, including: 4 through-maneuvres, 3 merging manoeuvres, 3 diverging manoeuvres, and 1 ramp to ramp manoeuvre. This experimental design ensures that all lane-changing behaviours have a sufficient sample size to support statistical analysis, and effectively reproduces the actual distribution characteristics of driving path selection in the actual traffic environment, thus ensuring that the collected behaviour data are representative, authentic, and statistically valid, providing a reliable basis for subsequent driving behaviour modelling and feature analysis.

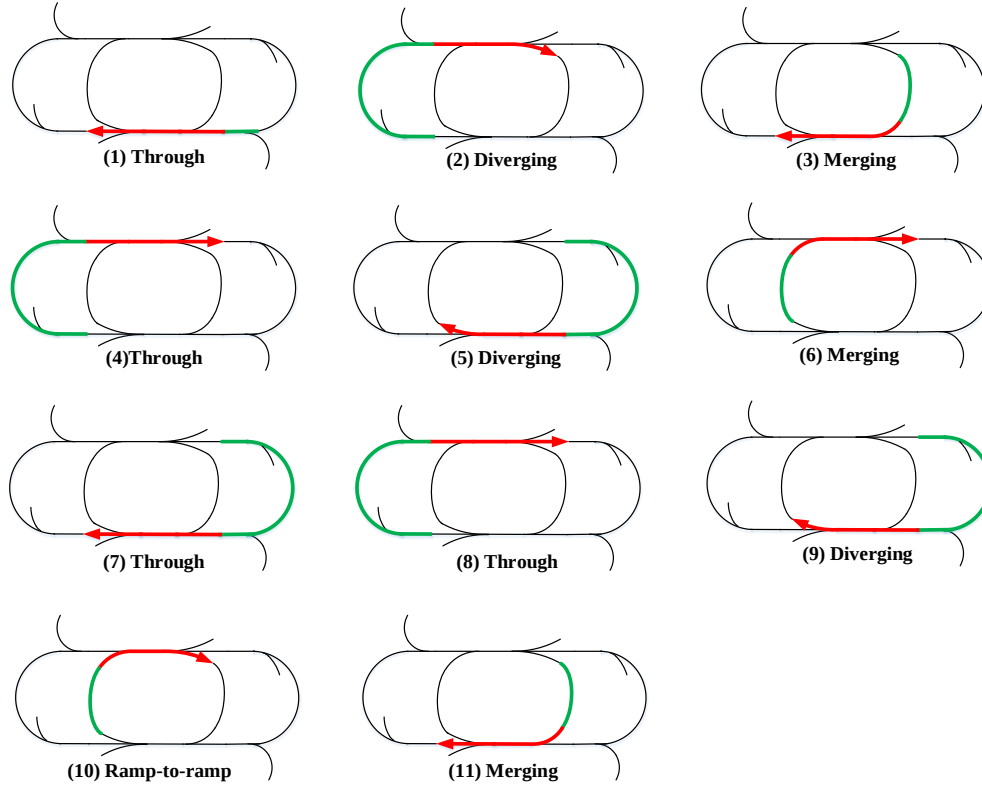


Figure 3.7 Driving route of each driver in the experiment.

(2) Experimental testing methods

In this study, three independent variables were considered for designing the experiments: two numeric factors (i.e., speed of surrounding vehicles and participant age) and one categorical factor (i.e., participant gender). Setting appropriate traffic flow parameters for the weaving section in driving simulation experiments is crucial to ensure an accurate replication of field traffic data collection scenarios. To determine the test range of simulated surrounding vehicles speed, a response surface central composite design was employed, treating speed as a numeric factor. Based on the field data fitted to a normal distribution data as shown in Figure 2.19 of Chapter 2; the 15th percentile corresponds to a speed of 44.1 km/h, while the 85th percentile corresponds to a speed of 67.7 km/h.

To control for variation due to participants, age and gender were included as factors. The age range of participants was set from 25 to 55 years to encompass diverse age categories, spanning from young to middle-aged drivers. A response surface central composite design was employed to structure the experiment (Montgomery & Runger, 2020). The corresponding codes and actual values for

each variable are presented in Table 3.1. The levels of continuous factors were selected to ensure a rotatable design space. To implement the response surface central composite design, a total of 26 experimental runs were conducted with Italian participants, as illustrated in Table 3.2. Five central runs for each gender were used to have reasonably stable variance for prediction. This design ensures the acquisition of effective and reliable results within a limited number of trials.

Since the field observations were collected in China, 16 young Chinese who had recently come to Italy and possessed no prior driving experience in Italy were also included. This minimises potential confounding effects arising from variations in driving environments across different countries. The speed levels of test scenarios for Chinese drivers were determined using a random extraction method, while ensuring that the proportion remains almost consistent with the experimental runs of central composite design as depicted in Table 3.3.

Table 3.1. Independent variables of test scenarios.

Variable type	Independent parameter	Level with the codes				
		-1.41	-1	0	+1	+1.41
Numeric variable	Speed (km/h)	44.1	47.6	55.9	64.2	67.7
	Age of participants	25	29	40	50	55
Categoric factor	Gender of participants	Level 1		Level 2		
		Male		Female		

Table 3.2. Speed levels of test scenarios for Italian drivers.

Speed level (km/h)	Age	Number of Italian test drivers
44.1	40	2 (male: 1; female: 1)
47.6	29	2 (male: 1; female: 1)
47.6	50	2 (male: 1; female: 1)
55.9	25	2 (male: 1; female: 1)
55.9	40	10 (male: 5; female: 5)
55.9	55	2 (male: 1; female: 1)
64.2	29	2 (male: 1; female: 1)
64.2	50	2 (male: 1; female: 1)
67.7	40	2 (male: 1; female: 1)

Table 3.3. Speed levels of test scenarios for Chinese drivers.

Speed level (km/h)	Age	Number of Chinese test drivers
44.1	25	2 (male: 1; female: 1)
47.6	29	2 (male: 1; female: 1)
55.9	25	4 (male: 2; female: 2)
55.9	29	4 (male: 2; female: 2)
64.2	25	1 (male: 1; female: 0)
64.2	29	2 (male: 1; female: 1)
67.7	29	1 (male: 0; female: 1)

(3) Demographic characteristics of drivers

In accordance with the Code of Ethics of the World Medical Association (WMA, 2024), forty-two licensed drivers were recruited on a voluntary basis

without receiving any form of compensation or remuneration. Italian participants were recruited via email invitations sent to individuals followed by random selection from the pool of eligible candidates. Chinese participants were recruited through social media announcements. Prior to the experimental session, all participants provided informed consent by signing a consent form. Demographic characteristics of the test drivers are summarised in Table 3.4.

Table 3.4. Demographic characteristics of test drivers.

Nationality	Details	Distributions	Frequencies	Percentages
Italian	Gender	Male	13	50%
		Female	13	50%
	Age	(Min. 22, Max. 55, Mean=39.42, SD=8.92)		
	Years of holding a driving licence	Less than 3 years	0	0%
		3 years to 10 years	3	11.54%
		More than 10 years	23	88.46%
	km drive annually	Less than 1,000 km	2	7.69%
		1,000 km to 10,000 km	8	30.77%
		More than 10,000 km	16	61.54%
	Gender	Male	8	50%
Female		8	50%	
Chinese	Age	(Min. 20, Max. 35, Mean=26.56, SD=3.42)		
	Years of holding a driving licence	Less than 3 years	2	12.50%
		3 years to 10 years	13	81.25%
		More than 10 years	1	6.25%
	km drive annually	Less than 1,000 km	11	68.75%
		1,000 km to 10,000 km	4	25%
		More than 10,000 km	1	6.25%

Gender distribution was balanced between male and female participants. Italian participants represented a broader range of age groups and include more experienced drivers, whereas Chinese participants were predominantly young and less experienced. The differences in gender, age, and driving experience may influence driving behaviour in simulators (De Blasiis et al., 2017; Cai et al., 2018; Yuan et al., 2019). Additionally, cultural differences between Italian and Chinese participants may also affect their behaviour in simulated environments (Wang et al., 2019). Field data consist of vehicle trajectories collected from drones. Due to the lack of demographic data, the age distribution and driving experience of these field individuals remain undetermined. Nevertheless, based on citywide driver statistics, approximately 67% of drivers in this city are male, and roughly 20% have accumulated more than ten years of driving experience. This suggests that the Chinese drivers represented in the field data differ from the Chinese test drivers participated in simulation experiments, who typically consist of younger, more educated individuals. Consequently, the two groups of Chinese drivers may exhibit different driving behaviours due to variations in age, experience, and the data collection environments (field vs. simulation).

(4) Experiment protocol and data collection

The experimental driving simulator protocol is illustrated in Figure 3.8. Prior to the main experiment, participants were provided with an introductory session on the fundamental functions and operations of the experimental driving simulator. Subsequently, they were instructed to peruse a document elucidating the meaning of performing various manoeuvres as indicated by arrows in Figure 3.9. During the experimental driving session, the participants followed the indicating arrows to perform manoeuvres. Indicating arrows were displayed upon the test driver's entry into the weaving section, ensuring sufficient time for manoeuvre execution. Afterwards, participants engaged in a brief training driving test, wherein they drove for five minutes on a trial track equipped with ramps to enhance their comprehension of indicating arrows and familiarise themselves to the simulator. Following this, participants completed a pre-drive questionnaire designed to collect basic demographic information. Then, participants proceeded with the main experiment by completing the driving path which lasted approximately 20 minutes. After the experiment, the subjects filled out the post-experiment questionnaire to assess the possible symptoms of motion sickness that might occur during the simulated driving (Gianaros et al., 2001).

To ensure consistency between the simulated data and the field observations, the frequency of the simulated scenario data collection was also set at 30Hz. The driving behaviour data obtained from the simulation experiment will serve as the basis for the subsequent extraction and analysis of lane-changing behaviour characteristics, supporting the in-depth exploration of lane-changing behaviour characteristics in the weaving in this study.

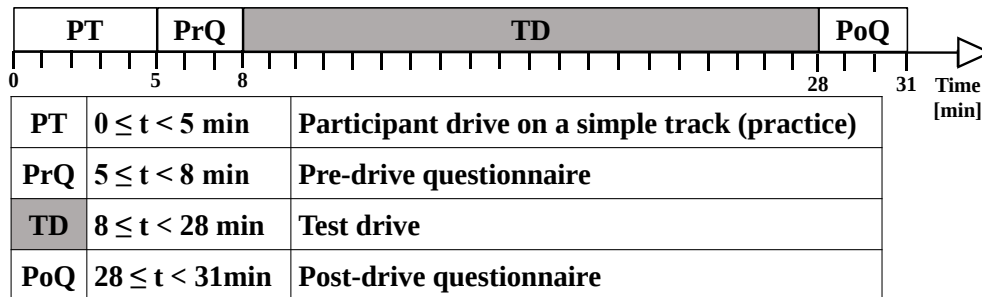


Figure 3.8 Driving simulator experiment protocol.



(a)



(b)



(c)

Figure 3.9 Frames of three different indicating arrows. (a) merging, (b) diverging, and (c) ramp to ramp.

3.3 Results analysis

Based on the driving simulation experiment process set out in Section 3.2, this study systematically carried out drivers' recruitment and experiment implementation, and fully collected multi-dimensional dynamic behaviour data of the vehicle during operation in the weaving section. The data collected covered four main categories: basic vehicle information (including geometric attributes such as the horizontal and vertical coordinates of the centre of gravity, length and width), driving operation data (such as operation inputs such as accelerator pedal opening, brake pedal position, steering wheel angle), vehicle operation status data (including motion parameters such as speed, acceleration, angular velocity) and vehicle interaction data with surrounding traffic elements (dynamic relationship metrics such as relative speed difference, acceleration difference, distance difference, etc.). At the end of the experiment, all data were exported in .csv format via SCANeR Studio[®] simulation platform to provide a structured data basis for subsequent quantitative analysis. To further improve the quality of the data, this study cleaned and pre-processed the original dataset, with a focus on identifying and processing abnormal observations, and used appropriate signal denoising methods to suppress high-frequency interference introduced during data acquisition. The pre-processing process effectively reduced the impact of outliers and noise on the analysis results, thus ensuring good accuracy and robustness in subsequent lane-changing behaviour modelling and characteristics extraction processes.

3.3.1 Extraction of lane-changing behaviour characteristic metrics

This study selected speed and headway as the core traffic flow characteristic variables and systematically conducted a comparative analysis of traffic operation characteristics within the weaving section. Here, speed is defined as the instantaneous speed at which a vehicle travels in the direction of travel; The headway indicates the time gap between two consecutive vehicles passing through the same section in the same lane, that is, the time it takes for the front of the rear vehicle to reach the rear of the front vehicle. Based on the different motivations for lane-changing, lane-changing behaviours are classified into four categories: (i) discretionary lane-changing, (ii) mandatory lane-changing, (iii) merging, and (iv) diverging.

These types of lane changes are distinguished by the direction and purpose of the lane ID change when vehicles switch lanes. Notably, a discretionary lane change is a spontaneous decision made by drivers without external compulsion, typically aimed at achieving more favourable driving conditions. In contrast, a mandatory lane change is compelled by traffic rules or route requirements, where drivers must change lanes to reach their intended destination. It is notable that since merging and diverging occur in the ramp junction area and involve obvious acceleration or deceleration processes, this study distinguishes them from the regular forced lane changes on the main road in the weaving section. In this study, mandatory lane-changing specifically refers to drivers in the leftmost lane moving to the right prior to executing a diverging manoeuvre.

It is important to highlight that, given the aim of this study is to examine the microscopic characteristics of lane-changing behaviour, each individual lane change by a vehicle is documented as a single lane-changing event. For instance, if a vehicle changes lane twice in succession, these are recorded as two distinct lane-changing events. Based on this, four key metrics defined in Section 2.4 of Chapter 2 are selected as the characteristic parameters of lane-changing behaviour, including: lane-changing duration, accepted target lane lead and lag gap, and *GTTC*. These metrics describe the dynamic characteristics and safety level of the lane-changing process from different dimensions, providing a quantitative basis for subsequent behaviour modelling and comparative analysis.

3.3.2 Data analysis methods

(1) Two-sample Kolmogorov–Smirnov (K-S) test

In this study, a two-sample K-S test was used to statistically analyse the distribution differences of lane-changing behaviour characteristic metrics in both field observations and simulation data. The two-sample K-S test, as a non-parametric hypothesis testing method, does not depend on the specific distribution form of the data and is suitable for comparing whether two independent samples come from the same distribution. The basic idea is to determine whether there is a significant difference between two distributions by calculating the maximum vertical distance (i.e., the D statistic) between the empirical cumulative distribution

functions of the two sets of samples. Studies have shown that the two-sample K-S test is highly effective when the sample size is sufficient, especially when each sample size is no less than 15, the method can effectively identify the actual distribution differences (Kanji, 2006; Karimi et al., 2020). Since the number of lane-changing behaviour events extracted in this study met the sample size requirement, using this method for comparative analysis of key lane-changing behaviour characteristic metrics such as lane-changing duration, accepted target lane lead and lag gap, and *GTTC* can systematically identify the consistency between simulation data and field observation data from the perspective of distribution morphology.

Let $x; (x_1, x_2, \dots, x_m)$ and $y; (y_1, y_2, \dots, y_n)$ be two independent random samples of sizes m and n , respectively, drawn from populations characterised by their respective F and G cumulative distribution functions (CDFs). The null hypothesis (H_0) can be tested against the two-sided alternative hypothesis (H_a) (Berger and Zhou, 2014):

$$H_0: F(t) = G(t), \quad \text{for every } t \quad (\text{Eq3.1})$$

$$H_a: F(t) \neq G(t), \quad \text{for at least one value of } t \quad (\text{Eq3.2})$$

The null hypothesis (H_0) can also be tested against one of the following one-sided alternative hypotheses:

$$H_a: F(t) > G(t), \quad \text{for all } t, \text{ strictly greater for at least one value of } t \quad (\text{Eq3.3})$$

$$H_a: F(t) < G(t), \quad \text{for all } t, \text{ strictly smaller for at least one value of } t \quad (\text{Eq3.4})$$

The test statistic for alternative hypothesis of $F(t) \neq G(t)$ was calculated as follows:

$$D = \max |F_m(t) - G_n(t)|, \min(x, y) \leq t \leq \max(x, y) \quad (\text{Eq3.5})$$

where $F_m(t)$ and $G_n(t)$ are empirical CDFs for the samples x and y , respectively.

To test the two alternative hypotheses of $F(t) > G(t)$ and $F(t) < G(t)$ for some value(s) of t , the test statistics were calculated as Equation (3.6) and (3.7), respectively:

$$D^+ = \max[F_m(t) - G_n(t)], \min(x, y) \leq t \leq \max(x, y) \quad (\text{Eq3.6})$$

$$D^- = \max[G_n(t) - F_m(t)], \min(x, y) \leq t \leq \max(x, y) \quad (\text{Eq3.7})$$

To test H_0 at the significance level of 0.01, H_0 could be rejected in favour of H_a if the calculated p-value is lower than 0.01.

(2) Two-sample Kolmogorov–Smirnov(K-S) test after probability sampling

As the sample size grows, the K-S test's statistical power increases, making it easier to detect even small differences. Consequently, this leads to a higher

likelihood of obtaining statistically significant results for very minor differences, thereby increasing the false positive rate (Drezner et al., 2010; Nguyen, 2017). In order to address the issue, some researchers have proposed a method involving re-sampling followed by the K-S test (Olea et al., 2009; Wang et al., 2011). Referring to the methods of previous researches, this thesis employed a K-S two-sample test method based on probability sampling. Continuous variables were segmented into multiple intervals according to their distribution ranges, and the probability density for each interval was computed, as presented in Equation (3.8). Finally, as illustrated in Equation (3.9), the required number of samples for each interval was determined by multiplying the total number of samples by the corresponding probability distribution:

$$p_i = \frac{m_i}{N} \quad (\text{Eq3.8})$$

$$n_i = n \times p_i \quad (\text{Eq3.9})$$

where, i represents the index of the data interval, p_i refers to the distribution probability of the i^{th} data interval, m_i refers to the amount of data in the i^{th} data interval, N represents the number of the population, n_i represents the number of samples in the i^{th} data interval, and n represents the total number of samples.

3.3.3 Comparative analysis of lane change behaviour characteristics

(1) Descriptive statistical results of lane-changing behaviour characteristic metrics

Table 3.5 summarises the descriptive statistical results of the lane-changing behaviour characteristic metrics collected in field observations and driving simulation experiments. All continuous behavioural variables, including speed, headway and *GTTC*, were recorded synchronously at a sampling frequency of 30Hz to ensure consistency and comparability of the data in the time dimension. The data collected covered the operational status of all vehicles throughout the weaving section, including both through manoeuvre and those performing lane-changing behaviour, to fully reflect the dynamic characteristics of different traffic participants. Additionally, outliers falling outside the predefined threshold range were excluded to facilitate subsequent probability sampling and enable easier comparison of distribution characteristics. The threshold range was determined based on both the practical significance and percentile distributions of the variables. Specifically, data points with speeds exceeding 120 km/h, headways greater than 20 s, accepted gaps less than -50 s or greater than 200 s, and *GTTC* values exceeding 100 s were removed. These outliers constitute approximately 5% of the total dataset and were likely attributable to errors in video extraction trajectory coordinates or calculations.

In the simulation study, there are 399 lane-changing manoeuvres that were recorded. Specifically, Chinese drivers conducted a total of 153 lane changes while Italians conducted 246 (112 by those younger than 40 and 134 by those older than

40). Simulation data are categorised into three groups: (i) Chinese drivers under 40, (ii) Italian drivers under 40, and (iii) Italian 40 and over. The impact of age on driving behaviour was assessed by comparing younger and older groups. Additionally, a comparative analysis between Chinese and Italian was conducted to enhance the generalizability and robustness of the findings. A preliminary analysis of the overall simulation sickness score after driving (mean = 22.57, range = 11.11-100) suggests that the average level of simulation sickness experienced by participants was relatively low. This suggests that the impact of simulation sickness on the experimental outcomes is relatively minor.

Table 3.5. Descriptive statistics of observed variables in field and driving simulator.

Group	Variable	#	Mean	SD	Min.	Max.
Field (Chinese)	Speed (km/h)	921,076	55.90	14.43	0.41	119.97
	Headway (s)	814,864	2.87	2.48	0.02	20.00
	Lane change duration (s)	1,660	6.40	3.64	0.50	20.3
	AG_TLead (s)	995	3.37	7.16	-2.24	116.63
	AG_TLag (s)	1,128	1.38	1.62	-4.57	14.82
	<i>GTTC</i> (s)	322,515	19.39	18.58	0.10	100.00
Simulator (All Italian)	Speed (km/h)	229,086	55.73	9.21	9.99	89.52
	Headway (s)	228,799	3.13	2.39	0.06	19.99
	Lane change duration (s)	246	6.01	1.97	0.96	15.42
	AG_TLead (s)	223	7.26	20.64	-0.33	194.71
	AG_TLag (s)	202	7.33	15.86	-37.77	114.20
	<i>GTTC</i> (s)	57,768	28.23	22.41	0.10	99.98
Simulator (Chinese < 40 years old)	Speed (km/h)	138,573	54.37	11.73	7.57	94.48
	Headway (s)	137,276	4.48	3.44	0.03	20.00
	Lane change duration (s)	153	5.15	1.99	1.29	12.96
	AG_TLead (s)	120	8.99	21.71	-0.43	178.51
	AG_TLag (s)	109	7.23	18.46	-23.83	160.24
	<i>GTTC</i> (s)	29,279	21.93	19.85	0.11	99.94
Simulator (Italian < 40 years old)	Speed (km/h)	105,732	54.92	9.49	9.99	89.52
	Headway (s)	105,634	2.76	2.15	0.06	19.99
	Lane change duration (s)	112	6.01	1.74	2.08	14.66
	AG_TLead (s)	100	6.41	19.90	-0.11	194.71
	AG_TLag (s)	86	6.13	13.04	-37.77	77.83
	<i>GTTC</i> (s)	24,900	28.17	22.35	0.47	99.92
Simulator (Italian ≥ 40 years old)	Speed (km/h)	123,354	56.42	8.91	19.10	85.35
	Headway (s)	123,165	3.45	2.54	0.13	19.92
	Lane change duration (s)	134	6.01	2.15	0.96	15.42
	AG_TLead (s)	123	7.95	21.29	-0.33	180.31
	AG_TLag (s)	116	8.22	17.67	-19.93	114.20
	<i>GTTC</i> (s)	32,868	28.27	22.46	0.10	99.98

Note: #: the number of data; AG_TLead: accepted target lane lead gap; AG_TLag: accepted target lane lag gap; *GTTC*: *GTTC* between the lane-changing vehicle and the leading and following vehicles on both the current and target lanes during a lane change.

In the field study, a total of 1,660 lane changes (including 658 discretionary lane changes, 343 mandatory lane changes, 102 merging manoeuvres, and 557 diverging manoeuvres) were observed. Descriptive statistical parameters of

headway show no significant differences between the field-collected data and the simulation data. The observed speed in the field, although similar in average value to the simulated data, exhibits a wider range between the minimum and maximum values. The lane change duration observed in the field is comparable to the average value from simulations; however, the field data demonstrates a higher standard deviation and maximum value. These variations might be due to the limited range of traffic flow conditions that can be simulated. Simulation experiments primarily represent typical field scenarios (i.e., the 15th to the 85th percentile of speed) but do not account for extreme low- or high-speed conditions. For AG_TLead, AG_TLag, and *GTTC*, field-collected data exhibit lower average values and smaller standard deviations compared to simulation data. Notably, the simulation data shows significantly higher maximum values for AG_TLead and AG_TLag, with AG_TLag also displaying a smaller negative minimum value. These differences could be influenced by the driving perspective during simulated lane changes. In the simulated environment, drivers may not be fully accustomed to the virtual setting, leading to difficulties in accurately judging distances, especially the distance to vehicles behind based solely on rear-view mirrors. As a result, more forced lane changes (characterised by negative AG_TLag) and hesitant lane changes occur, which necessitate larger lane change gaps.

From the descriptive statistical information, it is evident that while the observed variables exhibit some similarity between field and simulation data, notable differences also exist. Therefore, further statistical analysis is necessary to explore these variations in greater depth.

(2) Comparison of lane-changing behaviour characteristic metrics before and after probability sampling

Probability sampling was implemented for observed continuous variables (i.e., speed, headway and *GTTC*). The proportional relationship among the grouped data was considered. A sample size of 300 was applied to field data. For Italians' data in simulation, a sample size of 100 was used (including 50 Italians < 40 years old and 50 Italians $\geq$ 40 years old). Furthermore, a sample size of 60 was designated for Chinese data in simulation. It is important to highlight that probability sampling was conducted based on distinct manoeuvres, considering the varying distributions of variables across different manoeuvres. To ensure the accurate representation of the distribution characteristics of the entire population, various statistical tests including χ^2 test, F-test, and t-test were conducted. The results indicated a high level of consistency (over 95%) between the sampled data and population data in terms of their distribution characteristics. The cumulative distribution probability graphs for sampled and population data are illustrated in Figure 3.10. The solid line represents the population data, while the dashed line represents the sampled data. It is evident that the sampled data effectively captures the distribution characteristics of the population data. The results provide compelling evidence that the employed probability sampling method ensured a robust representation of the population dataset's distribution characteristics.

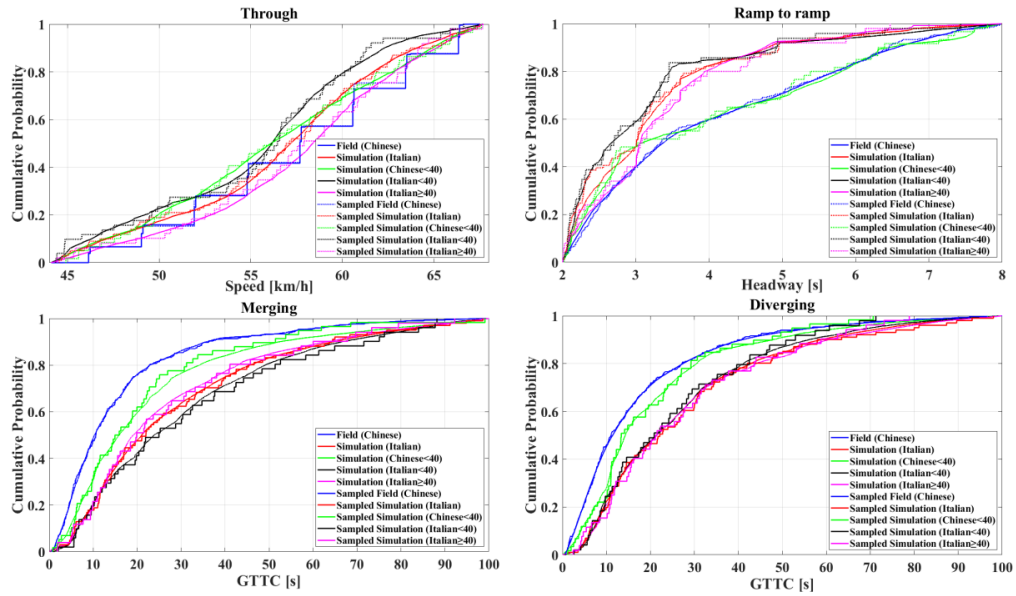


Figure 3.10 Comparison of continuous variable between sample and population.

(4) Results of the K-S test for characteristic metrics of lane-changing behaviour

The K-S test results and analysis of all lane-changing behaviour characteristic metrics are presented one by one below. To facilitate the comparison of the results, the lane-changing behaviour characteristic metrics representing traffic efficiency (speed and headway) are divided into four different trajectories according to the different driving routes in the weaving section (i.e., through, merging, diverging, ramp to ramp) were compared respectively, and the lane-changing behaviour characteristic metrics representing the micro-behaviour of lane-changing (lane-changing duration, accepted target lane lead and lag gap, and *GTTC*) were divided into four different types of lane-changing (i.e., discretionary lane change, mandatory lane change, merging, and diverging.) according to different lane-changing motivations were compared respectively.

①Speed

Since only the 15th to 85th percentiles of the speed distribution are considered when designing the experiment, the K-S test was consequently performed only on the distribution within this interval. It is worth noting that Figure 3.11 indicate that the cumulative probability distribution of speed derived from field data exhibits a step-wise pattern. This characteristic may result from the discretisation of speed during the data acquisition and processing procedure. Furthermore, Figure 3.11 display only a limited speed range (44.1 to 67.7 km/h), the visual appearance of discretisation is amplified. The results in Table 3.6 indicate that, for the through manoeuvre, Italians, Chinese and old Italians exhibit similar speeds to field. Conversely, the speeds of young Italians differed significantly from field. Therefore, a one-sided alternative hypothesis was tested against the null hypothesis. The results demonstrate that the speed distribution in the field was significantly lower than of young Italians ($D^- = 0.2502$, $p = .0034$). For merging manoeuvre, the results of two-sided K-S test indicated no significant difference in the cumulative

probability distribution of speed across different pairs. This demonstrates that the speed distribution of field and simulation exhibited a high degree of similarity during merging manoeuvre. Nevertheless, it is important to note that despite the lack of significant differences in cumulative probability distribution, Figure 3.12 reveals notable differences in the spatial distribution of average speed. During both through and merging manoeuvres, the average speed of the field data was consistently higher than that of the simulation data in weaving sections 2 and 3, with the peak difference occurring at the end of weaving section 2. This disparity can primarily be attributed to the differences in available headways between field and simulation vehicles, as the upper limit of headways in the simulation was truncated at 2-8 seconds. In contrast, in real-world scenarios, drivers had greater flexibility to adjust their acceleration profiles, enabling them to achieve higher speeds. Additionally, the average speed of the simulation data fell within the experimental design range (44.1-67.7 km/h). Since some field data values exceeded this range, this likely explains the observed differences in the spatial distribution of speeds during through and merging manoeuvres. Regarding the diverging manoeuvre, the cumulative probability distribution of speed for Italians and old Italians from the simulation study was significantly different from that of field study. The results of one-sided alternative hypothesis test indicate that the cumulative probability distribution of speed in the field was greater than those in the simulation. Nonetheless, no significant difference was observed between Chinese, young Italians, and field data. The results for the ramp-to-ramp manoeuvre show that only Chinese had a statistically similar cumulative probability distribution of speed to the field data. The outcomes of one-sided alternative hypothesis test also indicate that the cumulative probability distribution of speed in the field was greater than those of Italians, young Italians, and old Italians.

Table 3.6. The results of two-sided K-S test for speed (44.1-67.7 km/h).

Manoeuvre	Comparison Group Pairs			
	Field (Chinese) vs. Simulation (Italian)	Field (Chinese) vs. Simulation (Chinese<40)	Field (Chinese) vs. Simulation (Italian<40)	Field (Chinese) vs. Simulation (Italian≥40)
Through	$D=0.1767$ $p=.0160$	$D=0.1563$ $p=.1638$	$D=0.2502$ $p=.0068$	$D=0.1139$ $p=.6193$
Merging	$D=0.1564$ $p=.0467$	$D=0.1381$ $p=.2675$	$D=0.1716$ $p=.1440$	$D=0.1287$ $p=.4497$
Diverging	$D=0.2051$ $p=.0030$	$D=0.1905$ $p=.0461$	$D=0.1851$ $p=.0935$	$D=0.2716$ $p=.0024$
Ramp to ramp	$D=0.2418$ $p<.0001$	$D=0.1507$ $p=.1890$	$D=0.2452$ $p=.0093$	$D=0.2711$ $p=.0025$

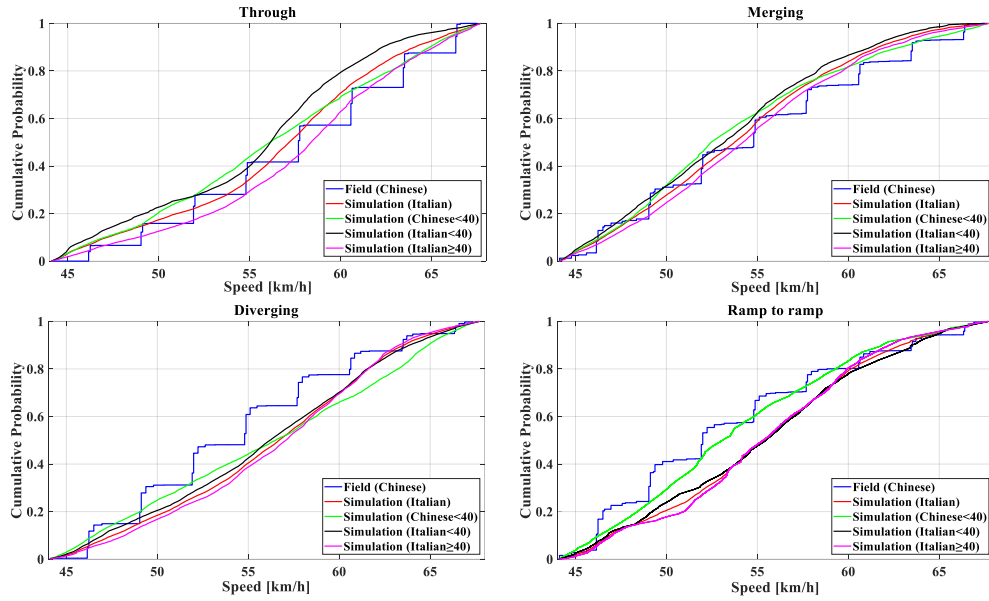


Figure 3.11 Comparison of cumulative probability for speed (44.1-67.7 km/h).

The results of two-sample K-S test presented in Table 3.6 indicate that only the speed distribution of young Italians field was significantly lower than that of field during through manoeuvre. Although no significant difference was found in speed distribution between field and simulation for merging manoeuvres, Figure 3.12 reveals differences in the spatial distribution of average speed within the weaving section. Specifically, compared to field data, the simulation data showed higher average speeds at the on-ramp, exceeding the speed limit by up to 40 km/h, and lower speeds after merging into the main road. For diverging and ramp-to-ramp manoeuvres, the findings in Table 3.6 and Figure 3.11 demonstrate that the speed in field was significantly lower than simulation in some groups (i.e., Italians and old Italians). Furthermore, Figure 3.12 indicates that the average speed in the simulation data at the ramp section is significantly higher than that observed in the field data. This discrepancy may be attributed to the fact that the simulation environment could affect participants' speed perception and control, especially on curved sections like ramps (Godley et al., 2002; Chen et al., 2021). In real-world driving scenarios, the propensity to accelerate is significantly influenced by the driver's perceived risk, which escalates with increasing speed, particularly during ramp manoeuvres. Nevertheless, this effect is less pronounced in simulator environments, which often results in higher driving speeds (Fuller, 2005; Bella, 2008). This discrepancy is consistent with previous studies indicating that driving simulator speeds tend to be slightly higher than real-world data (Godley et al., 2002; Hussain et al., 2019). Additionally, a study conducted using the same simulator further validates these findings (Bassani et al., 2018).

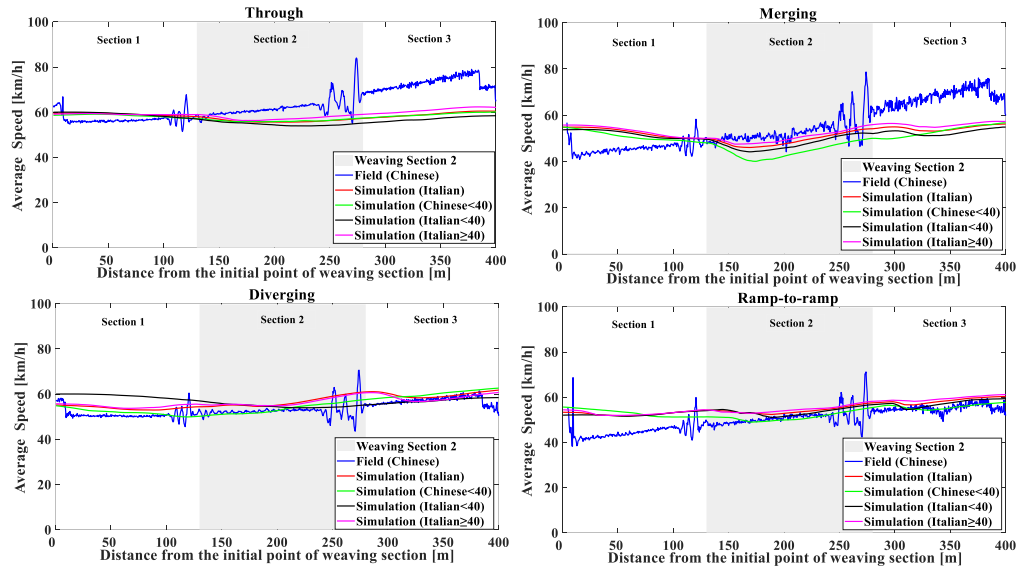


Figure 3.12 Comparison of spatial distribution for average speed.

Besides, as depicted in Figure 3.12, for diverging and ramp-to-ramp manoeuvres, the average speed of field was lower than that of simulation. This discrepancy can be attributed to the deceleration typically required when entering off-ramps, compounded by the static nature of the physical motion simulation environment in simulators, which may hinder drivers' ability to accurately perceive higher speed during off-ramp manoeuvres.

②Headway

Since only the headway distribution were truncated at 2-8 s when designing the experiment, the K-S test was consequently performed only on the distribution within this interval. The findings in Table 3.7 suggest that, for the through manoeuvre, only cumulative probability distribution of Chinese was significantly different with field ($D=0.2432$, $p=.0039$). Additionally, the results from the one-sided alternative hypothesis test confirm that the headway cumulative probability distribution of field was significantly higher than Chinese. Regarding the merging manoeuvre, both Italians and old Italians exhibited significant differences compared to field. A one-sided alternative hypothesis test confirms that headway for Italians and old Italians was significantly smaller than that of field data.

Furthermore, as depicted in Figure 3.14, the relationship between the average headway of field and that of simulation varied across the weaving section, with no significant difference observed in section 2. In section 1, field's average headway was slightly larger, while at the end of section 3, it was significantly smaller. Concerning the diverging manoeuvre, there is no significant difference between field and simulation. During ramp-to-ramp manoeuvre, Italians and young Italians exhibited significantly reduced headways compared to field. Meanwhile, as depicted in Figure 3.14, the average headway of field progressively decreases, closely mirroring the characteristics of merging manoeuvre. It is evident that the average headway of field exhibited significant fluctuations during merging and ramp-to-ramp manoeuvres. This phenomenon can likely be attributed to the higher speeds and increased traffic volumes observed in sections 2 and 3 downstream of

the on-ramp, as vehicles needed to accelerate to merge into the main road. Additionally, frequent lane changes exacerbated traffic congestion downstream.

Table 3.7. The results of two-sided K-S test for headway.

Manoeuvre	Comparison Group Pairs			
	Field (Chinese) vs. Simulation (Italian)	Field (Chinese) vs. Simulation (Chinese<40)	Field (Chinese) vs. Simulation (Italian<40)	Field (Chinese) vs. Simulation (Italian≥40)
Through	$D=0.0900$ $p=.5583$	$D=0.2432$ $p=.0039$	$D=0.1100$ $p=.6522$	$D=0.1300$ $p=.4592$
Merging	$D=0.2167$ $p=.0014$	$D=0.1405$ $p=.2499$	$D=0.2209$ $p=.0275$	$D=0.2614$ $p=.0050$
Diverging	$D=0.1083$ $p=.3286$	$D=0.2140$ $p=.0171$	$D=0.1112$ $p=.6380$	$D=0.0943$ $p=.8136$
Ramp to ramp	$D=0.2338$ $p<.0001$	$D=0.1444$ $p=.2286$	$D=0.3052$ $p<.0001$	$D=0.2223$ $p=.0241$

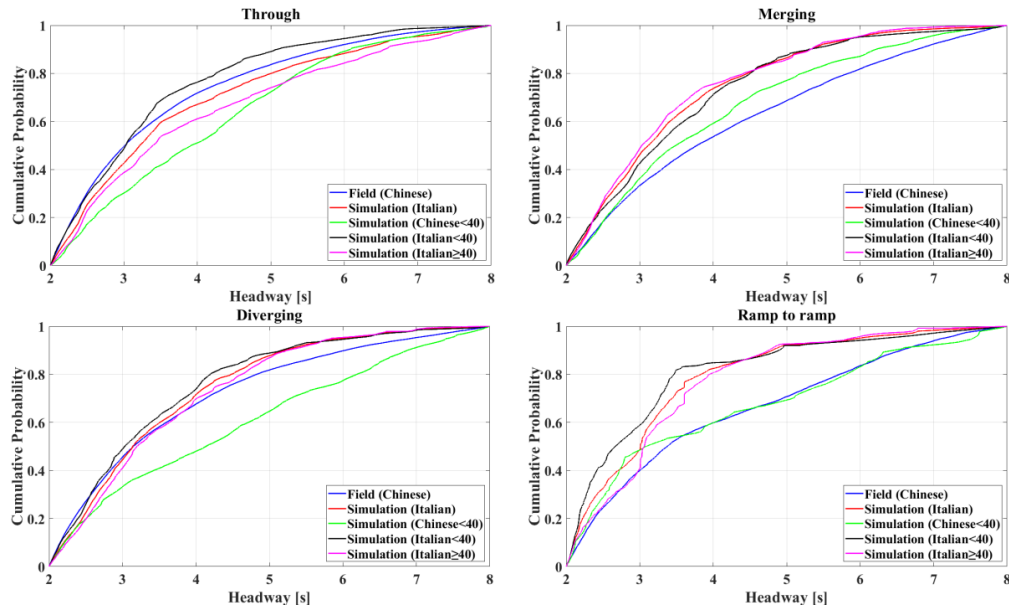


Figure 3.13 Comparison of cumulative probability for headway (2-8 s).

During the through manoeuvre, Chinese exhibit a lower headway distribution compared to field, whereas the other three groups demonstrate similar headway distribution compared to field. For the diverging manoeuvre, no significant difference in headway distribution is observed between field and simulation data. In the merging manoeuvre, both Italians and old Italians display notably lower headways compared to field. For the ramp-to-ramp manoeuvre, Italians and young Italians show significantly reduced headways with field. Conversely, Figure 3.14 reveals differences in the spatial distribution of headways during merging and ramp-to-ramp manoeuvres between simulation and field across all three sections. This discrepancy may be attributed to stop-and-go waves and frequent lane-changing behaviour in real-life scenarios, leading to traffic congestion propagation in the weaving section and affecting capacity at the tail of the weaving section (Oh & Yeo, 2015). In contrast, the simulation is constrained by general simulation

software's limitations and struggles to accurately model the vehicle interactions and complex congestion dynamics at the tail of the weaving section (Wan et al., 2014). Additionally, the average headway maintained by Chinese during the four manoeuvres was significantly higher compared to other groups. This phenomenon could be attributed to the driving behaviour of a larger proportion of novice drivers within the Chinese participant group, who tended to keep a greater headway (Yang & Wu, 2017; Yang et al., 2021). Nevertheless, due to the limited number of simulated vehicles, maintaining a continuous traffic flow in the downstream weaving section in simulation proves challenging. Additionally, as shown in Figure 3.14, it is noteworthy that Chinese exhibited relatively high average headways during all manoeuvres, which may be attributed to their driving styles.

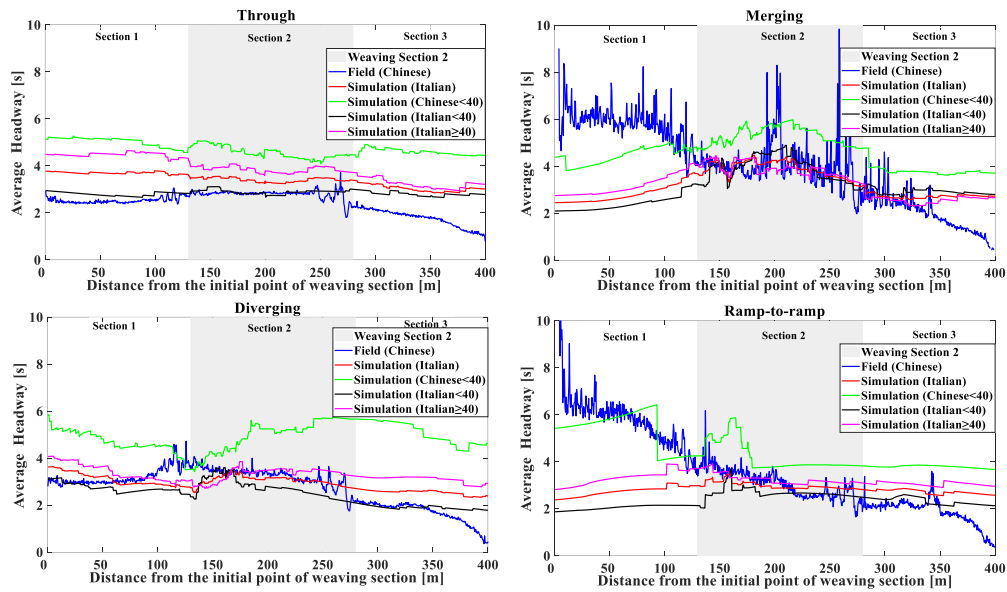


Figure 3.14 Comparison of average headway spatial distribution.

③ Lane change duration

As depicted in Table 3.8, for discretionary lane change, only young Italians showed no significant difference from field. In contrast, other groups exhibited significantly different distributions compared to field ($p < .0001$). One-sided alternative hypothesis tests revealed that field distribution was significantly lower than that of these three groups. Furthermore, as depicted in Figure 3.15, the discrepancy in distribution between simulation and field primarily resides in the right tail, where field data exhibit a higher frequency of longer lane change durations. For mandatory lane change, Italian and field exhibited a high degree of similarity. On the other hand, Chinese showed notable differences from field. The results of the one-sided alternative hypothesis test indicate that the distribution of field is significantly lower than that of Chinese ($D^- = 0.3591$, $p = .0011$), suggesting that Chinese tended to have shorter lane change durations during mandatory lane change. For the merging manoeuvre, the results indicate that there are statistically significant differences in lane change duration distribution between simulation and field ($p < .0001$). The one-sided alternative hypothesis test reveals that the field distribution was significantly greater than that of simulation. As depicted in Figure

3.15, this discrepancy is primarily observed on the left side, indicating that field exhibited more frequent merging manoeuvres with shorter lane change durations.

Table 3.8. The results of two-sided K-S test for lane change duration.

LC ^a Type	Comparison Group Pairs			
	Field (Chinese) vs. Simulation (Italian)	Field (Chinese) vs. Simulation (Chinese<40)	Field (Chinese) vs. Simulation (Italian<40)	Field (Chinese) vs. Simulation (Italian≥40)
DLC^b	$D=0.3222$ $p<.0001$	$D=0.4394$ $p<.0001$	$D=0.2999$ $p=.0203$	$D=0.4153$ $p<.0001$
MLC^c	$D=0.2030$ $p=.1041$	$D=0.3591$ $p=.0022$	$D=0.1852$ $p=.6612$	$D=0.2618$ $p=.0866$
Merging	$D=0.4917$ $p<.0001$	$D=0.4654$ $p<.0001$	$D=0.4690$ $p<.0001$	$D=0.5210$ $p<.0001$
Diverging	$D=0.3765$ $p<.0001$	$D=0.4093$ $p<.0001$	$D=0.4937$ $p<.0001$	$D=0.2776$ $p=.0037$

Note: ^a: lane change; ^b: discretionary lane change; ^c: mandatory lane change.

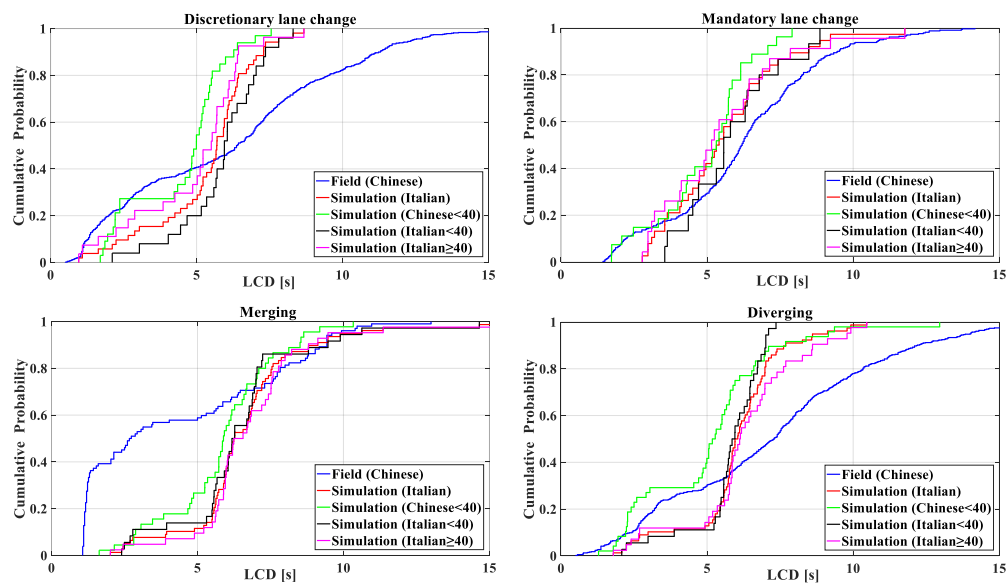


Figure 3.15 Comparison of cumulative probability for lane change duration.

As depicted in Figure 3.16, the cumulative probability distribution of distance between on-ramp and merge effectively start position in field was significantly smaller compared to simulation. This analysis reveals that simulation drivers initiated merging at a significantly shorter distance from the on-ramp compared to field, potentially leading to inadequate acceleration. As illustrated in Figure 3.17, there is minimal difference between field and simulation at the effectively merge end position. This suggests that simulation may require a longer lane change distance for merging, which could account for the extended duration observed. In contrast, field vehicles merging from a greater distance from the on-ramp, allowing for adequate acceleration, thereby enabling smoother integration into the main road.

For diverging manoeuvres, the lane change duration distribution from simulation and field exhibited significant differences. The results of the one-sided

alternative hypothesis test indicate that field lane change duration distribution was significantly lower than that of simulation. As depicted in Figure 3.15, the field data showed a relatively uniform distribution. In contrast, simulation data was predominantly concentrated between 5 and 8 s. Additionally, as depicted in Figure 3.16, the cumulative probability distribution of distance between the on-ramp and diverge effectively start position in field was significantly smaller than that in simulation. This suggests that field drivers tended to travel longer distances on the main road before changing lane, leading to more interactions with weaving traffic and consequently lower speeds compared to simulation (Figures 3.11-3.12). This may explain for a longer lane change duration in field diverging scenarios.

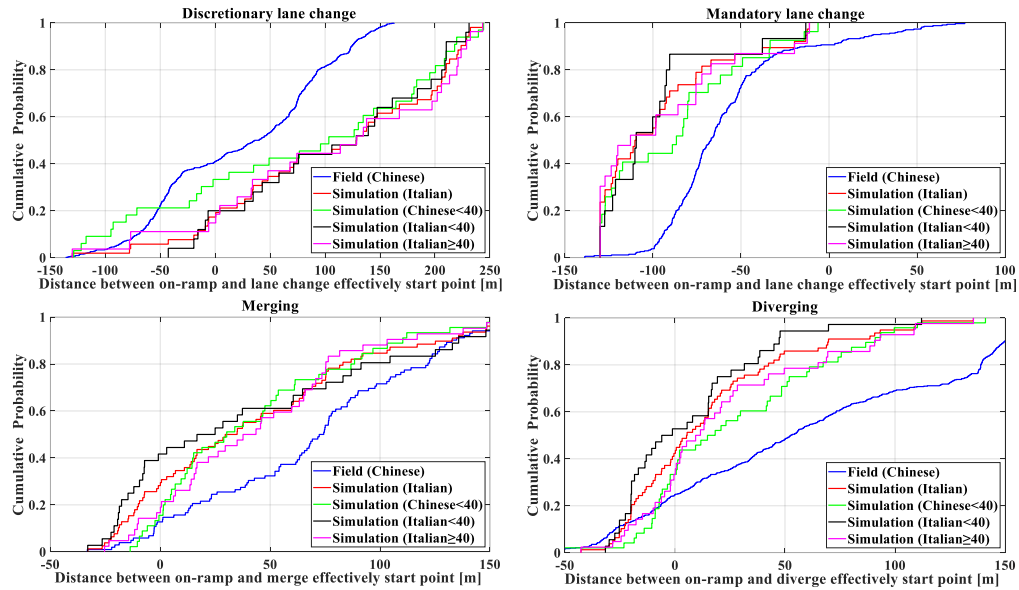


Figure 3.16 Comparison of cumulative probability for distance between on-ramp and lane change effectively start position (positive values indicate lane change starts ahead the on-ramp; negative values indicate otherwise).

The K-S test results presented in Table 3.8 indicate that simulation data exhibited a lower probability of discretionary lane changes taking a longer time. Discretionary lane change typically occurs when drivers seek better driving conditions, such as higher speeds or larger headways. Previous studies have demonstrated that as the complexity and risk of lane changes increase, the required duration for completing lane changes also increases (Toledo & Zohar, 2007; Aghabayk et al., 2011; Yang et al., 2019). In the simulation experiment, participants were not required to make a discretionary lane change, so they were more likely to abandon it if it took too long. For mandatory lane change, Chinese had a shorter lane change duration, which may be attributed to the operational characteristics of novice drivers. Research has demonstrated that novice drivers spend considerably less time checking the surrounding traffic compared to experienced drivers during lane changes (Yang et al., 2006).

Regarding the merging manoeuvre, the results presented in Figures 3.16 and 3.17 indicate that simulation participants tended to initiate merges closer to the on-ramp, necessitating a longer lane-changing distance and time. In contrast, field drivers began merging at a position farther from the on-ramp, which allowed for

sufficient acceleration and resulted in both a shorter lane-changing distance and time, thereby facilitating a smoother transition onto the main road. These findings align with prior research. Kou & Machemehl (1997) observed that some drivers prefer to remain in the acceleration lane for a longer duration, merging with the freeway traffic at a higher speed. Daamen et al. (2010) similarly noted that vehicles merging late during congestion tend to have a higher average speed.

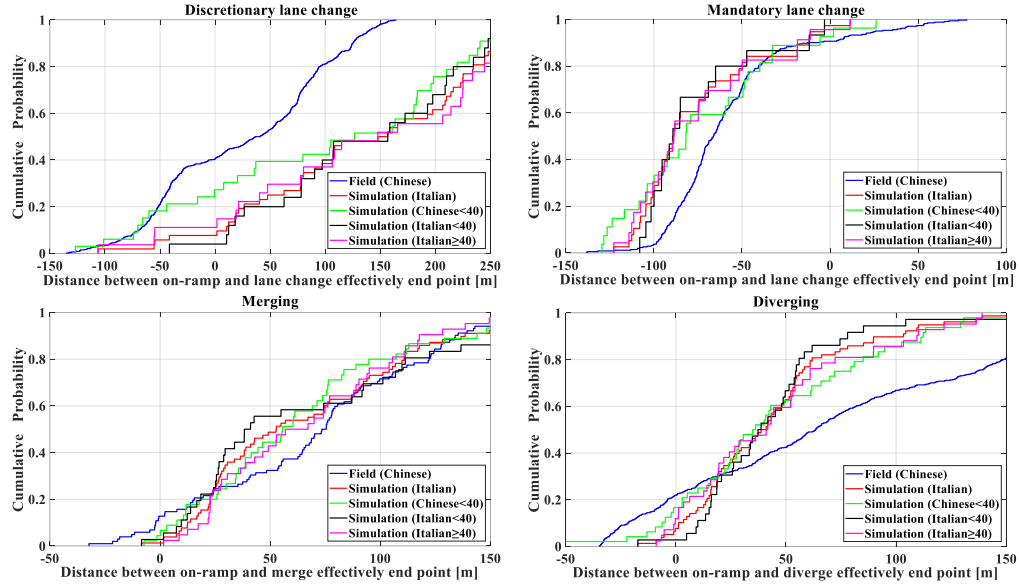


Figure 3.17 Comparison of cumulative probability for distance between on-ramp and lane change effectively end position (positive values indicate lane change ends ahead the on-ramp; negative values indicate otherwise).

For the diverging manoeuvre, field data exhibited a more uniform lane change duration distribution, while simulation data show a higher concentration between 5 and 10 s. Figure 3.17 indicates that field drivers needed a greater distance before initiating diverging, leading to increased interactions with weaving traffic and lower speeds, as shown in Figures 3.11-3.12. According to Hu et al. (2019), vehicles approaching the diverging nose encountered progressively more complex and hazardous conditions, which led to prolonged lane change times. Additionally, when executing merging and diverging manoeuvres in both simulation and field data, the initiation points for these manoeuvres varied. This variation may stem from differences in depth perception and distance estimation between driving simulators and real-world environments (Kemeny & Panerai, 2003; Baumberger et al., 2005). Furthermore, depth perception and distance estimation can differ across simulators depending on their varying levels of fidelity (Himmels et al., 2024).

④ Accepted target lane gap

a. Accepted target lane lead gap (AG_TLead)

The results in Table 3.9 show that AG_TLead distribution for discretionary lane changes differs significantly between field data and simulation. The one-sided alternative hypothesis test confirms the field distribution was significantly higher. Field data shows that AG_TLead was mostly within 0 to 5 s, while simulations had a more even distribution. This suggests that during discretionary lane changes, field

drivers preferred smaller gaps with the target lane's leading vehicle. For mandatory lane change, the AG_TLead distribution in field data and simulations was nearly identical, indicating similar lead gaps with the target lane's leading vehicle during the manoeuvre. As shown in Figure 3.18, the differences between simulation data and field data for manoeuvres are relatively small, except in the case of discretionary lane changes. Discretionary lane changes represent spontaneous decisions made by drivers, whereas the other three manoeuvres are mandatory, allowing drivers limited flexibility in selecting accepted gaps. As a result, in the simulation experiments, the accepted gaps for mandatory manoeuvres were significantly smaller than those observed for discretionary lane changes. Regarding merging manoeuvres, there was no significant difference in the AG_TLead distribution among Italians, young Italians, old Italians, and field. Nevertheless, significant differences were observed between field and Chinese. The results of one-sided alternative hypothesis test indicated that the AG_TLead distribution for Chinese was significantly smaller compared to field, suggesting that Chinese accepted a larger gap with the leading vehicle of target lane during merging manoeuvres in simulation environment. A comparison of AG_TLead distribution in diverging manoeuvres shows that simulation significantly differed from field. The results of one-sided alternative hypothesis test show that, the AG_TLead distribution in field was significantly higher than that of simulation, suggesting that simulation drivers accepted a larger lead gap.

Table 3.9. The results of two-sided K-S test for AG_TLead.

LC ^a Type	Comparison Group Pairs			
	Field (Chinese) vs. Simulation (Italian)	Field (Chinese) vs. Simulation (Chinese<40)	Field (Chinese) vs. Simulation (Italian<40)	Field (Chinese) vs. Simulation (Italian≥40)
DLC^b	$D=0.5265$	$D=0.5064$	$D=0.5094$	$D=0.5483$
	$p<.0001$	$p<.0001$	$p<.0001$	$p<.0001$
MLC^c	$D=0.1613$	$D=0.2182$	$D=0.1452$	$D=0.1819$
	$p=.3648$	$p=.2565$	$p=.9117$	$p=.4736$
Merging	$D=0.2070$	$D=0.4430$	$D=0.2991$	$D=0.2606$
	$p=.0809$	$p<.0001$	$p=.0350$	$p=.0490$
Diverging	$D=0.3096$	$D=0.3068$	$D=0.3540$	$D=0.2820$
	$p<.0001$	$p=.0039$	$p<.0001$	$p=.0079$

Note: ^a: lane change; ^b: discretionary lane change; ^c: mandatory lane change.

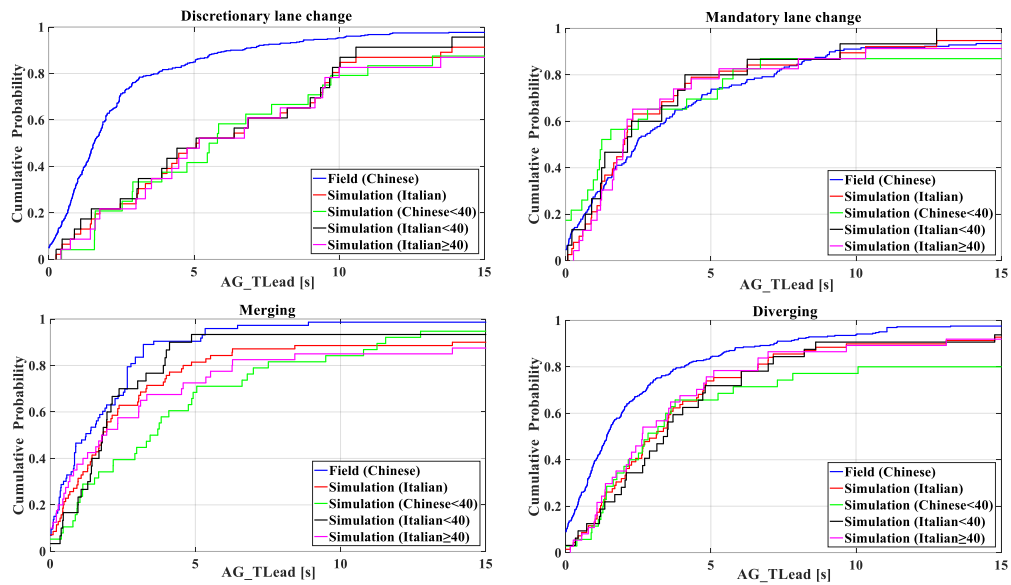


Figure 3.18 Comparison of the cumulative probability of AG_TLead.

b. Accepted target lane lag gap (AG_TLag)

As depicted in Table 3.10, in discretionary lane change, only Chinese and young Italians exhibited no significant differences in AG_TLag distribution compared to field, while Italians and old Italians showed significant differences. The one-sided alternative hypothesis tests indicate that field distribution was significantly larger than that of two groups, suggesting that Italian and older Italians accepted a larger lag gap. For mandatory lane change, the one-sided alternative hypothesis test results show that field distribution was significantly larger, indicating that the AG_TLag values in simulation tended to be larger than those in field. Additionally, it is observed that the proportion of AG_TLag values exceeding 15 s in simulation was higher compared to other manoeuvres.

Table 3.10. The results of two-sided K-S test for AG_TLag.

LC ^a Type	Comparison Group Pairs			
	Field (Chinese) vs. Simulation (Italian)	Field (Chinese) vs. Simulation (Chinese<40)	Field (Chinese) vs. Simulation (Italian<40)	Field (Chinese) vs. Simulation (Italian≥40)
DLC^b	$D=0.4000$	$D=0.2900$	$D=0.4818$	$D=0.4118$
	$p<.0001$	$p=.1685$	$p=.0340$	$p=.0051$
MLC^c	$D=0.8904$	$D=0.7600$	$D=0.9898$	$D=0.8416$
	$p<.0001$	$p<.0001$	$p<.0001$	$p<.0001$
Merging	$D=0.5345$	$D=0.5568$	$D=0.5822$	$D=0.5064$
	$p<.0001$	$p<.0001$	$p<.0001$	$p<.0001$
Diverging	$D=0.4596$	$D=0.5402$	$D=0.4045$	$D=0.5419$
	$p<.0001$	$p=.0015$	$p<.0001$	$p<.0001$

Note: ^a: lane change; ^b: discretionary lane change; ^c: mandatory lane change.

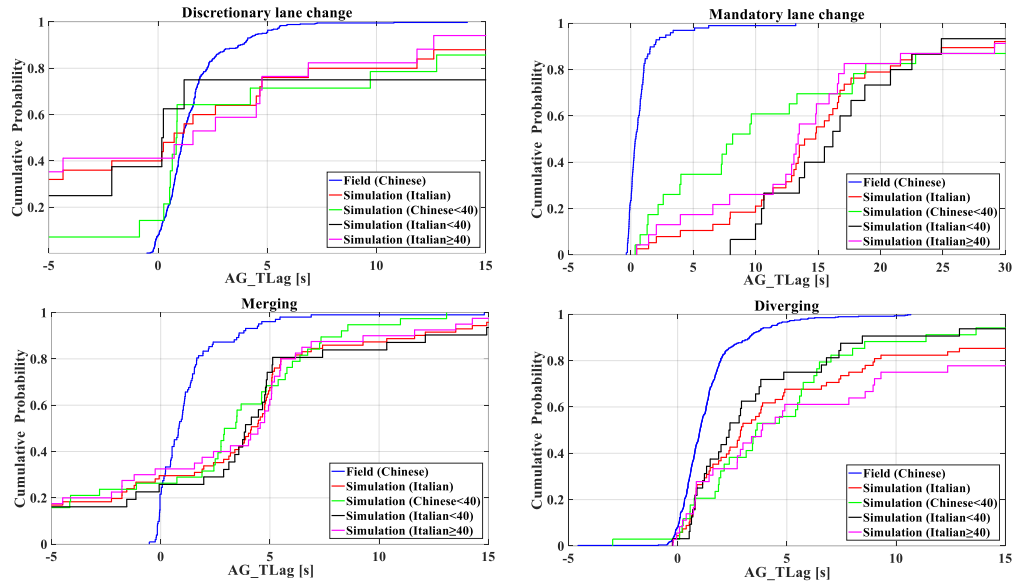


Figure 3.19 Comparison of the cumulative probability of AG_TLag.

For the merging scenario, the results of one-sided alternative hypothesis test indicate that the AG_TLag distribution of field was significantly lower than that of Italian and old Italians, but significantly higher than that of Chinese and young Italians. This indicates that during the merging manoeuvre, the accepted lag gaps in ascending order were: Italian and old Italians, followed by those based on field data, and finally Chinese and young Italians. Given that all Chinese participants in simulation were under 40, this implies that young drivers may accept larger lag gaps when merging. Regarding diverging, the two-sided K-S test results indicate that the AG_TLag distribution of simulation significantly differed from that of field data. The significant differences are primarily concentrated on the right side, as illustrated in Figure 3.19. Specifically, AG_TLag values for field predominantly fell within the 0 to 5 s, whereas simulation exhibited a notable proportion of larger AG_TLag values.

During discretionary lane change simulation groups tended to accept larger AG_TLag values compared to field. Additionally, no significant difference was observed in AG_TLag distribution among Chinese, young Italians, and field data. Conversely, old Italians demonstrated greater AG_TLag characteristics. These results are consistent with previous findings suggesting that when discretionary lane change requires longer time, the simulation groups opt not to perform discretionary lane change due to accepting larger accepted gaps. Several studies have also demonstrated that accepted gaps are critical factors influencing a driver's decision to make a discretionary lane change (Xie et al., 2019; Alshehri & Abdul Aziz, 2022).

For mandatory lane change, the distribution characteristics of AG_TLag between field and simulation showed no significant difference, supporting the conclusion that the lane change duration distribution in this scenario were similar. In contrast, one-sided K-S test results indicate that simulation groups exhibited significantly larger AG_TLag values. As illustrated in Figure 3.16, simulation drivers changed lanes to the right earlier to create more favourable conditions for diverging. Consequently, this resulted in a notably larger lag gap. Regarding

merging, no significant difference in the AG_TLead distribution characteristics was found between Italians, young Italians, old Italians, and field data, whereas Chinese exhibited larger AG_TLead values than field data. Additionally, the AG_TLag values were ranked in ascending order: Italians, old Italians, followed by field data, and finally Chinese and young Italians. This suggest that younger participants accepted larger lag gaps during merging. This observation contrasts with prior research (Chityala, 2017; Chityala et al., 2020). The discrepancy may be attributed to the fact that most young drivers in this study were students from universities and novice drivers, who generally display more conservative driving behaviours.

Additionally, as shown in Figure 3.19, certain simulation data during the merging process exhibited a negative AG_TLag, indicative of forced lane changes. This phenomenon can be attributed to the proximity of the simulation drivers' merge position to the curve, as illustrated in Figure 3.16, which could obstruct the drivers' rear view of vehicles. The analysis reveals that simulation data consistently exhibited significantly higher AG_TLead and AG_TLag values compared to field data during diverging manoeuvres. It is evident that the AG_TLag distribution between simulation and field shows more discrepancies than the AG_TLead distribution. A plausible explanation is that drivers relied on mirrors to estimate the lag gap, which may result in less accurate perception than when estimating the lead gap (Yang et al., 2019). Furthermore, most drivers turned their heads to check the blind spot when changing lanes (Chovan et al., 2014; Barat & Das, 2024), but the field of view offered by the simulator utilised in this study is somewhat restricted. Consequently, simulation participants demonstrated reduced capability in detecting vehicles within the blind spot, resulting in more frequent forced lane changes and less confident lane changes that required larger lag gaps. Another possible cause of this phenomenon is the truncation of headway in the experimental design. Therefore, some relatively smaller headways were excluded from the simulation environment, leading to larger accepted gap being observed in the simulated vehicle data compared to those in the field.

⑤ *GTTC*

The two-sided K-S test results in Table 3.11 indicate no significant difference in *GTTC* between field and simulation during discretionary lane change. Notably, the difference between Chinese participants and field data was minimal ($D=0.0925$, $p=.7952$). In contrast, during mandatory lane change, one-sided alternative hypothesis test results show that Italians and old Italians had greater *GTTC* values than field. Still, there were no significant differences in *GTTC* distribution between Chinese and young Italians compared to field, with the difference between Chinese and field data being particularly small ($D=0.0672$, $p=.9783$). Given that all Chinese participants were under 40, this suggests that younger drivers in simulation may exhibit smaller *GTTC* values more closely resembling those in field when performing mandatory lane change. Regarding merging manoeuvres, there was no significant difference in *GTTC* distribution between Chinese and field. Conversely, the other three groups (Italians, young Italians, and old Italians) exhibited significant differences from field. One-sided alternative hypothesis test results

indicate that these groups had larger *GTTC* values than field. For the diverging scenarios, the two-sided K-S test results showed no significant difference in *GTTC* distribution between the Chinese and field data ($D=0.1862$, $p=.0413$). The one-sided alternative hypothesis test results demonstrate that, similar to merging scenarios, the three sets of simulation data exhibited higher *GTTC* values than the field data during diverging.

Table 3.11. The results of two-sided K-S test for *GTTC*.

LC ^a Type	Comparison Group Pairs			
	Field (Chinese) vs. Simulation (Italian)	Field (Chinese) vs. Simulation (Chinese<40)	Field (Chinese) vs. Simulation (Italian<40)	Field (Chinese) vs. Simulation (Italian≥40)
DLC^b	$D=0.1652$ $p=.0286$	$D=0.0925$ $p=.7952$	$D=0.1605$ $p=.1854$	$D=0.2150$ $p=.0323$
MLC^c	$D=0.2000$ $p=.0041$	$D=0.0672$ $p=.9783$	$D=0.1669$ $p=.1527$	$D=0.2577$ $p=.0044$
Merging	$D=0.3401$ $p<.0001$	$D=0.1975$ $p=.0388$	$D=0.3783$ $p<.0001$	$D=0.3172$ $p<.0001$
Diverging	$D=0.2771$ $p<.0001$	$D=0.1862$ $p=.0413$	$D=0.2678$ $p=.0037$	$D=0.3152$ $p<.0001$

Note: ^a: lane change; ^b: discretionary lane change; ^c: mandatory lane change.

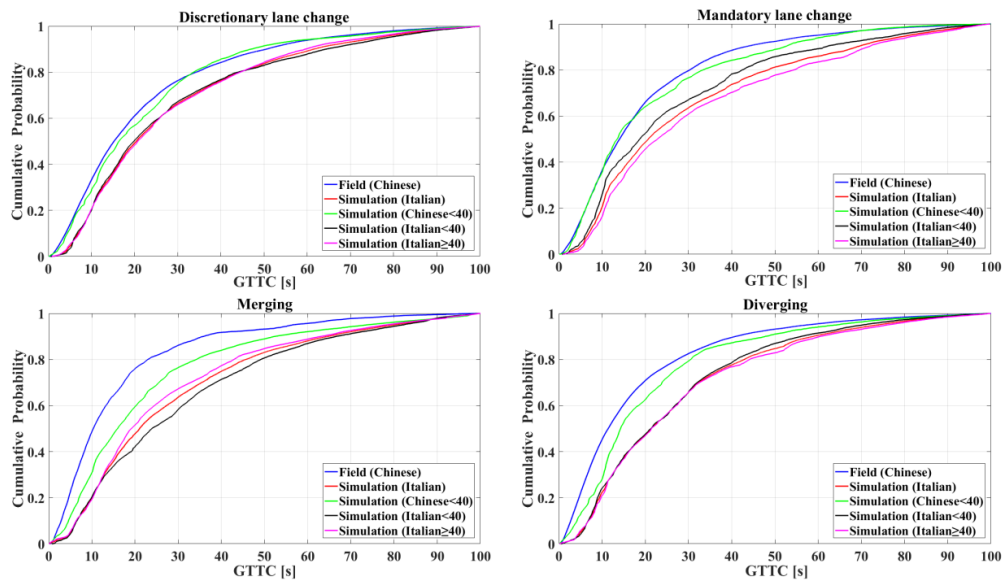


Figure 3.20 Comparison of the cumulative probability of *GTTC*.

From the previous analysis, it can be inferred that *GTTC* may correlate with observed variables during lane change manoeuvres. Mwesige et al. (2016) and Karimi et al. (2021) demonstrated that TTC decreases as passing duration increases and effective accepted gap decreases. They also established a significant relationship between TTC and the ratio of lane change duration to the effective accepted gap. To investigate the potential relationships between observed variables of this study and *GTTC*, further data processing was conducted. Specifically, the minimum *GTTC* between the ego vehicle and the leading and following vehicles of

target lane during each lane change is denoted as $minGTTC$, lane change duration is denoted as LCD , and the accepted gap of target lane at the initiation of lane change is represented by AG . The scatterplot illustrating the relationship between lane change duration to accepted gap ratio and $minGTTC$ is presented in Figure 3.21. The distribution of data points between field and simulation datasets is largely consistent. Most data points from both sources are concentrated in the region where the LCD/AG ratio ranges from 0 to 1. Specifically, when this ratio is within 0 to 1, a significantly higher number of data points exhibit $minGTTC$ greater than 5 s. Conversely, when the ratio exceeds 1, the likelihood of $minGTTC$ being less than 5 s increases. Field data shows a higher frequency of data points with larger LCD/AG ratios, possibly due to smaller accepted gaps observed in field compared to simulation as depicted in Figure 3.19. Notably, even within the 0 to 1 ratio range, numerous data points still have $minGTTC$ less than 5 s. This discrepancy may be attributed to the dynamic nature of lane changes, where the observed variables represent only a single time segment and could be influenced by unobserved heterogeneity. Therefore, further statistical analysis is recommended.

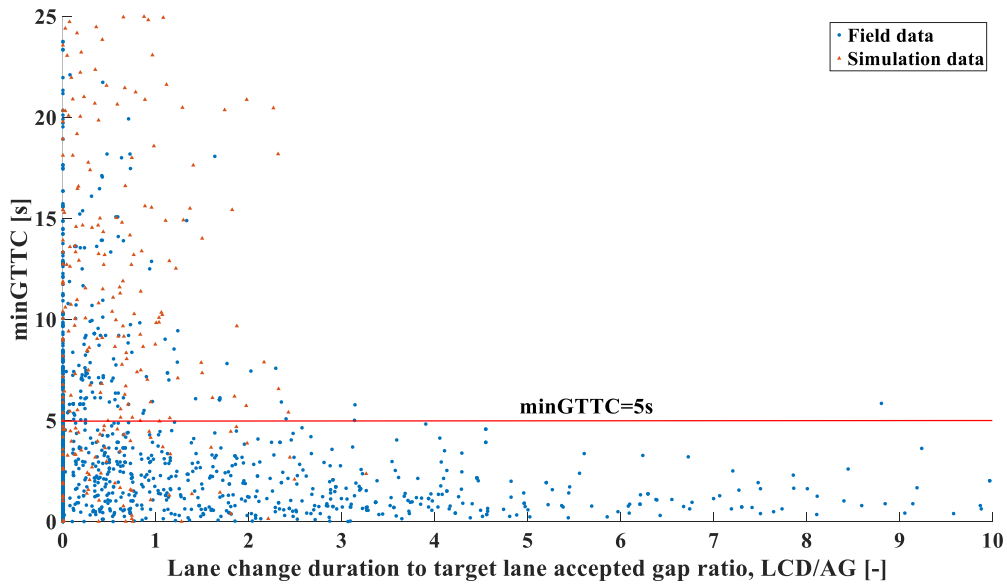


Figure 3.21 Relationship between LCD/AG ratio and $minGTTC$.

The results indicate that during the discretionary lane change scenarios, there was no significant difference in $GTTC$ distribution between field and simulation. During mandatory lane change, Chinese and young Italians exhibited $GTTC$ distributions that closely resemble those from field data, whereas Italians and old Italians displayed significantly higher $GTTC$ values compared to field. This suggests that younger drivers had lower $GTTC$ values during mandatory lane change, which aligns with previous findings (Montgomery et al., 2014; Ali et al., 2019). Regarding the merging and diverging scenarios, apart from Chinese data and field data showing no significant difference in $GTTC$ distribution, the other three sets of simulation data' $GTTC$ values were significantly higher than those of field data. This phenomenon may be attributed to the substantially smaller AG_TLag

observed in field data (Figure 3.19). Previous studies have demonstrated that a lower accepted gap correlates with a lower TTC value (Mwesige et al., 2016; Karimi et al., 2021). By analysing the scatter plot of LCD/AG ratio versus $minGTTC$, it is observed that the distribution of data points in the field data and simulation data was largely consistent, though some discrepancies remain. Additionally, field data exhibited a higher frequency of data points with larger LCD/AG ratios, likely attributable to the smaller accepted gaps observed in real-world scenarios. This indicates that simulation data may not fully capture the extremely hazardous conditions present in field data. Considering that lane changes entail a multifaceted process, risk assessment is inherently multidimensional and may be influenced by unobserved heterogeneity, thus warranting further investigation.

⑥Summary of statistical test results of lane-changing behaviour characteristic metrics

Based on the systematic analysis results of the two-sample K-S test, Table 3.12 summarises the statistical comparison of all lane-changing behaviour characteristic metrics. Through an in-depth examination of the metrics, it can be found that the simulation data and the field observation data show both a certain degree of statistical similarity in distribution characteristics and systematic differences of research significance. From the perspective of metrics that represent traffic operation efficiency at the macro level, variables related to traffic capacity, including speed and headway, show a high degree of statistical consistency between the simulated and field data. Particularly notable is that the distribution characteristics of the Chinese driver group involved in the simulation experiment were closest to the field observation data. This finding not only achieved the absolute validation of the simulation system but also the goal of relative validation, thereby confirming from multiple perspectives the effectiveness of the simulation system in reproducing the characteristics of the macroscopic traffic flow.

In terms of the characteristic metrics characterizing specific lane-changing behaviour at the micro level, such as lane-changing duration, accepted target lane gap, and $GTTC$ during the lane-changing process, the simulation data showed more significant distribution differences compared to the field observations. Nevertheless, these metrics still achieved the goal of relative validation, mainly by maintaining basically consistent pattern characteristics in terms of relative size relationships and changing trends between the simulation and field data. The formation of this pattern of disparity may stem from the essential differences in modelling complexity, where variables related to traffic efficiency are typically governed by relatively simple following rules, while lane-changing behaviour itself, as a complex process involving multi-factor decision-making, faces greater technical challenges in its precise simulation. The results of this study have important methodological implications for subsequent related research. When researchers used driving simulators to study driving behaviour in weaving sections, they were relatively confident that driving behaviour variables related to traffic efficiency could better reflect real-world observations. However, for microscopic parameters involving

specific lane-changing behaviour, their correspondence to field observations needs to be treated with caution. It is recommended that the sensitivity of these parameters be fully considered in the research design and their reliability be ensured through multiple validation methods. This finding also points to the improvement of future driving simulation models, especially the need for more research efforts in the refinement of lane-changing decision models and the improvement of validation methods.

In addition, the findings suggest that there are differences in behavioural representation among different driver groups in the simulation environment, and this group specificity provides a new entry point for further research. Future work should focus on examining the intrinsic mechanisms that cause such group differences, including the influence paths of factors such as cultural background, driving experience, and risk preference on driving behaviour in simulated environments, thereby further enhancing the depth and breadth of driving behaviour research.

Table 3.12. Summary of statistical test results and corresponding interpretations.

Metrics	Statistical similarity	Statistical difference	Explanations and implications
Speed	Italians: through, merging; Chinese: through, merging, diverging, ramp to ramp.	Italians showed higher speeds, particularly in ramps.	Simulation could affect speed perception and control, especially on curved sections like ramps (Godley et al., 2002; Chen et al., 2021).
Headway	Italians: through, diverging; Chinese: merging, diverging, ramp to ramp.	Differences found in the spatial distribution during merging and ramp-to-ramp manoeuvres. Chinese maintained larger headways.	Simulation struggles to accurately model the vehicle interactions and complex congestion dynamics at the tail of the weaving section (Wan et al., 2014). Novice drivers tended to keep greater headways (Yang & Wu, 2017; Yang et al., 2021).
Lane change duration	Italians: mandatory lane change.	Longer discretionary lane change durations in field. Chinese had shorter mandatory lane change durations. Simulation drivers required more time to merge compared to field drivers. Field drivers needed longer time to diverge.	Fewer discretionary lane changes were observed in simulation. Novice drivers spend less time checking the traffic compared to experienced drivers during lane changes (Yang et al., 2006). Field drivers merged from a position farther from the on-ramp, allowing enough acceleration and a smoother entry onto the main road (Kou & Machemehl, 1997; Daamen et al., 2010). Field drivers needed more distance to diverge, leading to increased interactions with weaving traffic and consequently lower speeds (Hu et al., 2019).
Accepted gap	AG_Lead (Italians: mandatory lane change, merging; Chinese: mandatory lane change); AG_Lag (Chinese: discretionary lane change).	Simulation groups accepted larger gaps during discretionary lane changes. Simulation groups exhibited larger lag gaps during mandatory lane change. Younger drivers accepted larger gaps during merging and diverging.	Simulation groups opt not to perform discretionary lane change due to accepting larger accepted gaps (Xie et al., 2019; Alshehri & Abdul Aziz, 2022). Simulation drivers changed lanes to the right earlier to create more favourable conditions for diverging. This observation contrasts with prior research (Chityala, 2017; Chityala et al., 2020), which may be due to the fact that most young

<i>GTTC</i>	Italians: discretionary lane change; Chinese: discretionary lane change, mandatory lane change, merging, diverging.	Forced lane changes occurred in the simulation.	drivers in this study were university students and novice drivers, who tend to drive more conservatively. Drivers relied on mirrors to estimate the lag gap, which may result in less accurate perception than estimating the lead gap (Yang et al., 2019). Simulation drivers exhibited a diminished ability to detect vehicles within the blind spots (Chovan et al., 2014; Barat & Das, 2024).
		Young drivers appeared to have lower <i>GTTC</i> values compared to other groups.	Though young drivers accepted larger gaps, they may not control speed well, leading to smaller <i>GTTC</i> values (Montgomery et al., 2014; Ali et al., 2019).
		Field drivers exhibited smaller <i>GTTC</i> values.	Substantially smaller lag gaps observed in the field. Previous studies have demonstrated that a lower accepted gap correlates with a lower TTC value (Mwesige et al., 2016; Karimi et al., 2021).

3.4 Conclusions

Based on the video trajectory data of the weaving section collected by drones in Chapter 2, this chapter constructs a high-fidelity driving simulation experimental environment, which fully reproduces the complex scenarios of the weaving section including static road infrastructure and dynamic traffic flow operation states. By using the scientific experimental route design and response surface central composite design method, the driving simulation experiment scheme was systematically planned to accurately reproduce the geometric linear features and traffic operation conditions of the field weaving section.

To explore the cross-cultural differences in driving behaviour, this study recruited representative Italian and Chinese drivers to participate in the experiment and systematically collected their complete driving behaviour data in the complex traffic environment of the weaving section. Based on the established lane-changing behaviour characteristic index system, a two-sample K-S test method was used to conduct a comprehensive comparative analysis of the distribution characteristics of the simulation data and the field observation data.

The statistical test results show that in terms of speed and headway variables that represent macro-traffic efficiency, the simulation data and field observation data have achieved the dual goals of absolute validation and relative validation. In terms of metrics such as the lane change duration, accepted target gap, and *GTTC*, the basic requirements for relative validation were achieved. This series of validation results fully demonstrated that the experimental design scheme adopted in this study was highly scientific and effective, and the driving behaviour data obtained had good reliability and validity.

It should be particularly noted that there are certain systematic differences between the experimental data collected through the driving simulator and the field trajectory data extracted based on drone video in Chapter 2. The differences are mainly due to three aspects: the essential differences in data collection methods, the differences in data processing accuracy, and the limitations of the simulation technology itself. However, it is these differences that make the two types of data complement each other well: driving simulation data provides an accurate record of behaviour in a controlled environment, while field observation data truly reflects driving performance in a natural traffic environment. This cross-validation strategy for multi-source data not only significantly enhances the reliability of the research conclusions, but also expands the depth and breadth of the research results at the methodological level.

The findings of this study have dual implications for the field of driving behaviour research: on the one hand, they provide a clear technical path for improving the accuracy of driving simulation models; on the other hand, they offer a new theoretical perspective for a deeper understanding of driving decision-making mechanisms. The pattern of differences between simulation and field observations further indicates that drivers' lane-changing behaviour in weaving sections is influenced by the complex interaction of multiple levels of factors such

as data sources and lane-changing types, an important finding worthy of further exploration in subsequent studies. Based on the weaving section driving behaviour database jointly constructed in this chapter and Chapter 2, subsequent studies will focus on modelling the risk decision-making mechanism and causation mechanism of weaving section lane-changing behaviour, providing theoretical basis and practical guidance for the safety design and operation management of weaving sections.

Chapter 4

4. Modelling heterogeneity in lane-changing behaviour decisions at the weaving section using a hierarchical Bayesian framework

4.1 Background

Based on the database of drone video trajectories established in Chapter 2, Chapter 3 further designs and implements systematic driving simulation experiments to obtain multi-dimensional driving behaviour data of representative Italian and Chinese drivers in complex weaving section scenarios. By using statistical methods such as the two-sample K-S test for comparative analysis of the two sets of data, the study not only revealed the probability distribution patterns and spatial distribution characteristics of different types of lane-changing behaviours, but also systematically explained the influence mechanisms of demographic variables such as age and nationality on lane-changing behaviour characteristics. The results of Chapter 3 also show significant systematic differences between the driving simulation data and the field observation data, which reveal the complex interaction of multiple factors such as data collection methods and lane-changing types in the weaving section. Although the study in Chapter 3 has systematically described the representational characteristics of lane-changing behaviour, there is still a lack of in-depth exploration of the underlying formation mechanism behind the behaviour characteristics, especially the traffic environmental risk factors that affect the lane-changing decision-making process have not been effectively identified. To this end, based on the reliable datasets established in the previous two chapters, this chapter will focus on the following three aspects of in-depth research: First, to explore the intrinsic logical mechanism and individual heterogeneity characteristics of drivers' lane-changing decisions. Second, to identify the key risk factors for high-risk

behaviours such as forced lane changes observed in the data. Third, build a mathematical model that reflects the lane-changing decision-making mechanism to reveal the underlying mechanism of risk formation. The specific research approach includes: integrating the high-precision trajectory data from Chapter 2 with the multi-dimensional simulation data from Chapter 3, based on the theoretical framework of lane-changing decision-making, fully considering the multi-level structure characteristics of the data, screening the key influencing metrics in the lane-changing decision-making process, and establishing a lane-changing behaviour decision-making model in the weaving section that can represent individual heterogeneity. Through the application of this model, the aim is to systematically identify the key risk factors in lane-changing decisions, deeply analyse the heterogeneous characteristics of different lane-changing behaviours in the decision-making process, and thereby fully reveal the risky decision-making mechanism behind lane-changing behaviours in weaving section. The advancement of these research contents will effectively expand the depth of Chapter 3 research and provide more solid theoretical support and practical guidance for the safety design and operation management of weaving sections.

4.2 Data collection and processing

4.2.1 Extraction of the trajectories of lane-changing vehicles and key lane-changing participants

Based on the previous research accumulation, the empirical data used in this chapter for the risky decision-making study of lane-changing behaviour in the weaving section mainly comes from two sources: one is the trajectory data of field observation videos collected by drones, and the other is the simulation behaviour data obtained through driving simulation experiments. These two types of data form an effective complementarity in the spatiotemporal dimension, laying a solid empirical foundation for the subsequent system identification and analysis of risk factors in the lane-changing decision-making process. In terms of data size, the field observations have successfully captured 1,666 effective lane-changing behaviours, which can be further subdivided based on their behavioural characteristics as follows: 660 discretionary lane changes, 343 mandatory lane changes, 102 merging manoeuvres, and 561 diverging manoeuvres. In the simulation experiment, a total of 395 lane changes were recorded, of which 152 were completed by Chinese drivers and 243 by Italian drivers. By lane-changing type, it included 85 discretionary lane changes, 65 mandatory lane changes, 123 merging manoeuvres and 122 diverging manoeuvres. By systematically integrating the field observation data extracted in Chapter 2 with the simulation data collected in Chapter 3, a research sample library containing 2,061 lane-changing behaviours was finally constructed, a size that provides sufficient data support for conducting in-depth statistical analysis and modelling. In terms of data processing methods, this study conducted a complete trajectory extraction of key traffic participants during each lane-changing process, including continuous trajectory data of the leading vehicle

in the current lane, the following vehicle in the current lane, the leading vehicle in the target lane, and the following vehicle in the target lane. Based on the wavelet transform analysis method established in Chapter 2, the exact start and end time of each lane change were precisely identified, thereby accurately defining the spatial-temporal boundaries of the lane change process. This technical approach effectively ensures the consistency of the data used in the subsequent analysis of the lane-changing phases.

To ensure the quality and reliability of the research data, all data undergo a systematic sorting and screening process before entering the formal analysis. During the data quality control process, it was found that some of the original trajectories had incomplete lane change execution phases. The main contributing factors identified through analysis are as follows: some vehicles initiate lane-changing manoeuvres before entering the detection range of the drone, while others exit the monitoring area before completing their lane-changing process. For such cases, this study established strict data cleaning standards: (1) if the trajectory of the lane-changing vehicle itself is incomplete during the critical lane-changing execution stage, that record is removed; (2) if only the associated vehicle (such as the leading or following vehicle in the current/target lane) has a missing track during the lane-changing process, the lane-changing record is retained. This processing principle ensures data quality while maximising sample size and ensuring continuity and statistical power for subsequent analysis. Through the above-mentioned systematic data collection, integration and quality control process, this chapter establishes a database of weaving section lane-changing behaviour with high reliability and validity, providing a reliable empirical basis for in-depth study of lane-changing decision-making mechanisms.

4.2.2 Selection of metrics for lane-changing behaviour decision-making

To explore the lane-changing decision-making mechanism of vehicles in weaving sections, this study selects three key decision-making metrics that are most representative of the lane-changing behaviour decision-making stage as the analysis objects: the lane-changing start position, accepted target lane lead gap (AG_TLead), and accepted target lane lag gap (AG_TLag). The establishment of these metrics is based on the specific traffic operation characteristics of weaving section and their significant influence on driving behaviour decisions. Unlike the lane-changing behaviour in regular sections, the lane-changing behaviour in weaving sections has a distinct mandatory feature. The focus of decisions in weaving sections is not on the decision of whether to change lanes (such as discretionary lane changes) and how to choose the appropriate target lane, but on how to complete the necessary lane changes under spatial constraints. This compulsion stems from the special geometric design of weaving section, a particular type of road connection structure whose core feature is that vehicles must complete the necessary lane changes within a limited spatial distance. This spatial constraint, when combined with the frequent lane-changing behaviour, is highly

likely to create traffic conflict points that have a significant impact on the efficiency and safety level of the road section. In this context, the rational choice of lane-changing start position is not only related to the smoothness of the vehicle's trajectory, but also directly affects the stable operation of the traffic flow in the entire weaving section (Marczak et al., 2016; Sulejic et al., 2017; Ma et al., 2020).

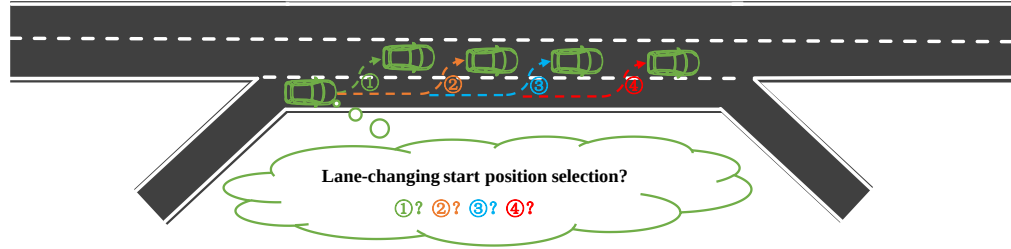


Figure 4.1 Schematic diagram of the decision on the lane-changing start position in the weaving section.

As found in Chapter 3, the selection of lane-changing effectively start and end position is significantly correlated with the lane-changing duration and the state of surrounding traffic flow. Based on this, this study will use the longitudinal distance between lane change start position and the starting point of the weaving section as a key metric to measure the timing of the lane change, reflecting the driver's utilisation strategy of the spatial resources in the weavings section. The acceptance criteria by which the accepted target lane lead and lag gap reflect the driver's judgement and decision on risk in a complex traffic environment. As a core element in the lane-changing decision-making process, it has been widely proven to be of great value in existing studies. This metric is not only closely related to real-time traffic flow density and speed, but also effectively represents the individual characteristics of drivers, including dimensions such as driving style, risk preference, and situational awareness (Balal et al., 2014; Sun and Elefteriadou, 2014; Yang et al., 2019; Das et al., 2020).

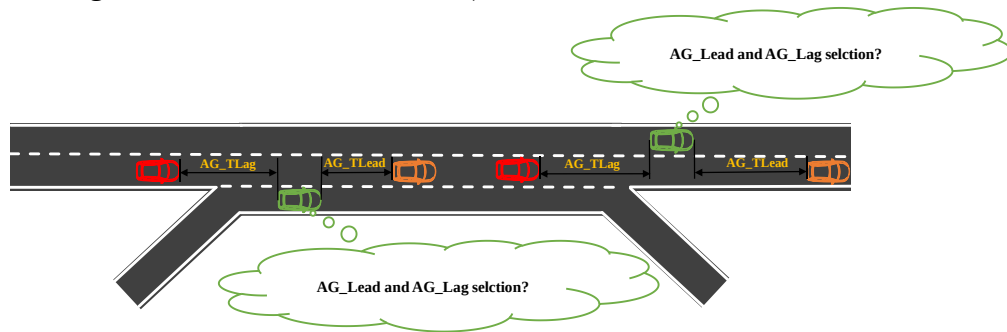


Figure 4.2 Schematic diagram of the decision on the AG_Lead and AG_Lag in the weaving section.

To analyse the risk formation mechanism in lane-changing decisions more precisely and to be consistent with the research framework in Chapters 2 and 3, this chapter further subdivides the accepted target lane gap into two separate metrics: the accepted target lane lead gap (AG_TLead) and the accepted target lane lag gap (AG_TLag). This subdivision approach helps to deeply reveal the differential impact of vehicles at different relative positions on lane-changing decisions,

thereby providing a theoretical basis for constructing more accurate risk assessment models. Through systematic analysis of these three-key metrics, an association model between lane-changing decision-making behaviour in weavings section and potential risk factors is established to provide scientific support for subsequent risk warning and intervention measures.

4.2.3 Variable screening and description

Based on a comprehensive review of the relevant literature, a variety of potential risk factors that may affect the lane-changing decision-making process were comprehensively considered, mainly including lane-changing type, lane-changing direction, vehicle size, surrounding vehicle type, vehicle dynamics parameters, and interaction relationship variables between lane-changing vehicles and relevant traffic participants.

Table 4.1 presents the definitions, units of measurement and descriptive statistical characteristics of all the study variables in detail. From the statistical results, the standard deviation of the starting position of the lane-changing is large, indicating significant heterogeneity in the choice of lane-change position among different types of lane-changing behaviours, reflecting the differentiated decision-making strategies adopted by drivers in different lane-changing situations. An analysis of the accepted target lane gap showed that AG_TLag was lower than AG_TLead, and there were negative gap observations. This finding corroborates the forced lane change observed in Chapter 3, further confirming that in complex traffic conditions in the weaving section, some drivers adopt more aggressive driving strategies and insist on completing the lane change under unfavourable gap conditions. This phenomenon highlights the need to specifically identify the risk factors of forced lane change behaviour. In terms of the composition of data sources, approximately 18% of the lane-changing behaviour samples were derived from driving simulation experiments, providing a comparative basis for exploring the heterogeneity of lane-changing behaviour decisions under different data collection methods. In terms of the distribution of lane change directions, approximately 80% of the lane changes were directed to the right side of the driving direction, a feature consistent with the actual situation in field observations where export behaviour is dominant. In terms of surrounding vehicle types, passenger cars account for more than 90 percent of the relevant vehicles, accurately reflecting the basic characteristics of road traffic composition. Further analysis of the vehicle dynamics parameters reveals that at the lane-changing start position, the speed of the lane-changing vehicle shows a specific gradient feature, with a speed value slightly lower than that of the leading vehicle of current lane, but maintaining a relatively high-speed level relative to the following vehicle of current lane, and the leading and following vehicle of the target lane. This differential pattern of speed distribution, combined with the observed gap distance distribution characteristics, may have a significant impact on the safety of lane-changing decisions and the success rate of execution.

Table 4.1. Variable definitions and descriptive statistics of lane-changing decisions.

Variable definitions	Unit	Mean	SD	Min.	Max.
LocLS: The distance from the starting point of the weaving section to the lane-changing start position.	m	122.52	84.61	4.18	396.54
AG_Lead: The accepted target lane lead gap when the vehicle initiates a lane change.	s	20.52	23.93	-2.24	194.71
AG_Lag: The accepted target lane lag gap when the vehicle initiates a lane change.	s	2.66	8.30	-37.77	160.24
LCTY: Lane-changing type: 0-discretionary lane change, 1-mandatory lane change, 2-merging, 3-diverging.	/	1.43	1.28	0	3
DT: Data type: 0-field data, 1-simulation data.	/	0.18	0.38	0	1
LCdir: Lane-changing direction: 0- change lanes to the right, 1- change lanes to the left.	/	0.20	0.40	0	1
Len_Ego: The length of the lane-changing vehicle.	m	3.70	0.83	2.27	11.43
Len_CL: The length of the leading vehicle in the current lane.	m	3.81	0.95	2.27	11.43
Len_CF: The length of the following vehicle in the current lane.	m	3.76	0.82	2.27	9.36
Len_TL: The length of the leading vehicle in the target lane.	m	3.98	0.84	2.27	10.34
Len_TF: The length of the following vehicle in the target lane.	m	3.89	1.10	2.27	13.97
Wid_Ego: The width of the lane-changing vehicle.	m	1.85	0.23	1.71	2.60
Wid_CL: The width of the leading vehicle in the current lane.	m	1.86	0.26	1.71	2.61
Wid_CF: The width of the following vehicle in the current lane.	m	1.84	0.25	1.71	2.80
Wid_TL: The width of the leading vehicle in the target lane.	m	1.87	0.22	1.73	2.54
Wid_TF: The width of the following vehicle in the target lane.	m	1.85	0.28	1.76	3.03
VT_CL: The type of the leading vehicle in the current lane: 0-passenger car, 1-van.	/	0.05	0.21	0	1
VT_CF: The type of the following vehicle in the current lane: 0-passenger car, 1-van.	/	0.04	0.20	0	1
VT_TL: The type of the leading vehicle in the target lane: 0-passenger car, 1-van.	/	0.04	0.19	0	1
VT_TF: The type of the following vehicle in the target lane: 0-passenger car, 1-van.	/	0.07	0.25	0	1
V_Ego: The speed of the lane-changing vehicle when the vehicle initiates a lane change.	m/s	16.40	3.65	2.53	32.08
V_CL: The speed of the leading vehicle in the current lane when the vehicle initiates a lane change.	m/s	16.77	5.03	0	37.66
V_CF: The speed of the following vehicle in the current lane when the vehicle initiates a lane change.	m/s	14.35	5.85	0	33.65
V_TL: The speed of the leading vehicle in the target lane when the vehicle initiates a lane change.	m/s	16.08	4.30	0	36.05
V_TF: The speed of the following vehicle in the target lane when the vehicle initiates a lane change.	m/s	14.21	4.94	0	33.65

Table 4.1. Variable definitions and descriptive statistics of lane-changing decisions (continued).

Variable definitions	Unit	Mean	SD	Min.	Max.
GD_CL: The gap distance between the lane-changing vehicle and the leading vehicle in the current lane when the vehicle initiates a lane change.	m	46.05	42.67	-0.08	342.48
GD_CF: The gap distance between the lane-changing vehicle and the following vehicle in the current lane when the vehicle initiates a lane change.	m	56.66	57.68	-2.44	222.10
GD_TL: The gap distance between the lane-changing vehicle and the leading vehicle in the target lane when the vehicle initiates a lane change.	m	85.95	84.29	-1.36	331.91
GD_TF: The gap distance between the lane-changing vehicle and the following vehicle in the target lane when the vehicle initiates a lane change.	m	46.29	62.35	-2.81	392.38
VDif_CL: The speed difference between the lane-changing vehicle and the leading vehicle in the current lane when the vehicle initiates a lane change.	m/s	-0.36	4.91	-19.26	32.09
VDif_CF: The speed difference between the lane-changing vehicle and the following vehicle in the current lane when the vehicle initiates a lane change.	m/s	2.05	5.79	-27.19	24.85
VDif_TL: The speed difference between the lane-changing vehicle and the leading vehicle in the target lane when the vehicle initiates a lane change.	m/s	0.32	4.45	-16.83	29.65
VDif_TF: The speed difference between the lane-changing vehicle and the following vehicle in the target lane when the vehicle initiates a lane change.	m/s	2.19	5.30	-27.19	25.26

Before conducting formal modelling analysis, strict data pre-processing must be carried out on the potential risk factors included in the model to ensure the validity and stability of the model's estimation results. First, in view of the possible multicollinearity among the independent variables, this study systematically examined the correlations among the variables and used the Variance Inflation Factor (VIF) as the discriminant. VIF is used to quantify the extent to which the variance of the regression coefficient estimates increases due to the high correlation between independent variables, and its calculation equation is as follows:

$$VIF = \frac{1}{1 - R^2} \quad (\text{Eq4.1})$$

where, R^2 is the coefficient of determination obtained by linear regression of one independent variable over the rest of the independent variables.

It is generally believed that when the VIF value is greater than 10, it indicates severe multicollinearity among the variables, which may affect the accuracy of parameter estimation. After testing, all the VIF values of the variables included in the modelling in this study were below this threshold, so it can be considered that there is no multicollinearity problem among the variables that seriously affects the stability of the model.

To further improve the convergence efficiency and parameter comparability of the model, all continuous variables were standardised in this study. The processing transformed the raw data into a distribution with a mean of 0 and a standard deviation of 1, thereby eliminating the impact on model fitting caused by differences in dimensions and ranges of values among different variables. The specific calculation equation for the normalisation process is as follows:

$$z = \frac{x - \mu}{\sigma} \quad (\text{Eq4.2})$$

where, z represents the normalised variable, x is the original variable value, μ represents the sample mean of the variable, σ represents the standard deviation of the variable.

Through the above systematic pre-processing process, both the potential interference of multicollinearity among variables to model inference was effectively controlled, and the comparability of different variables in the model was enhanced, laying a methodological foundation for the subsequent construction of robust and interpretable lane-changing behaviour decision models.

4.3 Methods

Multilevel data structure is a form of data organisation that can effectively represent the intrinsic hierarchical relationships and complex organisational structure of data. In the real world, many phenomena and processes have inherent hierarchical characteristics, and the multilevel data structure is a scientific description and

systematic expression of these hierarchical characteristics. Hierarchical models, also known as multilevel models, are advanced statistical methods for processing such data. By constructing mathematical models with a hierarchical structure, they can capture variations within and between groups simultaneously and effectively analyse the interaction of different levels of factors on the observed results. This method can not only more accurately identify the differences in effects between different subgroups or populations, but also handle the problem of missing data well, improving the reliability of statistical inference (Tuerlinckx et al., 2006). With the advent of the big data era, data with nested structures or hierarchical features have become increasingly common in various research fields, and hierarchical models have thus been widely applied in multiple disciplines such as social sciences, biomedicine, economics, and engineering technology.

In the field of traffic safety research, multilevel data structures are also widespread (Huang and Abdel-Aty, 2010). Researchers have successfully conducted a series of important studies using hierarchical models, including traffic crash frequency modelling (Yannis et al., 2008; El-Basyouny and Sayed, 2009; Wang and Huang, 2016), crash severity analysis (Jones and Jørgensen, 2003; Kim et al., 2007; Huang et al., 2008), and driving behaviour and attitude research (Vanlaar, 2005a, 2005b). However, most of the existing research has focused on macro-level traffic safety analysis, and the application of hierarchical models for micro-level driving behaviour research, especially for specific driving operations, is still insufficient. In the study of lane-changing behaviour, the driver's decision-making process is complexly influenced by multiple levels of factors such as data type, lane-changing type, and dynamic characteristics of lane-changing events (Deligianni et al., 2017; Yang et al., 2019). This inherent hierarchy makes hierarchical models particularly suitable for the study of lane-changing behaviour decision-making mechanisms.

To verify the necessity of hierarchy in the data, this study conducted a preparatory analysis before formal modelling, constructed generalised linear models and hierarchical linear models respectively, and compared the two models through likelihood ratio tests. The test results showed that the hierarchical linear model provided significantly better goodness of fit than the generalised linear model, which fully demonstrated that the hierarchical structure in the data is an important feature that cannot be ignored. However, traditional hierarchical linear models still have certain limitations when dealing with complex data structures, especially when the data distribution deviates from classical assumptions, traditional methods are prone to estimation bias. For this reason, statisticians turn their attention to the Bayesian statistical framework. Hierarchical Bayesian Model (HBM), as a powerful multi-level data analysis tool, enable adaptive sharing and regularisation of information between different levels by introducing prior distributions and hyperprior distributions of parameters. This approach not only effectively alleviates the problem of overfitting, but also provides more robust statistical inferences in small sample scenarios. Based on the advantages of the hierarchical Bayesian theory, this chapter constructs two advanced Bayesian models: the Hierarchical Bayesian Model (HBM) and the Hierarchical Bayesian

Double-Hurdle model (HBDHM). The two models will explore the key risk factors influencing lane-changing behaviour decisions in weaving section from different perspectives, aiming to deeply analyse the complex mechanisms in the lane-changing decision-making process and provide a more scientific theoretical basis for weaving section safety management.

4.3.1 Hierarchical Bayesian Model (HBM)

(1) Bayesian analysis information sources

In the statistical theory system, the core information sources on which statistical inferences are based can be divided into three aspects: population information, sample information, and prior information. Population information, which reflects the probabilistic distribution characteristics or distribution family attributes of the study population, constitutes the theoretical basis of statistical inference. Sample information, on the other hand, is a collection of actual data obtained through sampling observations, providing empirical support for statistical inference. Classical frequency statistics, which is based on these two types of information, follows a basic paradigm of treating sample data as random realisations from a specific probability distribution. It focuses on inferring population parameters through the characteristics of the sampling distribution of sample statistics. This school considers the parameters to be estimated as fixed yet unknown constants and conducts parameter estimation and hypothesis testing by performing frequency analysis on all possible sample spaces. There is a third kind of important information in the practice of statistical inference: prior information, which refers to the initial understanding of the unknown parameters formed by the researcher based on historical experience, theoretical knowledge, or relevant domain knowledge before collecting the experimental data. It is through the systematic integration of prior information and sample information that Bayesian statistics builds a unique statistical inference system. The method is based on conditional probability theory and emphasises statistical inference based only on actual observed data, without considering the possibility of unobserved samples. In the Bayesian framework, the unknown parameter is given the characteristics of a random variable, its uncertainty is quantified by a prior distribution, and it is modelled using subjective probability. The core mechanism of Bayesian inference lies in the cognitive update through Bayes' theorem: using sample information to modify the prior distribution to obtain the posterior distribution. This way of inference not only achieves the organic integration of prior knowledge and experimental evidence, but also provides complete parameter probability distribution information rather than a single point estimation result.

In the field of traffic safety and driving behaviour research, Bayesian methods are particularly suitable for dealing with small sample problems, complex hierarchical data, and scenarios that require the integration of expert knowledge. This study employs a hierarchical Bayesian modelling framework precisely to effectively capture the multilevel structural features present in the weaving section lane-changing behaviour data, while making full use of the prior information

provided by existing research results, thereby obtaining more robust and reliable statistical inference conclusions.

(2) Hierarchical Bayesian theory

Assuming $Y_1, Y_2, \dots, Y_n$ independent and identically distributed samples drawn from the population Y , the joint probability density function can be expressed as $f(Y, \theta)$:

$$f(Y, \theta) = f(Y_1, Y_2, \dots, Y_n) \quad (\text{Eq4.3})$$

where, θ is the unknown parameter to be estimated.

When a specific observation sample $y = (y_1, y_2, \dots, y_n)$ is obtained, the joint probability density function of the sample under the given parameter θ conditions is the likelihood function $f(y|\theta)$, and its expression is:

$$f(y|\theta) = f(y_1, y_2, \dots, y_n, \theta) \quad (\text{Eq4.4})$$

The likelihood function, which combines information on the population distribution with sample observations, forms the basis of frequency statistical inference. Bayesian statistics regards the unknown parameter θ as a random variable with prior distribution characteristics, assuming its probability density function is $P(\theta)$, then the joint probability density function $P(y, \theta)$ of the sample y and the parameter θ can be expressed as:

$$P(y, \theta) = f(y|\theta)P(\theta) \quad (\text{Eq4.5})$$

Given a set of observations y , parameter θ can be inferred by $P(y, \theta)$. Then it is defined that the edge probability density function $P(y)$ of the sample y :

$$P(y) = \int_{\Theta} P(y, \theta) d\theta = \int_{\Theta} f(y|\theta)P(\theta) d\theta \quad (\text{Eq4.6})$$

where, Θ is the range of values for the parameter θ . According to Bayesian theory, the joint probability density function $P(y, \theta)$ of the sample y and the parameter θ can be expressed as:

$$P(y, \theta) = P(\theta|y)P(y) \quad (\text{Eq4.7})$$

$$P(\theta|y) = \frac{P(y, \theta)}{P(y)} = \frac{f(y|\theta)P(\theta)}{\int_{\Theta} f(y|\theta)P(\theta) d\theta} \quad (\text{Eq4.8})$$

where, $P(\theta|y)$ is the conditional probability density function of the parameter θ in the case of given sample observations y .

Since the edge probability density $P(y)$ is independent of the parameter θ , Equation (4.8) can be simplified as Equation (4.9):

$$P(\theta|y) \propto f(y|\theta)P(\theta) \quad (\text{Eq4.9})$$

Assume the prior distribution $P(\theta)$ is influenced by parameter λ , in Bayesian theory, λ can also be regarded as a random variable that conforms to one kind of distribution. And for the parameter λ involved in the prior distribution of the parameters, its distribution parameters are called hyperprior parameter ω , and its distribution is called the hyperprior distribution (Box and Tiao, 2011). According to Equation (4.9), the posterior distribution in the Hierarchical Bayesian Model can be expressed as Equation (4.10):

$$f(\theta|y) \propto f(y|\theta)f(\theta|\lambda)f(\lambda|\omega) \quad (\text{Eq4.10})$$

The parameters associated with the distribution of the unknown parameters also follow a certain distribution, which causes certain parameters in the Bayesian model to be at different levels, and this multilevel prior structure forms the Hierarchical Bayesian Model (see Figure 4.3). In the field of traffic safety research, this modelling approach is particularly suitable for analysing driving behaviour data with nested structures, which can fully consider the heterogeneity among individuals and integrate prior information from different sources, making it a powerful tool for studying the decision-making mechanism of lane-changing behaviour in weaving section.

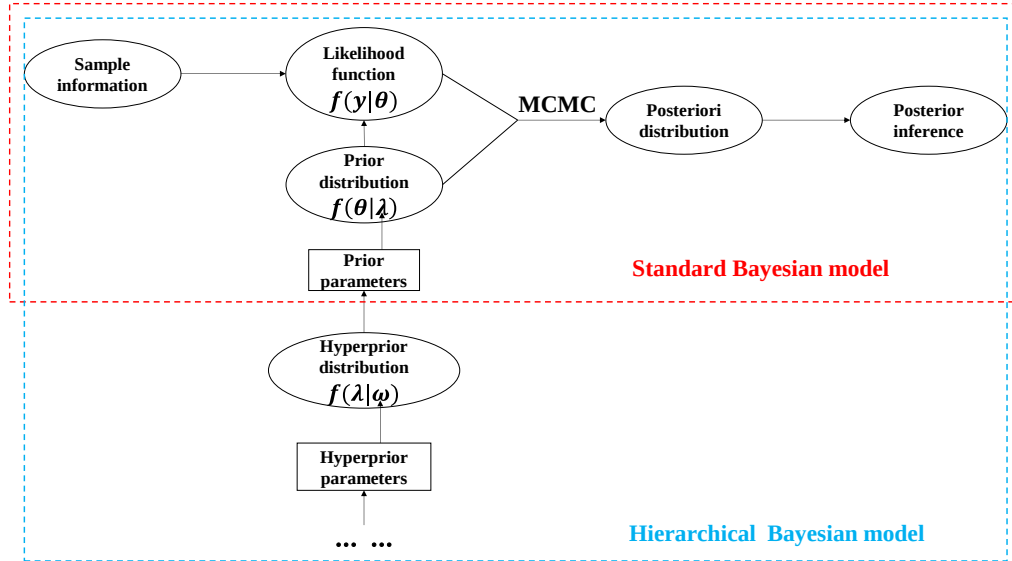
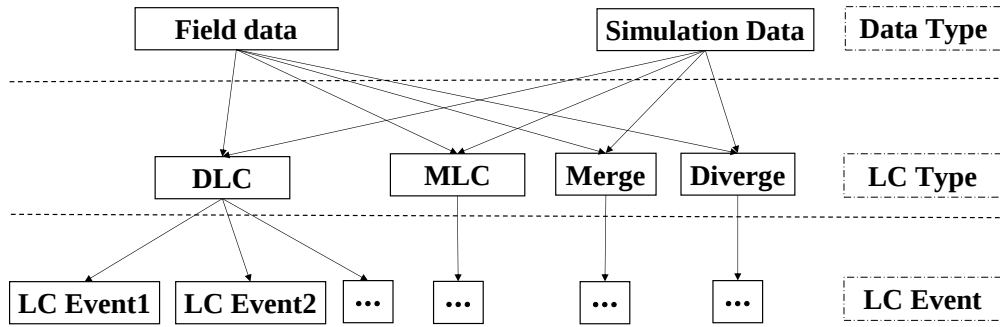


Figure 4.3 Schematic diagram of the standard Bayesian model and the Hierarchical Bayesian model.

(3) Hierarchical Bayesian Model (HBM)

Considering that the lane-changing decision process is influenced by the complex interaction of multiple levels of factors such as data type, lane-changing type, and dynamic characteristics of lane-changing events, and there are significant data nesting structures among the levels, this study specifically constructs a Hierarchical Bayesian Model to accurately capture this complex relationship. Based on the previous exploratory analysis, it was found that the key metrics selected for

the lane-changing decision stage (including the lane-changing start position, the accepted target lane lead gap and lad gap) all showed right-skewed distribution characteristics, in order to meet the model distribution assumption and improve the fitting effect, it was decided to adopt the three-level lognormal model under the complete Bayesian framework (Gelman et al., 1995). The hierarchical structure of the established model is shown in Figure 4.4. It is divided into three logical levels: The first level is the data type level, which distinguishes between two different data sources, field observation data and simulation data, to control the systematic differences caused by the data collection method. The second level is the lane-changing type level, covering four basic lane-changing types: discretionary lane change, mandatory lane change, merging, and diverging, to capture the inherent patterns of different lane-changing behaviour. The third level, the lane-changing event level, represents individual lane-changing observations and serves as the basic unit for model analysis.



Note: LC: lane change; DLC: discretionary lane change; MLC: mandatory lane change.

Figure 4.4 The structure of Hierarchical Bayesian Model.

Let the dependent variable $y_{ijk} > 0$, represent the observations (i.e., lane-changing decision stage metrics) of the lane-changing event i under the data type j and the lane-changing type k , then the model sets its logarithmic transformation values to follow a normal distribution:

$$\log(y_{ijk}) \sim (\mu_{ijk}, \sigma_{\varepsilon}^2) \quad (\text{Eq4.11})$$

Equivalently, Equation (4.11) can also be expressed as follows:

$$y_{ijk} \sim \text{LogNormal}(\mu_{ijk}, \sigma_{\varepsilon}) \quad (\text{Eq4.12})$$

where, μ_{ijk} is the positional parameter on the logarithmic scale (i.e., the expectation of $\log(y_{ijk})$), the subscripts i, j and k are the units of observation at levels 1, 2, and 3 respectively, σ_{ε} is the standard deviation on the logarithmic scale, where *LogNormal* represents the lognormal distribution, and its probability density function is:

$$f(y_{ijk} | \mu_{ijk}, \sigma_\varepsilon) = \frac{1}{y_{ijk} \sigma_\varepsilon \sqrt{2\pi}} \exp\left(-\frac{(\log y_{ijk} - \mu_{ijk})^2}{2\sigma_\varepsilon^2}\right) \quad (\text{Eq4.13})$$

In a three-level structure, the linear predictor μ_{ijk} is defined as:

$$\begin{aligned} \mu_{ijk} = & \beta_0 + \sum_{p=1}^P \beta_p x_{pijk} + \mu_{0jk}^{(2)} + \sum_{p=1}^P \mu_{pjk}^{(2)} x_{pijk} + \mu_{00k}^{(3)} \\ & + \sum_{p=1}^P \mu_{p0k}^{(3)} x_{pijk} \end{aligned} \quad (\text{Eq4.14})$$

where, β_0 is the fixed intercept term, P is the number of independent variables in the model, p represents the index of independent variables, β_p represents the fixed effect coefficient x_{pijk} of the p th independent variable, is the observed value ijk of the p th independent variable, $\mu_{0jk}^{(2)}$ represents the random intercept at the second level, $\mu_{pjk}^{(2)}$ represents the random slope of the p th independent variable at the j th second level unit, $\mu_{00k}^{(3)}$ represents the random intercept at the second level, $\mu_{p0k}^{(3)}$ represents the random slope of the p th independent variable at the k th third level unit.

The distribution of random effects at the second level is:

$$\begin{pmatrix} \mu_{0jk}^{(2)} \\ \mu_{1jk}^{(2)} \\ \vdots \\ \mu_{pjk}^{(2)} \end{pmatrix} \sim MVN(0, \Sigma^{(2)}) \quad (\text{Eq4.15})$$

where, MVN represents the multivariate normal distribution, $\Sigma^{(2)}$ represents the covariance matrix of the second level.

The distribution of random effects at the third level is:

$$\begin{pmatrix} \mu_{00k}^{(3)} \\ \mu_{10k}^{(3)} \\ \vdots \\ \mu_{p0k}^{(3)} \end{pmatrix} \sim MVN(0, \Sigma^{(3)}) \quad (\text{Eq4.16})$$

where, MVN represents the multivariate normal distribution, $\Sigma^{(3)}$ represents the covariance matrix at the third level.

The expression of the covariance matrix is as follows:

$$\Sigma^{(l)} = \begin{pmatrix} \sigma_0^{(l)^2} & \sigma_{01}^{(l)} & \cdots & \sigma_{0p}^{(l)} \\ \sigma_{01}^{(l)} & \sigma_1^{(l)^2} & \cdots & \sigma_{1p}^{(l)} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{0p}^{(l)} & \sigma_{1p}^{(l)} & \cdots & \sigma_p^{(l)^2} \end{pmatrix}, l = 2, 3 \quad (\text{Eq4.17})$$

where $\sigma_0^{(l)^2}$ represents the degree of variation in baseline responses among hierarchical units, with larger values indicating greater differences in average responses among different units; $\sigma_p^{(l)^2}$ represents the degree of variation in the response of the independent variable effect among different units, with a larger value indicating a greater variation in the effect of the independent variable among different units; $\sigma_{0p}^{(l)}$ represents the covariant relationship between the baseline response and the independent variable effect, indicating the strength of the association between the average response level of the unit and the predictor effect; $\sigma_{pq}^{(l)}$ represents the covariance relationship between different predictor effects, representing the association pattern of different predictor effects among units.

4.3.2 Hierarchical Bayesian Double-Hurdle model (HBDHM)

Based on the basic assumptions of the three-level lognormal Bayesian model described in the previous section, the model requires dependent variable $y_{ijk} > 0$. However, the two lane-changing decision stage metrics selected in this chapter (the accepted target lane lead gap (AG_TLead), and the accepted target lane lag gap (AG_TLag)) are not exactly positive in the observed data. There are a few negative values in the data as shown in Figures 3.18 (Comparison of the cumulative probability of AG_TLead) and 3.19 (Comparison of the cumulative probability of AG_TLag) of the study results in Chapter 3. These negative time gap values characterise specific forced lane changes, reflecting the high-risk decision of drivers to insist on completing the lane change under adverse traffic conditions. The presence of negative gaps can be either a result of deteriorating traffic conditions or a manifestation of a driver's stronger tendency to take risks.

Given the presence of meaningful negative values in the dependent variable, the traditional continuous response model is no longer applicable. For this purpose, the double-hurdle model framework is introduced in this study to systematically explore the risk decision-making mechanism by which drivers choose the accepted target lane gap. The double-hurdle model, originally proposed by economist Cragg when analysing household durable goods consumption behaviour, is specifically designed to handle data generation processes with two-stage decision-making characteristics (Cragg, 1971). The basic theoretical assumption of the model is that an individual's final decision requires crossing two separate "hurdles": the first stage determines whether to participate in an activity (participation decision-making), and the second stage determines the degree of participation (quantity decision-making). The key advantage of this modelling framework lies in its ability to distinguish between two different types of zero observations: one is structural

zero (choosing not to participate regardless of environmental conditions), and the other is merging zero, which is influenced by current environmental conditions. Therefore, the double-hurdle model not only considers the existence of the natural zero type, but also allows the probability of zero selection to be determined by individual observable features.

Based on this theoretical framework, this study reconceptualises the driver's decision process of choosing the accepted target lane gap into two consecutive cognitive stages: the first stage is the risk decision, which decides whether to accept the negative gap (i.e., implement a forced lane change); the second stage is the safety decision, which further determines the specific value of the gap size based on accepting the positive target lane gap. The main model for describing the second-stage decision was established in the previous section, and this section will specifically construct the risk decision model (hurdle model) for the first stage.

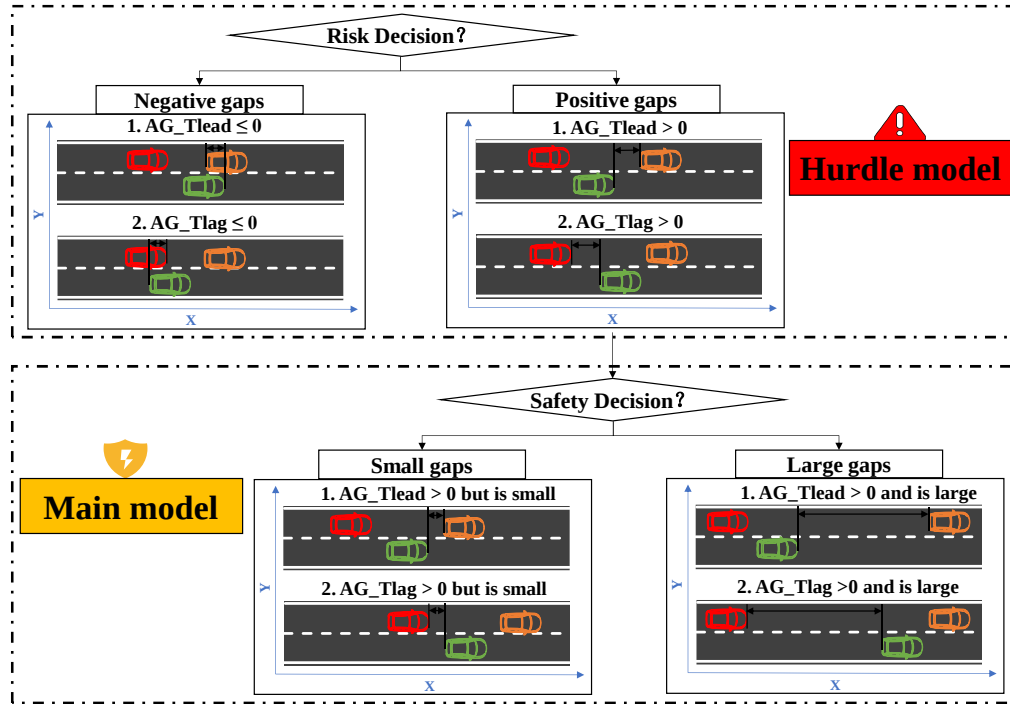


Figure 4.5 Schematic diagram of the Hierarchical Bayesian Double-Hurdle Model structure.

Defining a binary response variable $Y_{mnq} \in \{0, 1\}$ to characterise the outcome of a high-risk lane-changing decision, $Y_{mnq} = 0$ means choosing a negative gap between the leading vehicles in the target lane or the following vehicle in target lane (forced lane-changing), and $Y_{mnq} = 1$ means a positive gap between the leading vehicles in target lane or the following vehicle in target lane. It is assumed that the binary variable Y_{mnq} follows a Bernoulli distribution:

$$Y_{mnq} \sim \text{Bernoulli}(p_{mnq}) \quad (\text{Eq4.18})$$

where, the probability of high-risk lane-changing behaviour is modelled through the logit link function, consistent with the main model, and establishes a three-level

random effects structure model of “data type – lane-changing type – lane-changing event”:

$$\begin{aligned} \text{logit}(p_{mnq}) = & X_{1,mnq}^T \beta_m + Z_{1,mnq}^T (\mu_m) + Z_{2,mnq}^T (v_{mn}) \\ & + Z_{3,mnq}^T (\omega_{mnq}) \end{aligned} \quad (\text{Eq4.19})$$

where, the subscripts, m , n and q are the observation units at levels 1, 2, and 3 respectively, $X_{1,mnq}^T$ are the fixed effect independent variable matrix that affects the probability of risk decision, β_m are the fixed effect coefficients that are allowed to vary with data type m (i.e., different data types have different fixed effects), and $Z_{1,mnq}^T$, $Z_{2,mnq}^T$ and $Z_{3,mnq}^T$ are the random effect design matrix divided into three levels, μ_m , v_{mn} and ω_{mnq} represents the random effects at each level (including random intercept and random slope), and all are assumed to follow a multivariate normal distribution.

In the Bayesian framework, the choice of the prior distribution directly affects the posterior estimation results of the parameters. Ideally, the prior setting should be based on extensive domain knowledge and prior research experience, especially the determination of prior expectations and variances requires careful consideration. Due to the lack of reliable prior information in this study, a weak-information prior strategy was adopted to fully rely on sample data to drive parameter estimation. The specific settings are as follows: the regression coefficients of the main model and the hurdle model, as well as the intercepts of the main model, follow the standard normal distribution $N(0, 102)$. Considering that the proportion of negative accepted target lane gap is relatively low, the intercepts of the hurdle model are set to follow the standard normal distribution $N(0, 1.52)$. The standard deviation of the random effects of the main model and the hurdle model follows an Exponential distribution (0.5), the standard deviation of the lognormal distribution follows an Exponential distribution (1), and the correlation between the random effects is set to $\text{lkj}(2)$, where lkj is the LKJ correlation matrix (Lewandowski et al., 2009). This prior setting ensures the robustness of parameter estimation and provides the model with sufficient flexibility to effectively capture the complex hierarchical structure features in the lane-changing decision-making process.

4.3.3 Model parameter estimation methods

Bayesian estimation, as an important parameter inference method in statistics, has a theoretical core that deduces the posterior probability distribution of parameters by fusing the prior distribution with the sample likelihood function. Under this framework, the prior information can be derived from historical research or domain knowledge (informative prior), or from uninformative prior to demonstrate objectivity (Spiegelhalter et al., 2002). However, the posterior distribution in Bayesian inference often involves high-dimensional complex integrals that are difficult to solve with traditional analytical methods, which becomes the main bottleneck for its practical application. The emergence of Markov Chain Monte

Carlo (MCMC) methods provides an effective solution to this problem. As a stochastic simulation technique, MCMC builds a specially designed Markov chain that smoothly converges to the target posterior distribution, and then obtains posterior samples through on-chain sampling (Sorensen et al., 2002).

However, traditional MCMC algorithms, which employ random walk strategies, have inherent flaws such as low exploration efficiency and high autocorrelation. To enhance sampling performance, researchers have successively proposed improved methods such as Metropolis-Hastings algorithm, Gibbs sampling, and Hamiltonian Monte Carlo (HMC). In this study, Bayesian modelling was implemented using the Stan platform in the R language environment (Stan Development Team, 2023), with its built-in NUTS (No-U-Turn Sampler) algorithm as an optimised version of HMC, which was systematically proposed (Hoffman and Gelman, 2014). The algorithm effectively addresses the inefficiency of Metropolis-Hastings in parameter space exploration by introducing a Hamiltonian dynamical system instead of the traditional random walk mechanism. The core innovation of NUTS lies in its intelligent path search mechanism: it dynamically constructs left and right subtrees through binomial distribution sampling while meeting the constraints, and generates candidate parameter sets using a recursive strategy. When specific acceptance conditions are met, the candidate set is accepted probabilistically and then the search tree continues to expand. Terminate the current iteration immediately when the constraint is violated, and start a new round of sampling after recording the optimal parameter set. This adaptive path control mechanism ensures both sampling integrity and significantly improves convergence efficiency in high-dimensional complex models. Specifically, the NUTS algorithm achieves performance optimisation through the following technical path: First, using gradient information to guide the direction of parameter space exploration to avoid blind random walks. Second, adaptive adjustment of path length is achieved through the recursive binary tree expansion mechanism. Finally, slice sampling techniques are used to ensure that the fine-balance condition holds. These characteristics make it particularly suitable for the Bayesian model with a multi-level random effects structure constructed in this study, providing a solid technical guarantee for estimating the risk factors of lane-changing decisions.

4.3.4 Evaluation metrics for model performance

This study uses a systematic evaluation framework to comprehensively evaluate the established Hierarchical Bayesian Model from two dimensions: model convergence performance and goodness-of-fit. In terms of convergence diagnosis, it was mainly judged by two metrics: potential scale reduction factor ($\hat{R}$) and effective sample size (ESS); In terms of fitting performance evaluation, the intra-group correlation coefficient (ICC) and the criterion of leaving one cross-validation information (LOOIC) are used for quantitative analysis.

(1) Potential scale reduction factor ($\hat{R}$)

Model convergence performance was evaluated using the latent scale reduction factor proposed by Gelman and Rubin (also known as the Gelman-Rubin statistic)

(Gelman and Rubin, 1992). The basic principle of this statistic is to test whether each Markov chain reaches a stable distribution by comparing the variance between the Markov chains and the variance within the chains. The statistic $\hat{R}$ reflects the degree of fusion of sampling results from different Markov chains. When the Markov chains do not converge, the inter-chain variance will be significantly greater than the intra-chain variance, resulting in the value of $\hat{R}$ significantly greater than 1. Conversely, when the chains are fully mixed and reach a stable distribution, the value of $\hat{R}$ will approach 1. According to academic consensus, when the value of $\hat{R}$ is less than 1.05, it can be considered that the model has reached a satisfactory convergence state (Gelman and Rubin, 1992). The specific calculation equation is as follows:

$$\hat{R} = \sqrt{\frac{\widehat{var}(\theta|y)}{W}} \quad (\text{Eq4.20})$$

where W represents the average variance within each Markov chain, $\widehat{var}(\theta|y)$ is an estimate of the variance of the target posterior distribution calculated based on the combined sample of all chains. The statistic $\hat{R}$ provides a reliable basis for determining whether MCMC sampling is adequate by quantifying the ratio of inter-chain to intra-chain variability.

(2) Effective sample size (ESS)

Effective sample size is a core metric for evaluating the quality of Monte Carlo sampling in Markov chains and is primarily used to measure the actual number of independent samples available, considering sample autocorrelation. Due to the autocorrelation between adjacent samples during the MCMC sampling process, the effective sample size is usually significantly smaller than the nominal sample size. The greater the ESS value, the stronger the independence and representativeness of the sample, and the higher the accuracy of the estimation of the posterior distribution statistic (Gelman et al., 1995). The theoretical calculation equation is as follows:

$$ESS = \frac{M \times N}{\tau} \quad (\text{Eq4.21})$$

where, M represents the number of parallel running Markov chains, N is the number of valid iterations retained for each Markov chain after the preheating period, τ is the autocorrelation time, which reflects the rate of decay of the correlation between samples, and the calculation process of τ is given by Equation (4.22):

$$\tau = 1 + 2 \sum_{t=1}^{\infty} \rho_t \quad (\text{Eq4.22})$$

where, ρ_t is the autocorrelation coefficient representing the lag order t , which is estimated by the sample sequence.

When the sample autocorrelation is strong (τ is large), the value will decrease accordingly. In such cases, the number of sampling iterations needs to be increased or the sampling algorithm improved to enhance efficiency. Essentially, *ESS* reflects the number of equivalent independent samples contained in the sample. For example, if *ESS* = 1,000, it indicates that the estimation accuracy of the current sample is equivalent to that of 1,000 completely independent samples, which is usually considered to have sufficient statistical accuracy. In modern Bayesian computational diagnostics, *ESS* is further subdivided into two key metrics: Bulk effective sample size (Bulk-*ESS*) and Tail effective sample size (Tail-*ESS*). The overall effective sample size estimates the reliability of the distribution centre (such as median and mean), and the tail effective sample size estimates the reliability of the distribution tail. The combination of the two can comprehensively assess the robustness of the posterior inference. In general, a value of *ESS* greater than 400 is considered the minimum acceptable standard, and when *ESS* is below this threshold, any statistic calculated based on the sample will have a large error, and the reliability of the results will be significantly reduced.

(3) Intraclass correlation coefficient (ICC)

The intraclass correlation coefficient (ICC) is an important auxiliary statistic for assessing the necessity of hierarchical model structure, used to quantify the degree of homogeneity of intraclass observations, and to reflect the proportion of between-to-group variation in total variation. The ICC ranges from 0 to 1. The larger the value, the greater the contribution of the differences between groups to the overall variation and the more sufficient the necessity of using the hierarchical model. For the three-level data structure (data type – lane-changing type – lane-changing event) constructed in this study, ICC values at different levels need to be calculated separately. For the main model of continuous response variables, the intraclass correlation coefficient calculation equation for the first level (data type level) is as follows:

$$ICC_0 = \frac{\delta_0^2}{\delta_0^2 + \delta_{00}^2 + \sigma^2} \quad (\text{Eq4.23})$$

where, δ_0^2 and δ_{00}^2 represents the variance of the group level random-parameter term, σ^2 represents the variance of the individual level random-parameter term, in the study of this chapter, δ_0^2 represents the variance of the data type level random-parameter term, δ_{00}^2 represents the variance of the lane-changing type level random-parameter term, σ^2 represents the variance of the lane-changing event level random-parameter term. The ICC_0 calculated by Equation (4.23) reflects the extent to which the differences between data types explain the total variance after controlling for other variables.

The ICC calculation equation for the second level of the main model (the lane-changing type level) is:

$$ICC_{00} = \frac{\delta_{00}^2}{\delta_0^2 + \delta_{00}^2 + \sigma^2} \quad (\text{Eq4.24})$$

The ICC_{00} calculated by Equation (4.24) reflects the contribution of differences between lane-changing types to the total variation after controlling for other variables.

Since the hurdle model is a Bernoulli process and its link function is a Logit function, the residual variance is not a fixed value in theory. There are various approximations for calculating ICC, the most used of which is the “latent variable method”. In a mixed model of Logit linkages, its latent variables are assumed to follow a logical distribution, whose variance is $\pi^2/3 \approx 3.29$. The ICC calculated by the hurdle model represents the proportion of variance caused by the group to the total variance (between-to-group variance + variance of underlying latent variables), which measures the extent to which the group affects “whether an event occurs”.

The ICC_h calculation equation for the first level (data type level) of the hurdle model is:

$$ICC_h = \frac{\delta_h^2}{\delta_h^2 + \delta_m^2 + \frac{\pi^2}{3}} \quad (\text{Eq4.25})$$

where, δ_h^2 and δ_m^2 represents the variance of the group level random-parameter term in the hurdle model, which represents the degree of variation in the “logarithmic ratio of event occurrence probability” among different groups. In the study of this chapter, δ_h^2 represent the variance of the random-parameter term at the data type level in the hurdle model, and δ_m^2 represent the variance of the random-parameter term at the lane-changing type level in the hurdle model. The ICC_h calculated by Equation (4.25) reflects the intensity of the influence of the data type on the decision of whether a negative lane-changing accepted target lane gap occurs, after controlling for other variables.

The ICC_m calculation equation for the second level (lane-changing type level) of the hurdle model is:

$$ICC_m = \frac{\delta_m^2}{\delta_h^2 + \delta_m^2 + \frac{\pi^2}{3}} \quad (\text{Eq4.26})$$

The ICC_h calculated by Equation (4.26) reflects the extent to which the lane-changing type affects “whether a negative lane-changing accepted target lane gap occurs” after controlling for other variables. By systematically calculating these ICC metrics, a comprehensive assessment can be made of the relative importance of each level in explaining the variation of lane-changing behaviour decisions, providing a statistical basis for the rationality of the model setting. It should be

particularly noted that when calculating ICC in a Bayesian Hierarchical Model, the null model is usually used for estimation. This is because the null model provides a baseline variance decomposition result that is not disturbed by other covariates or effects, which can more accurately reflect the original variation distribution in the hierarchical structure.

(4) Leave-one-out cross-validation (LOOIC)

In this study, the LOOIC was used to systematically evaluate the generalisation ability of the models. This metric provides an objective basis for model comparison by measuring the predictive performance of the models on untrained data (Vehtari et al., 2017). As one of the core metrics for Bayesian model comparison, LOOIC is based on the theoretical premise that a model with good generalisation ability should be able to provide accurate predictions for new observational data. The theoretical basis is based on the expected logarithmic prediction density of the retention method, and the specific calculation equation is:

$$elpd_{loo} = \sum_{i=1}^N \log(p(y_i|y_{-i})) \quad (\text{Eq4.27})$$

where, N represents the number of observations, $p(y_i|y_{-i})$ is the leave-one-out posterior prediction distribution of the i th data point, which represents the probability density of the model predicting y_i after training on all data y_{-i} except the i th data point, and $elpd_{loo}$ is the sum of all these logarithmic probability densities. The larger the value of $elpd_{loo}$, the better the predictive performance of the model. To be consistent with the interpretation of information criteria such as AIC, BIC, DIC (where a smaller value indicates a better model), multiply $elpd_{loo}$ by -2 to get LOOIC:

$$LOOIC = -2 \times elpd_{loo} \quad (\text{Eq4.28})$$

However, directly computing LOOIC requires N independent model fits, which incurs an extremely high time cost for structure-complex Hierarchical Bayesian models. To address this issue, Vehtari et al. (2017) proposed Pareto Smoothed Importance Sampling (PSIS), which enables efficient approximation of LOOIC through a single model fitting. The method stably estimates each value of $p(y_i|y_{-i})$ through the importance weighting technique, significantly improving computational efficiency. The PSIS method generates a Pareto k shape parameter for each observation, which is a key diagnostic indicator for evaluating the reliability of the approximation results. When k is greater than or equal to 0.7, it indicates a significant deviation in the PSIS approximation corresponding to the observation, and a more precise calculation method is required. This diagnostic mechanism ensures the accuracy and reliability of the model evaluation results and provides researchers with an important means of quality monitoring.

4.4 Model results and analysis

This study adopts a hierarchical Bayesian modelling framework. Four independent Markov chains are set for the constructed model for parameter estimation. Each chain undergoes 10,000 iterative sampling operations, with the first 5,000 being discarded as the pre-burning period to ensure the stability and convergence of the chains. Based on the last 5,000 valid iteration samples, the posterior distribution estimates of the model parameters and the corresponding model performance metrics were obtained. In terms of the presentation of parameter estimation results, this study reports the posterior mean, standard error and 95% confidence interval of each parameter. In the Bayesian statistical inference framework, the 95% confidence interval is usually used as the criterion for determining the significance of a variable. If the 95% confidence interval of a variable does not contain zero values, it is considered statistically significant at the 95% confidence level. Conversely, if the confidence interval contains zero values, it indicates that the variable is not statistically significant at the corresponding confidence level. Based on the preliminary analysis, for different subjects, three separate Hierarchical Bayesian Models were constructed in this study: a standard Hierarchical Bayesian Model (HBM) was established for the lane-changing start position; a more appropriate Hierarchical Bayesian Double-Hurdle Model (HBDHM) was employed for the accepted target lane lead gap (AG_TLead) and the accepted target lane lag gap (AG_TLag), where zero and negative values exist. This differentiated modelling strategy considers the distribution characteristics of each dependent variable and the essential requirements of the research question.

The model convergence diagnosis shows that the potential scale reduction factors ($\hat{R}$) of all three models is less than the critical standard of 1.05, indicating that each Markov chain has reached a good convergence state. At the same time, the effective sample size (ESS) of all key parameters was far above the recommended threshold of 1,000, ensuring the accuracy and reliability of the posterior statistics estimation. The results show that the model setup used in this study (4 chains, 10,000 iterations) has been well pre-tested and can strike a good balance between computational efficiency and estimation accuracy. The introduction of the Double-Hurdle model effectively solves the modelling problem when the dependent variable has zero and negative values, providing appropriate methodological support for a deeper understanding of the lane-changing behaviour decision-making mechanism in the weaving section. Based on the above verification, the parameter estimation results of the three models will be analysed and discussed in detail below.

4.4.1 Results and analysis of the lane-changing start position decision model

Based on the statistical analysis results shown in Tables 4.2 to 4.4, this study delves into the key influencing factors of vehicle lane-changing start position decisions in the weaving section.

(1) Model performance evaluation

The parameter estimation results of the Hierarchical Bayesian Null Model in Table 4.2 show that the variances of random effects at all three levels are significant at the 95% confidence level (none of the confidence intervals contain zero), fully demonstrating the necessity of using the three-level modelling framework. By intraclass correlation coefficient analysis, it was found that the ICC value for the data type level was 0.13, indicating that 13% of the variation in the lane-changing start position, after controlling for other variables, could be attributed to systematic differences in the data types (field observations and simulation data). The ICC value of the lane-changing type level reached 0.57, indicating that approximately 57% of the variation, after controlling for the influence of data types, originated from the specific attributes of different lane-changing types. The remaining 30% of variation comes from random effects at the individual lane-changing event level. This distribution pattern is highly consistent with the spatial layout characteristics of the weaving sections: since the on-ramps are usually set in front of the off-ramps, different lane-changing types are affected by this physical constraint, and their lane-changing start position selection naturally shows significant spatial differentiation characteristics.

Based on the system comparison results shown in Table 4.3, this study evaluated the performance of five modelling methods: Generalised Linear Model (GLM), Hierarchical Linear Model (HLM), Hierarchical Bayesian Null Model (HBNM), Hierarchical Bayesian Basic Model (with fixed effects and random intercept) (HBBM), and Hierarchical Bayesian Full Model (with fixed effects, random intercept, and random slope) (HBFM). Model comparison metrics showed that the LOOIC value of the HBFM is 22,302.2, significantly better than that of the other candidate models (GLM: 23,384.2, HLM: 22,735.7, HBNM: 22,847.1, HBBM: 22,384.8). The hierarchical model under the Bayesian framework demonstrated superior data adaptability compared to the traditional frequentist modelling method.

The superiority of the Hierarchical Bayesian Full Model is mainly reflected in three dimensions: First, by introducing a random slope parameter, it effectively captures the heterogeneous characteristics of the influence of variables among different groups. Second, the setting of the hierarchical prior structure ensures model flexibility and effectively avoids the risk of overfitting. Third, the posterior distribution based on the MCMC method provides a richer probabilistic interpretation space for parameter inference. To sum up, the Hierarchical Bayesian Full Model was selected as the final analysis tool in this study. The specific parameter estimation, convergence diagnosis, and variance decomposition results are detailed in Table 4.4. These results lay a solid mathematical foundation for the subsequent revelation of the lane-changing decision-making mechanism in the weaving section.

(2) Analysis of parameter estimation results

Based on the estimation results of the Hierarchical Bayesian Full Model (as shown in Table 4.4), this study deeply dissects the influence of multiple traffic environment variables on the decision of the lane-changing start position.

Among them, lane change direction (LCdir) has a significant positive impact on the lane-changing start position, that is, when a vehicle changes lane to the left, it is further away from the starting point of the weaving section compared to changing lanes to the right. This may be due to the fact that changing lanes to the left typically requires accelerating to merge into higher-speed, more complex main road traffic, which requires a longer driving distance to accelerate compared to changing lanes to the right off the main road. As a result, drivers tend to take advantage of the longer weaving length to safely complete the task of changing lanes to the left. The model results further suggest that the size of the surrounding vehicles has an impact on the choice of lane-changing position. An increase in the length of the leading vehicle in the current lane (Len_CL) leads to a further back starting position for the lane change, which may result from the occlusion effect of the longer vehicle in front on the forward view, requiring drivers more time to observe and judge, thereby delaying the lane change. In contrast, an increase in the length of the leading vehicle in the target lane (Len_TL) leads to a significant advance in the starting position of the lane change. Following a longer vehicle leads to a compression of the driver's perceived effective following space, creating a sense of psychological oppression and discomfort. To escape this restricted following environment, drivers tend to complete lane changes at an earlier stage in search of a perceived looser and safer lane position. An increase in the width of the lane-changing vehicle itself (Wid_Ego) and the width of the surrounding vehicles (Wid_CL, Wid_CF, Wid_TF) leads to a significant advance in the starting position of the lane change. This is because wide-body vehicles increase the driver's psychological stress and operational difficulty estimation, prompting the driver to adopt a more conservative strategy when feeling pressured and complete the lane change as early as possible to avoid the risk (Peng and Yang, 2012; Moridpour et al., 2012).

The type of vehicle has also been shown to have a significant impact on the decision of lane-changing start position, significantly further back when the following vehicle in the target lane is a van (VT_TF). Vans, due to their braking performance, visual volume perception and potential crash severity, give drivers a stronger sense of risk, resulting in longer observation and decision-making windows for changing lanes and thus affecting the lane-changing start position (Kong et al, 2019). The speed status of the surrounding vehicles also affects the choice of lane-change position. The faster the speed of the following vehicle in the current lane (V_CF), the further back the lane-change position. The fast-approaching following vehicles increase the time pressure on the lane-changing decision, and to avoid conflict, drivers tend to delay the lane change in search of a safer opportunity. In addition, the greater the gap distance (GD_CL) between the lane-changing vehicle and the leading vehicle in the current lane, the further back the lane-changing start position. A greater GD_CL means a more comfortable following state, a lower sense of urgency, and thus the driver has more waiting time and is not in a hurry to perform the lane change.

To analyse the data type heterogeneity impact of the speed of the following vehicle in the current lane (V_CF) on the decision of the vehicle's lane-changing

start position, this study plotted a random effects visualisation graph based on the estimation results of the Hierarchical Bayesian Full Model (Figure 4.6), where the horizontal and vertical dotted lines represent the overall average level of the model. In the visualisations of the random intercept (top left) and the random slope (top right), there were no significant differences between the baseline levels of the simulation and field observations and the overall average. The subgraph at the lower left corner reveals a negative correlation between the random intercept and the random slope. Field observations show higher V_{CF} random slopes at lower levels of random intercept. Simulation data, on the other hand, showed a weaker V_{CF} random slope effect at a higher random intercept level. This finding suggests that in the field observation environment, even if the lane-changing vehicle is in the front half of the weaving section, an increase in the speed of the following vehicle in the current lane (V_{CF}) will still significantly prompt the vehicle to complete the lane change further back. This may be because the fast-approaching following vehicle sends a strong risk perception and time pressure signal to the lane-changing driver, who tends to extend the decision-making process to complete the lane change safely, thus causing the lane-changing start position to move back. In contrast, the decision to choose lane-changing start position in a simulated environment is insensitive to changes in V_{CF} . Despite the use of multi-screen technology, the field of view of the static driving simulator is still difficult to fully reproduce the external field of view and dynamic visual cues of the real vehicle, which may cause the driver to have a lag in perceiving the pose and speed changes of the following vehicles (Mao et al, 2025).

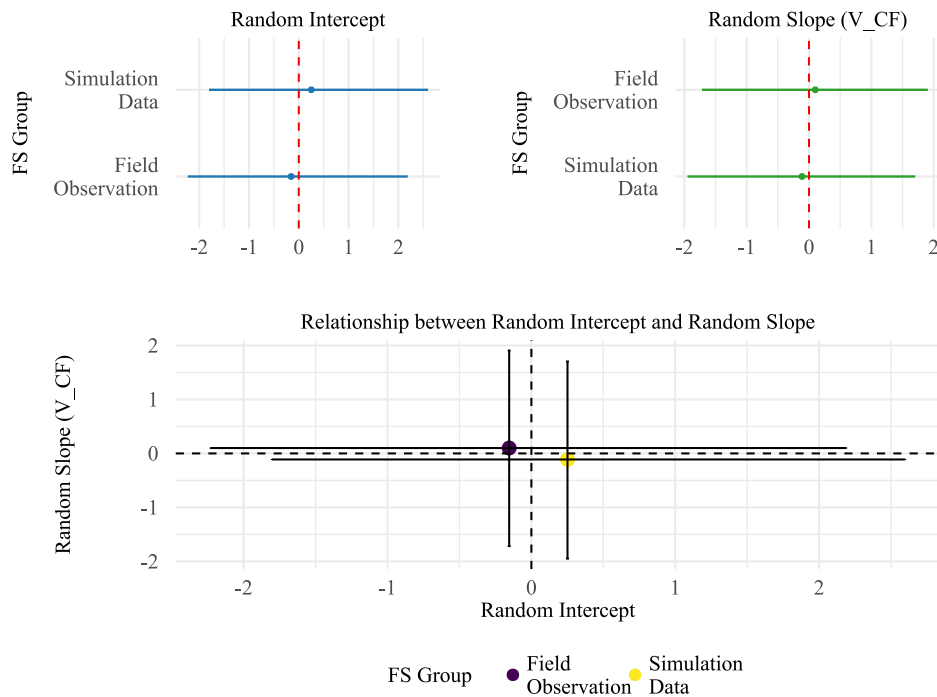


Figure 4.6 Visualisation of random effects at the data type level for lane-changing start position decision (variable V_{CF}).

To analyse the lane-changing type heterogeneity impact of the speed of the following vehicle in the current lane (V_{CF}) on the decision of the vehicle's lane-changing start position, this study plotted the random effects visualisation graph based on the estimation results of the Hierarchical Bayesian Full Model (Figure 4.7). The model results revealed systematic differences in the baseline position of different lane-changing behaviours. The baseline level of mandatory lane-changing was significantly lower than the overall average, indicating that it was more likely to be completed in the first half of the weaving section. This stems from the inherent compulsion and urgency of the behaviour, and drivers typically choose to perform lane changes early to avoid missing off-ramps. In contrast, the baseline level of the diverging manoeuvre is higher than the overall average, meaning it occurs closer to the end of the weaving section, which is in line with the physical layout of the off-ramp and the external constraints on vehicle behaviour imposed by traffic rules.

In the random slope graph in the upper right corner of Figure 4.7, the V_{CF} random slope of the mandatory lane change is lower than the overall average effect, indicating that due to the strong purposefulness and non-delay ability of the mandatory lane change itself, even if the driver perceives that the following vehicle is approaching at high speed, it is not easy to change the decision on the lane-changing start position. The V_{CF} random slope of discretionary lane-changing is higher than the overall average effect, indicating that the decision on the lane-changing start position of discretionary lane-changing is more sensitive to the following traffic dynamics.

From the graph of the relationship between the random intercept and the random slope in the lower left corner, the merging, diverging, and mandatory lane changes are all in the first or third quadrant, where the random intercept is positively correlated with the slope, except for the discretionary lane change, which is in the second quadrant, showing a unique negative correlation. This phenomenon reflects the core motivation of discretionary lane-changing as a spontaneous, optimised behaviour (Balal et al, 2014). When the speed of the following vehicle in the current lane (V_{CF}) is high, there is a “push effect” that prompts the driver to actively seek better driving conditions. To get rid of the pressure of the current lane, drivers are willing to adjust their pre-set lane-change position, thereby showing higher environmental sensitivity.

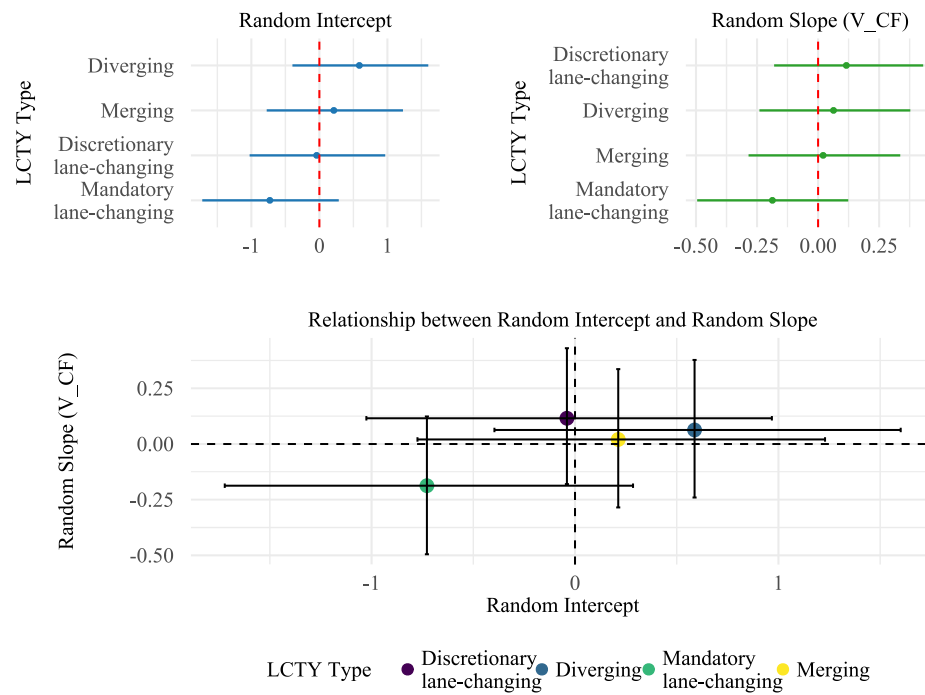


Figure 4.7 Visualisation of random effects at the lane-changing type level for lane-changing start position decision (variable V_CF).

Table 4.2. Results of lane-changing start position decision model (Hierarchical Bayesian Null Model (HBNM)).

Variable	Mean	Standard error	95% confidence interval
Standard deviation (Lane-changing event level)	0.80	0.01	(0.77, 0.82)
Intercept	4.42	0.84	(2.59, 6.11)
Standard deviation (Data type level)	0.52	0.81	(0.01, 2.90)
Standard deviation (Lane-changing type level)	1.09	0.62	(0.45, 2.74)

Table 4.3. Comparison of model performance metrics of lane-changing start position decision models.

Model	$elpd_{loo}$	Standard error	LOOIC
Generalised Linear Model (GLM)	-11692.1	29.1	23384.2
Hierarchical Linear Model (HLM)	-11367.8	33.1	22735.6
Hierarchical Bayesian Null Model (HBNM)	-11423.6	46.0	22847.1
Hierarchical Bayesian Basic Model (HBBM)	-11192.4	48.1	22384.8
Hierarchical Bayesian Full Model (HBFM)	-11151.1	49.5	22302.2

Table 4.4. Results of lane-changing start position decision model (Hierarchical Bayesian Full Model (HBFM)).

Variable	Mean	Standard error	95% confidence interval
Standard deviation (Lane-changing event level)	0.69	0.01	(0.67, 0.72)
Intercept	4.30	1.14	(1.79, 6.59)
LCdir (Lane change direction: 0- change lanes to the right of the driving direction, 1- change lanes to the left of the driving direction.)	0.54	0.06	(0.42, 0.66)
Len_CL (The length of the leading vehicle in the current lane.)	0.15	0.03	(0.10, 0.20)
Len_TL (The length of the leading vehicle in the target lane.)	-0.14	0.02	(-0.18, -0.10)
Wid_Ego (The width of the lane-changing vehicle.)	-0.11	0.02	(0.15, 0.08)
Wid_CL (The width of the leading vehicle in the current lane.)	-0.16	0.02	(-0.21, -0.11)
Wid_CF (The width of the following vehicle in the current lane.)	-0.11	0.02	(-0.14, -0.07)
Wid_TF (The width of the following vehicle in the target lane.)	-0.06	0.02	(-0.10, -0.02)
VT_TF (The type of the following vehicle in the target lane: 0-passenger car, 1-van.)	0.29	0.07	(0.15, 0.42)
V_CF (The speed of the following vehicle in the current lane when the vehicle initiates a lane change.)	0.11	0.89	(-1.73, 1.99)
GD_CL (The gap distance between the lane-changing vehicle and the leading vehicle in the current lane when the vehicle initiates a lane change.)	0.04	0.02	(0.00, 0.07)
Standard deviation (Data type level)	1.09	1.09	(0.16, 4.13)
Random slope V_CF (Data type level)	0.85	1.03	(0.08, 3.70)
Cor (Random intercept, Random slope V_CF) (Data type level)	-0.07	0.45	(-0.85, 0.78)

Table 4.4. Results of the lane-changing start position decision model (Hierarchical Bayesian Full Model (HBFM)) (continued).

Variable	Mean	Standard error	95% confidence interval
Standard deviation (Lane-changing type level)	0.87	0.53	(0.35, 2.30)
Random slope V_CF (Lane-changing type level)	0.25	0.22	(0.08, 0.77)
Cor (Random intercept, Random slope V_CF) (Lane-changing type level)	0.26	0.39	(-0.57, 0.87)
Maximum of potential scale reduction factor ($\hat{R}$)	1.00		
Minimum of Bulk effective sample size (Bulk- <i>ESS</i>)	8320		
Minimum of Tail effective sample size (Tail- <i>ESS</i>)	6925		
Sum of logarithmic probability densities ($elpd_{loo}$)	-11151.1		
Leave-one-out cross-validation (LOOIC)	22302.2		
Pareto k shape parameter	<0.7		

4.4.2 Results and analysis of the accepted target lane lead gap (AG_TLead) decision model

Based on the model estimation results presented in Tables 4.5 to 4.7, this study systematically analysed the influencing factors of the accepted target lane lead gap decision process in the weaving section. The decision-making process was modelled as two associated stages: The first stage (the hurdle model) characterises the binary choice of whether the driver accepts the positive accepted target lane lead gap. The second stage (the main model) characterises consecutive decisions on the specific values of accepted target lane lead gap.

(1) Model performance evaluation

The parameter estimation results of the Hierarchical Bayesian Null Model (HBNM) in Table 4.5 show that the variances of random effects at all three levels of the null model and the main model are significant at the 95% confidence level (all confidence intervals do not include zero), confirming the correctness of the three-level model structure. At the hurdle model level, the ICC value at the data type level was 0.35, indicating that 35% of the decision difference in “whether to choose a positive accepted target lane lead gap” after controlling for other variables originated from systematic differences in data types (field observation versus simulation data). The ICC value of the lane-changing type level is only 0.04, indicating that the influence of the lane-changing type on binary decisions is relatively limited. The remaining 61% variation mainly stems from random effects at the lane-changing event level, highlighting the high context-dependent nature of individual driving decisions. As for the main model, the ICC value of the data type level reached 0.52, indicating that 52% of the “positive accepted target lane lead gap” difference can be attributed to the data type difference. The ICC value of the lane-changing type level was 0.02, which had a weak impact. The remaining 46% of variations originated from the lane-changing event level. This result suggests that data types (field observation and simulation data) are the dominant factor in explaining the difference in the choice of value of accepted target lane lead gap, possibly due to the inherent differences in drivers’ risk perception and decision-making mechanisms in different data collection environments.

By comparing the model performance metrics of the five models in Table 4.6, this study found that the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) demonstrated significant performance advantages in the modelling of the decision of accepted target lane lead gap. The LOOIC value of the model was 6061.1, which was significantly lower than that of the Generalised Linear Model (GLM) (10501.8), the Hierarchical Linear Model (HLM) (10467.8), the Hierarchical Bayesian Double-Hurdle Null Model (HBDHNM) (6470.7), and the Hierarchical Bayesian Double-Hurdle Basic Model (HBDHBM) (6181.1). This result not only confirms the superiority of the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) from the perspective of model selection, but more importantly reveals its unique value in dealing with complex driving decision-

making problems, that is, achieving the best balance of fitting accuracy and generalisation ability while maintaining the rationality of the model structure.

The architectural advantage of the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) is reflected in three key dimensions: First, the Double-Hurdle modelling framework accurately reflects the cognitive logic of driving decisions by separating the two stages of the decision-making process: the binary choice stage of whether the driver chooses a positive accepted target lane lead gap and the continuous decision-making stage of specific gap values. Second, the introduction of the random slope term enables the model to capture the heterogeneity of responses from different groups to influencing factors, enhancing the model's explanatory power. Third, the hierarchical Bayesian prior structure effectively controls the model complexity through regularisation effects, providing rich posterior inference information while avoiding overfitting problems. Based on the above analysis, this study uses the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) as the final modelling scheme. Table 4.7 presents in detail the model's parameter estimation results, convergence diagnostic indicators, and random effects decomposition. These statistical evidences lay a solid foundation for a deeper understanding of the accepted target lane lead gap decision mechanism in the weaving section lane-changing behaviour.

(2) Analysis of parameter estimation results

Based on the estimation results of the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) (Table 4.7), the variances of random effects at all three levels in the main model and the hurdle model were significant at the 95% confidence level, which fully confirmed the hierarchical structure and intraclass correlations in the lane-changing behaviour data and highlighted the necessity of using hierarchical modelling for this type of data. There is a significant difference in the set of significant variables between the main model and the hurdle model, which reveals that the decision mechanism influencing “whether to choose a positive accepted target lane lead gap” and the decision mechanism influencing “how much the value of accepted target lane lead gap” are independent of each other and dominated by different factors. This finding strongly justifies the use of the Double-Hurdle model framework to depict the two decision-making stages separately.

The results of the hurdle model in Table 4.7 show that lane-changing direction (LCdir) has a significant negative impact on choosing a positive accepted target lane lead gap. Vehicles that change lanes to the left in the weaving section are more likely to choose a negative accepted target lane lead gap compared to those that change lanes to the right. This conclusion is consistent with the analysis in Section 4.4.1 because changing lanes to the left typically requires vehicles to accelerate to fit into a faster, more complex main road traffic environment, a high level of complexity and strong task constraints that force drivers to lower their safety standards and thus accept a smaller or even negative accepted target lane lead gap. The results show that at the start of the lane change, the gap distance between the lane-changing vehicle and the leading vehicle in the target lane (GD_TL) have a significant positive impact on choosing a positive accepted target lane lead gap. The

greater the GD_TL, the more abundant the safety margin available for changing lanes, the lower the urgency of changing lanes, and thus the driver can wait longer to obtain a relatively larger gap (Ali et al., 2018; Toledo et al., 2003). And the intensity of the effect shows significant heterogeneity with data type, which is likely due to the differences in distance and speed perception reproduction between driving simulators and the real environment (Kemeny and Panerai, 2003; Baumberger et al., 2005). The results of the hurdle model in Table 4.7 suggest that the greater the speed difference (VDif_CL) between the lane-changing vehicle and the leading vehicle in the current lane, the more likely the driver is to choose the positive accepted target lane lead gap. This finding corroborates the research of Chen et al. (Chen et al, 2018), whose results also emphasise that incorporating the information of the leading vehicle in the current lane is crucial for improving model accuracy when predicting forced lane changes with negative gap. Larger positive speed differences typically indicate that the traffic flow is in a free or stable state rather than congested. In non-congested traffic, drivers have more decision-making space and better driving conditions and are reluctant to choose the negative accepted target lane lead gap (Gurupackiam and Jones, 2011). Additionally, the results show that the higher the speed of the lane-changing vehicle itself (V_Ego), the more likely the driver is to choose a negative accepted target lane lead gap. This suggests that at higher speeds, some drivers exhibit a more aggressive driving style with increased risk tolerance, and thus are willing to choose negative accepted target lane lead gaps in dynamic traffic flow (Ataelmanan et al., 2021).

The visualisation of the random effects in Figure 4.8 further reveals the systematic differences between the two sets of data from field observation and simulation data. The simulation data showed significantly lower random intercepts, meaning that in the simulation environment, drivers had a lower baseline propensity to choose the positive target lane lead gap. At the same time, the random slope of the variable GD_TL in the simulation data was also significantly lower than that in the field observations, indicating that simulation drivers were less sensitive to changes in gap distance between vehicles changing lanes and the leading vehicles in the target lane. The left subgraph shows that the joint distribution of random-parameters of the simulation data and field observation is located in different quadrants and has different correlations, which visually reveals the structural differences in driver lane-changing decision-making mechanisms in the two different environments. This difference is likely due to the inherent limitations of static driving simulators in terms of field of view, motion feedback, and multi-vehicle interaction fidelity, making it difficult for them to fully reproduce the dynamic risk assessment process of drivers in real traffic environments (Mao et al, 2025).

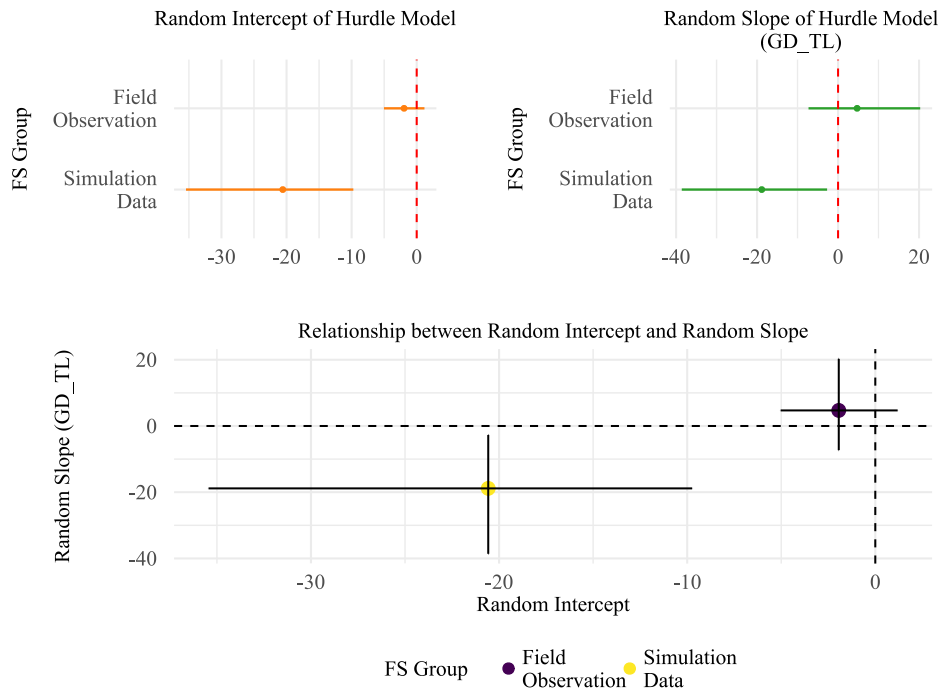


Figure 4.8 Visualisation of random effects of hurdle model at the data type level for accepted target lane lead gap decision (variable GD_TL).

An analysis of the results of the main model in Table 4.7 reveals that the size of the lane-changing vehicle has a significant impact on the size of accepted target lane lead gap. Among them, the longer the length of the lane-changing vehicle (Len_Ego), the smaller the accepted target lane lead gap chosen by the lane-changing vehicle. This contradicts previous research findings that heavy vehicles typically require a larger lane-changing gap due to their longer length (Aghabayk et al, 2011; Moridpour et al, 2012). This may be because the proportion of trucks in the data of this study is not high, the average length of vehicles is shorter (see Table 4.1), and the effect of reduced manoeuvrability due to increased length is not obvious enough. At the same time, drivers of longer vehicles may have shown greater “aggressiveness”, which may have led to a negative correlation. The model results also suggest that the wider the width of the lane-changing vehicle (Wid_Ego), the greater the accepted target lane lead gap chosen by the lane-changing vehicle. To absolutely avoid the risk of rear-end collisions, drivers of wider vehicles instinctively demand a larger gap in front, reserving longer braking distance and reaction time for themselves. Vehicle speed has also been found to significantly affect the size of accepted target lane lead gap when the lane change begins. The higher the speed of the lane-changing vehicle (V_Ego), the smaller the accepted target lane lead gap accepted when the lane change begins. At low speeds, the vehicle’s driving behaviour is conservative, relying on static space buffering and requiring a larger accepted target lane lead gap. At high speeds, vehicles use relative speed differences to make up for the lack of static space, resulting in a smaller accepted target lane lead gap. Toledo et al. (2003) also confirmed this, with model

calibration results showing that as speed increases, drivers' sensitivity to the space gap in front decreases, because high speeds often come with more stable traffic flow and the opportunity to take advantage of the speed difference.

Table 4.7 shows that both the fixed and random effects of the variable GD_TL are significant. At the start of a lane change, the greater the gap distance between the lane-changing vehicle and the leading vehicle in the target lane (GD_TL), the greater the accepted target lane lead gap chosen by the lane-changing vehicle. But this effect is not fixed and is also related to the lane-changing type. The model results show that the greater the gap distance between the lane-changing vehicle and the leading vehicle in the current lane (GD_CL), the smaller the accepted target lane lead gap chosen by the lane-changing vehicle. This finding is in line with the theory of dynamic gap acceptance based on relative speed (Choudhury, 2005). The intrinsic behavioural mechanism is that larger gaps typically mean that the lane-changing vehicle is in a free-moving state and at a higher speed, which enables it to take advantage of the positive speed difference with the leading vehicle in the target lane, and even if the initial time gap is small, the driver can expect that the gap will dynamically increase after the lane-changing is completed, thereby significantly reducing the risk of collision (WINSUM and Heino, 1996).

The results in Table 4.7 also show that the speed difference between the lane-changing vehicle and the surrounding vehicles significantly affects the size of the accepted target lane lead gap selected. Specifically, the greater the speed difference between the lane-changing vehicle and the following vehicle in the current lane ($VDif_CF$) and the following vehicle in the target lane ($VDif_TF$), drivers tend to choose a larger accepted target lane lead gap. Conversely, the greater the speed difference between the lane-changing vehicle and the leading vehicle in the target lane ($VDif_TL$), the smaller the accepted target lane lead gap selected. This phenomenon can be explained by the driver's coordinated lane-changing decision-making mechanism and dynamic gap acceptance behaviour. When $VDif_CF$ and $VDif_TF$ are large, it usually means that the lane-changing vehicle has a significant speed advantage over the following vehicles, and the rear traffic has a lower sense of lane change pressure on it. The driver does not need to rush to complete the lane change and thus can adopt a more conservative strategy, wait, and accept a larger accepted target lane lead gap to ensure higher safety and comfort (Toledo et al., 2003). When the $VDif_TL$ is large, the driver can rely on the forward speed difference to quickly increase the actual distance from the leading vehicle after changing lanes. At this point, even if a smaller initial gap is accepted, the risk of collision remains within a safe range. This behaviour is in line with Choudhury's theory of dynamic gap acceptance, where drivers consider the trend of dynamic gap changes caused by relative speed in lane-changing decisions (Choudhury, 2005).

Figure 4.9 shows the random effect distribution of the gap distance between the lane-changing vehicle and the leading vehicle in the target lane (GD_TL) estimated based on the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) across different lane-changing types, which reveals significant heterogeneity in the lane-changing decision-making mechanism. In terms of random intercept (upper left subgraph), the intercept for merging and diverging manoeuvres are close to the

overall baseline level, while the intercept for discretionary lane-changing are significantly negative and those for mandatory lane changes are significantly positive. This pattern suggests that, after controlling for other covariates, there are systematic differences in the probability of baseline gap acceptance among different lane-changing types. In terms of the random slope (upper right subgraph), the influence of the variable GD_TL also varies with the lane-changing type. The random slope for diverging and mandatory lane-changing is similar to the overall average effect, the slope for discretionary lane-changing is slightly below average, and the slope for merging is slightly above average. This suggests that in the typical high-urgency scenario of merging, drivers are most sensitive to changes in the gap distance between the lane-changing vehicle and the leading vehicle in the target lane (GD_TL), and a small increase in the GD_TL significantly increases the probability of choosing a larger accepted target lane lead gap. This difference in sensitivity confirms the findings of Choudhury et al. (2005), drivers respond differently to the same traffic environment variable in mandatory and discretionary lane changes. The left subgraph further reveals the positive covariance relationship between the random intercept and the random slope. The parameter pairs of all lane-change types are evenly distributed in the first and third quadrants, showing a clear positive correlation. This key finding suggests that the marginal effect (slope) of GD_TL is also often stronger for lane-changing types with a higher probability of accepting the baseline accepted target lane lead gap, such as merging and mandatory lane-changing.

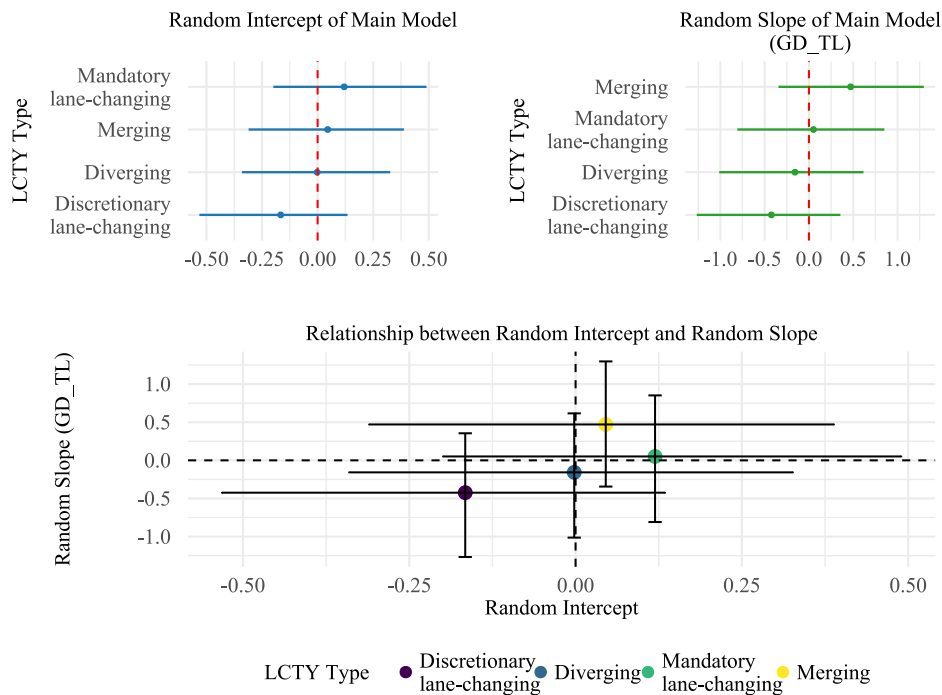


Figure 4.9 Visualisation of random effects of main model at the lane-changing type level for accepted target lane lead gap decision (variable GD_TL).

Table 4.5. Results of accepted target lane lead gap decision model (Hierarchical Bayesian Double-Hurdle Null Model (HBDHNM)).

Variables		Mean	Standard error	95% confidence interval
Standard deviation (Lane-changing event level)		1.29	0.03	(1.24, 1.34)
Hurdle model	Intercept	-2.11	1.07	(-3.53, 0.68)
	Standard deviation (Data type level)	1.37	1.33	(0.07, 5.05)
	Standard deviation (Lane-changing type level)	0.46	0.46	(0.02, 1.62)
Main Model	Intercept	0.78	1.17	(-1.71, 3.13)
	Standard deviation (Data type level)	1.37	1.33	(0.07, 5.05)
	Standard deviation (Lane-changing type level)	0.28	0.24	(0.04, 0.92)

Table 4.6. Comparison of model performance metrics of accepted target lane lead gap decision models.

Model	$elpd_{loo}$	Standard error	LOOIC
Generalised Linear Model (GLM)	-5250.9	218.8	10501.8
Hierarchical Linear Model (HLM)	-5233.9	216.0	10467.8
Hierarchical Bayesian Double-Hurdle Null Model (HBDHNM)	-3235.3	52.7	6470.7
Hierarchical Bayesian Double-Hurdle Basic Model (HBDHBM)	-3090.5	54.8	6181.1
Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM)	-3030.6	55.2	6061.1

Table 4.7. Results of accepted target lane lead gap decision model (Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM)).

Variable		Mean	Standard error	95% confidence interval
Hurdle Model	Standard deviation (Lane-changing event level)	1.13	0.02	(1.09, 1.18)
	Intercept	-0.56	1.52	(-3.55, 2.40)
	LCdir (Lane change direction: 0- change lanes to the right of the driving direction, 1- change lanes to the left of the driving direction.)	-1.03	0.64	(-2.53, -0.01)
	GD_TL (The gap distance between the lane-changing vehicle and the leading vehicle in the target lane when the vehicle initiates a lane change.)	-4.72	5.35	(-15.62, 5.77)
	VDif_CL (The speed difference between the lane-changing vehicle and the leading vehicle in the current lane when the vehicle initiates a lane change.)	0.43	0.13	(0.18, 0.68)
	V_Ego (The speed of the lane-changing vehicle when the vehicle initiates a lane change.)	-0.27	0.15	(-0.56, 0.01)
	Standard deviation (Data type level)	8.28	2.82	(3.81, 14.81)
	Random slope GD_TL (Data type level)	8.21	2.81	(3.90, 14.80)
	Cor (Random intercept, Random slope GD_TL) (Data type level)	0.45	0.30	(-0.22, 0.92)
	Standard deviation (Lane-changing type level)	0.73	0.71	(0.03, 2.55)
Main Model	Intercept	0.82	0.96	(-1.23, 2.87)
	Len_Ego (The length of the lane-changing vehicle.)	-0.13	0.05	(-0.23, -0.03)
	Wid_Ego (The width of the lane-changing vehicle.)	0.11	0.06	(0.00, 0.22)
	V_Ego (The speed of the lane-changing vehicle when the vehicle initiates a lane change.)	-0.23	0.04	(-0.31, -0.15)

GD_TL (The gap distance between the lane-changing vehicle and the leading vehicle in the target lane when the vehicle initiates a lane change.)	0.86	0.41	(0.06, 1.68)
GD_CL (The gap distance between the lane-changing vehicle and the leading vehicle in the current lane when the vehicle initiates a lane change.)	-0.06	0.04	(-0.13, 0.01)
VDif_CF (The speed difference between the lane-changing vehicle and the following vehicle in the current lane when the vehicle initiates a lane change.)	0.07	0.04	(-0.01, 0.14)
VDif_TL (The speed difference between the lane-changing vehicle and the leading vehicle in the target lane when the vehicle initiates a lane change.)	-0.09	0.04	(-0.16, -0.02)
VDif_TF (The speed difference between the lane-changing vehicle and the following vehicle in the target lane when the vehicle initiates a lane change.)	0.11	0.04	(0.03, 0.19)
Standard deviation (Data type level)	0.99	1.07	(0.12, 4.01)
Standard deviation (Lane-changing type level)	0.25	0.24	(0.05, 0.84)
Random slope GD_TL (Lane-changing type level)	0.66	0.46	(0.22, 1.89)
Cor (Random intercept, Random slope GD_TL) (Lane-changing type level)	0.20	0.41	(-0.63, 0.87)
Maximum of potential scale reduction factor ($\hat{R}$)		1.00	
Minimum of Bulk effective sample size (Bulk- <i>ESS</i>)		4556	
Minimum of Tail effective sample size (Tail- <i>ESS</i>)		6969	
Sum of logarithmic probability densities ($elpd_{loo}$)		-3030.6	
Leave-one-out cross-validation (LOOIC)		6061.1	
Pareto k shape parameter		<0.7	

4.4.3 Results and analysis of the accepted target lane lag gap (AG_TLag) decision model

Based on the model estimation results shown in Tables 4.8 to 4.10, this study systematically explores the key influencing factors in the decision-making process of accepted target lane lag gap in the weaving section. The decision-making process was also modelled as a two-stage mechanism: the first stage (the hurdle model) represents the binary decision of whether the driver accepts a positive lag gap; the second stage (the main model) describes the continuous selection behaviour of the specific values of the positive lag gap.

(1) Model performance evaluation

The model parameter estimation results in Table 4.8 show that the variances of the three levels of random effects of the hurdle model and the main model are all significant at the 95% confidence level (all confidence intervals do not include zero), fully verifying the rationality of the three-level model structure. Specifically, the intra-group correlation coefficient analysis at the hurdle model level shows that the ICC value at the data type level is 0.09, indicating that approximately 9% of binary decision differences result from data source differences. The ICC value of the lane-changing type level was 0.19, indicating that it had a more significant impact on decision-making. Up to 72% of the variation comes from the individual lane-changing event level, highlighting the strong individual context dependence in lag gap decision-making. At the main model level, the ICC value of the data type level reached 0.75, which became the dominant factor in explaining the difference in gap value selection. The influence of the lane-changing type level is minimal (ICC=0.01). The remaining 24% of variations originated from the lane-changing event level. This distribution pattern corroborates the findings of Chapter 3, reflecting systematic differences in drivers' perception of rear risks in different data collection environments.

The LOOIC value (5151.6) of the Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM) was significantly better than that of the competing models (GLM: 9600.4; HLM: 9703.5; HBDHNM: 5689.5; HBDHBM: 5259.0) as shown in Table 4.9. This result highlights the advantages of the full Bayesian model in capturing the two-stage characteristics of accepted target lane lag gap decisions and handling multi-level random effects. The HBDHFM framework shows better data adaptability compared to the traditional frequentist approach, indicating that its modelling structure can effectively represent the complex features in the actual data. The superiority of the HBDHFM is primarily reflected in the fit between its theoretical framework and the characteristics of the actual problem. The two-stage modelling accurately reflects the cognitive process of driving decisions, the hierarchical structure properly handles the nesting characteristics of data, and the Bayesian framework provides a richer inference space for parameter estimation. These features make it an ideal tool for analysing the decision mechanism of the accepted target lane lag gap in the weaving section.

(2) Analysis of parameter estimation results

According to the HBDHFM estimation results shown in Table 4.10, the variances of random effects at all three levels in the main model and the hurdle model are significant within the 95% confidence interval, fully confirming the non-negligible heterogeneity of individuals, scenarios, and behavioural types in lane-changing decisions. Crucially, there are systematic differences in the significant variables between the main model and the hurdle model, suggesting that the decision mechanism that drives the vehicle to accept the positive target lane lag gap and the mechanism that determines the specific size of the gap under the acceptance condition are dominated by different psychological and behavioural logics.

An analysis of the results of the hurdle model in Table 4.10 reveals that the length of the following vehicle in the target lane (Len_TF) has a significant positive effect, that is, when Len_TF is larger, the vehicle changing lanes is more likely to choose a positive accepted target lane lag gap. This can be explained by the risk compensation theory, where a larger vehicle behind is regarded as a more threatening potential collision source, and drivers thus seek greater safety buffer space to compensate for the perceived risk (Wilde, 1982). The model results suggest that at the start of a lane change, the higher the speed of the following vehicle in the current lane (V_CF), the less likely the vehicle changing lanes is to accept the positive target lane lag gap. This reflects the time pressure effect in a mandatory lane-changing scenario where the high speed of the following vehicle in the current lane exerts a strong urgency signal, forcing the driver to reduce their decision-making time and lower the requirements for safety conditions in the target lane to avoid hindering the traffic flow in the current lane (Toledo et al., 2003). The fixed effect of the gap distance between the lane-changing vehicle and the following vehicle in the target lane (GD_TF) is not significant, but the random effect is significant. At the beginning of the lane change, the greater the GD_TF, the more likely the vehicle changing lanes is to choose the positive target lane lag gap, but this effect is not globally consistent. Instead, it shows heterogeneity depending on the lane-changing type. Similarly, the distance from the starting point of the weaving section to the lane-changing start position (LocLS) also shows significant random effects. At the beginning of the change, the greater the LocLS, the more likely the changing vehicle is to choose the positive target lane lag gap, but this effect varies depending on the data type. This finding corroborates the conclusion of Van Beinum et al. regarding the spatial distribution of lane-changing behaviour in weaving sections. Their study observed that lane-changing behaviour was highly concentrated in the first half of the weaving sections, leading to concentrated traffic pressure in that area, while the lane-changing environment in the middle and later sections was relatively loose (Van Beinum et al., 2018, 2019, 2020).

To analyse the random effect of LocLS at the data type level in the hurdle model, the visualisation results of the random effect of the hurdle model were plotted, as shown in Figure 4.10. In terms of the random intercept (upper left subgraph), there is no significant difference between the intercept of the simulation and the field observation data and the overall baseline level, but the intercept of the field observation data is slightly lower than the baseline level. This suggests that drivers

in field traffic scenarios are more inclined to accept a negative lag gap in the target lane compared to the simulated environment. It is notable that this conclusion differs from the random intercept pattern of the accepted target lane lead gap in Section 4.4.2, highlighting the different attributes of accepting the target lane lead and lag gap in driving decisions. The acceptance of target lane lead gap is related to the risk of following, and the decision is more forward-looking. The acceptance of target lane lag gap involves coordination and trust, and relies more on the driver's precise perception of the traffic flow behind (Choudhury, 2005). In terms of the random slope (upper right subgraph), there is no systematic deviation between the LocLS random slope of the two types of data and the overall average effect. The slope of the simulation data is slightly higher, while that of the field data is slightly lower. The joint distribution in the left subgraph further reveals that, despite the lower baseline intercept of the simulation data, the random effect of LocLS is stronger. This means that in the simulation environment, the farther the lane-changing start position is from the starting point of the weaving section, the more significantly the probability of the driver accepting the positive target lane lag gap increases. This phenomenon may be related to the inherent limitations of simulations in reproducing complex traffic dynamics. The formation and dissipation of congestion at the end of field weaving sections involve complex vehicle-to-vehicle behavioural games, and simulation software often has shortcomings in simulating micro-behavioural interactions under high density, making it difficult to accurately reproduce the traffic pressure in the latter half of the weaving sections (Wan et al., 2014). Therefore, the simulation data may systematically underestimate the difficulty of lane-changing at the end of the weaving section, thereby amplifying the positive effect of LocLS at the far end.

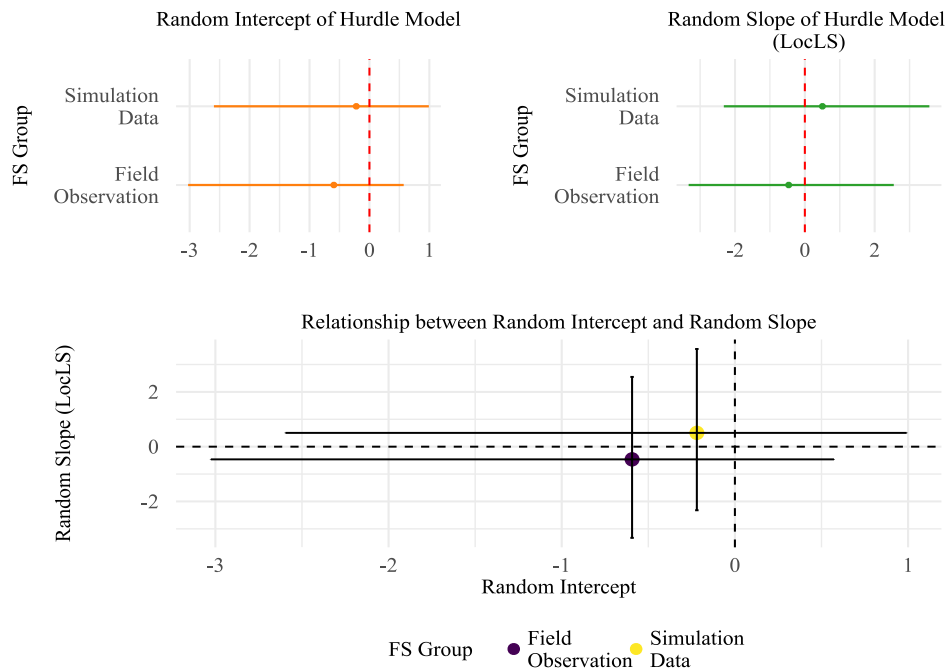


Figure 4.10 Visualisation of random effects of hurdle model at the data type level for accepted target lane lag gap decision (variable LocLS).

To analyse the random effects of GD_TF in the hurdle model, the distribution of the random effects of the hurdle model is plotted as shown in Figure 4.11. Regarding the random intercept (upper left subgraph), different lane-changing types show significant heterogeneity in baseline decision tendencies. The random intercept of diverging is significantly negative, indicating that it has the strongest tendency to accept the negative target lane lag gap in the baseline state. This may be due to the clear path constraints faced by the diverging vehicle, the forced spatiotemporal boundary of its lane change, the greater pressure of the lane change, and the large blind spot of the lane change in the direction the diverging vehicle is moving to the right front. In terms of the random slope (upper right subgraph), the intensity of the influence of the GD_TF variable also varies by lane-changing type. The random slope for diverging and mandatory lane-changing is slightly lower than the overall mean, while the slope for merging and discretionary lane changes is higher than the mean. The joint distribution of random-parameters in the left subgraph further reveals the key mechanism: diverging, mandatory lane-changing, and diverging are all in the first and third quadrants, showing a clear positive correlation. This means that the marginal effect (slope) of GD_TF is also relatively stronger for the type of lane change with a higher baseline level. The finding can be explained by the risk compensation theory, where drivers are more sensitive to changes in the GD_TF in high-risk or high-urgency lane-changing scenarios. Discretionary lane-changing, however, are in the second quadrant, showing a negative correlation between the intercept and the slope. Although its baseline level is not high, the random slope of GD_TF is strong. This unconventional phenomenon precisely captures the essential characteristics of discretionary lane-changing, as a free and optimised act, whose decisions are modulated most deeply by external traffic environment factors. When traffic conditions are favourable (such as a large GD_TF), drivers' willingness to perform the discretionary lane-changing increases sharply. In contrast, when conditions are slightly worse, drivers tend to give up easily, showing a high degree of environmental sensitivity.

The estimation results of the main model based on the HBDHFM (Table 4.10) show that LocLS has a significant random effect on the size of accepted target lane lag gap. Overall, an increase in LocLS is associated with a larger selection of the accepted target lane lag gap, as the middle and rear sections of the weaving section typically have better lane-changing conditions (Van Beinum et al., 2018, 2019, 2020), but the intensity of this effect is also significantly modulated by the lane-changing type. The size of the surrounding vehicles shows a systemic effect, with an increase in the width of the leading vehicle in the current lane (Wid_CL) causing the changing vehicle to choose a smaller accepted target lane lag gap, which may be due to the visual pressure caused by the leading vehicle prompting the driver to rush out of the current following state. Conversely, an increase in the width of the following vehicle in the current lane (Wid_CF) leads the vehicle changing lanes to seek a larger target lane lag gap, which is in line with the risk compensation theory that more threatening vehicles behind prompt drivers to demand a greater safety buffer (Wilde, 1982). The GD_TF has a significant random effect on the size of the accepted target lane lag gap, and this effect is modulated by the data type. An

increase in GD_TF generally prompts drivers to choose a larger accepted target lane lag gap, and a larger initial space distance provides a more lenient margin of safety and speed adjustment space for vehicles changing lanes. The type of following vehicle in the target lane (VT_TF) also has a significant impact. When the following vehicle in the target lane is a van, the accepted target lane lag gap selected by the lane-changing vehicle significantly increases. This result suggests that large vehicles are perceived by drivers as a greater source of risk due to their longer braking distance and potentially higher severity of collisions, thereby triggering a more conservative gap acceptance strategy. An increase in the speed of the following vehicle in the current lane (V_CF) significantly reduces the accepted target lane lag gap chosen by the lane-changing vehicle, a finding revealing the time pressure effect in mandatory lane-changing scenarios (Toledo et al., 2003). Lane-changing vehicles tend to have adverse effects on the traffic flow behind them (Zheng et al., 2013). The fast-approaching rear vehicle exerts a strong urgency signal, limits the decision window of the lane-changing vehicle, forces the driver to lower safety standards and choose a more compact accepted target lane lag gap in order to complete the necessary lane-changing operation, thereby avoiding greater disruption to the traffic flow in the current lane.

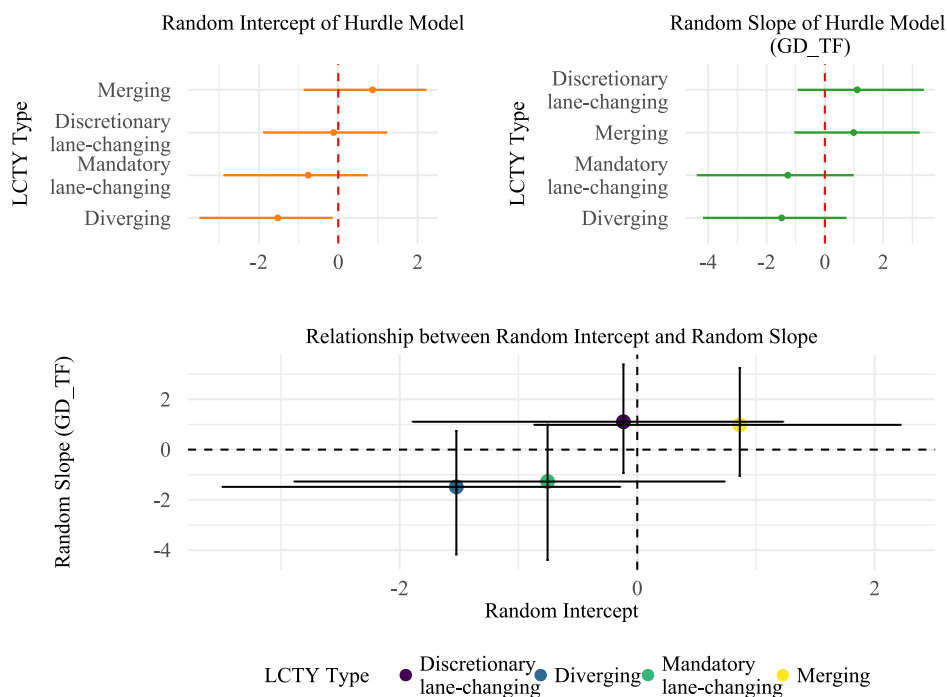


Figure 4.11 Visualisation of random effects of hurdle model at the lane-changing type level for accepted target lane lag gap decision (variable GD_TF).

To analyse the random effects of GD_TF at the data type level, the visualisation results of the random effects of the main model are plotted, as shown in Figure 4.12. The graphical results show that there are no significant differences in the random intercept and random slope between the simulation and field observation data and

the overall reference level. The joint distribution of random-parameters in the left subgraph shows that the two sets of data points are located in the second and fourth quadrants respectively, presenting a negative correlation. Specifically, the field observations show a lower random intercept but a higher random slope. This suggests that in field driving conditions, drivers have a smaller baseline tendency to choose the accepted target lane lag gap, but their decisions are sensitive to changes in GD_TF, and an increase in GD_TF can significantly prompt them to accept a larger accepted target lane lag gap. In contrast, the simulation data showed higher random intercepts and lower random slopes. This means that in the simulated environment, drivers have a greater tendency to choose the accepted target lane lag gap, but their behaviour is significantly less modulated by changes in GD_TF. This phenomenon aligns with the findings of Mullen et al. (2011), which indicate that there are systematic disparities between driving simulators and field road environments regarding speed perception, distance judgement, and risk assessment. The static driving simulator used in this study, although it uses a 130-degree triple screen and provides a rearview mirror view inside the vehicle, has inherent limitations in field of view and insufficient fidelity of dynamic visual cues, especially inaccurate perception of the pose and speed of objects on the side, rear and at a distance, making it difficult for drivers to accurately assess the traffic environment behind (Mao et al., 2025). This weakened perception renders the simulated driver's decision-making more reliant on inherent risk preferences, and it becomes challenging to make precise and sensitive adjustments to key environmental variables like GD_TF, as is the case in field driving.

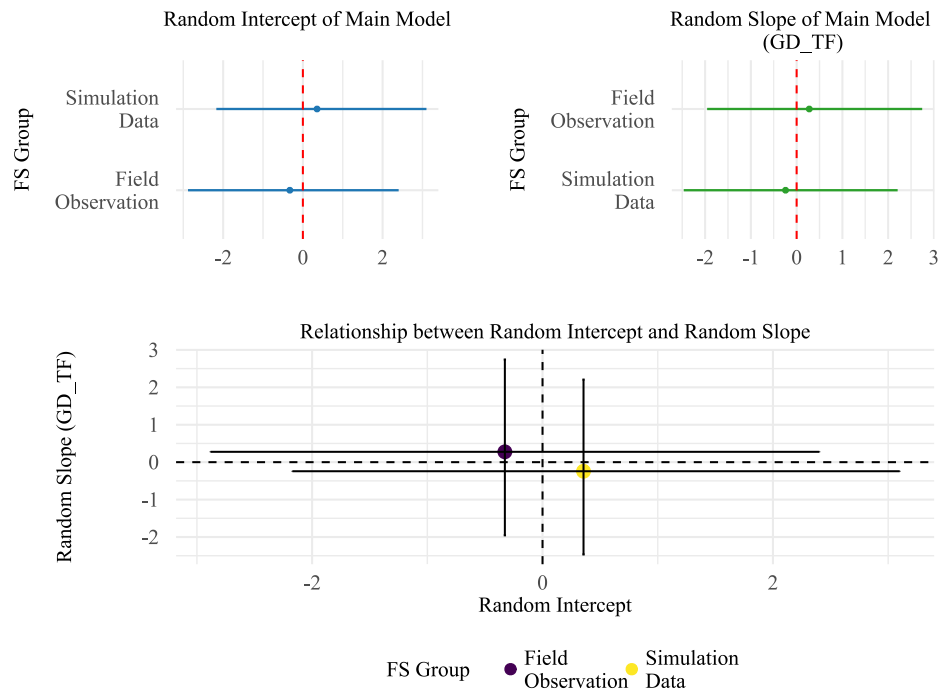


Figure 4.12 Visualisation of random effects of main model at the data type level for accepted target lane lag gap decision (variable GD_TF).

To analyse the random effects of LocLS in the main model at the lane-changing type level, the visualisation results of the random effects were plotted in Figure 4.13. In terms of the random intercept (upper left subgraph), the intercept for mandatory lane-changing is slightly below the baseline level, while that for diverging is slightly above the baseline level. This pattern reflects the inherent differences in baseline decision tendencies among different lane-changing types. In terms of the random slope (upper right subgraph), the intensity of the influence of LocLS on the lane-changing decision varies by lane-changing type. Among them, the random slope for diverging is slightly lower than the overall average, while the random slope for discretionary lane-changing is relatively higher. The left subgraph shows that the parameter pairs of all lane-changing types are evenly distributed in the second and fourth quadrants, showing a consistent negative correlation, and the negative correlation for diverging and discretionary lane-changing is more significant. This result can be explained by the differences in path constraints and spatial degrees of freedom of the lane-changing type. For the diverging, the location where the lane change occurs is strictly limited by the spatial position of the exit ramp and is usually concentrated at the end of the weaving section. This strong spatial constraint may result in its decisions being insensitive to changes in LocLS. Discretionary lane-changing, on the contrary, has the highest degree of behavioural freedom and its decisions are strongly dependent on traffic conditions. When LocLS increase, the tail of the weaving section usually has better traffic conditions (Van Beinum et al., 2018, 2019, 2020), which provides a more favourable environment for discretionary lane-changing. As a result, discretionary lane-changing behaviour shows greater sensitivity to LocLS, with drivers tending to perform lane changes in better conditions and choosing safer accepted target lane lag gap, reflecting typical opportunistic decision-making characteristics (Toledo et al., 2003).

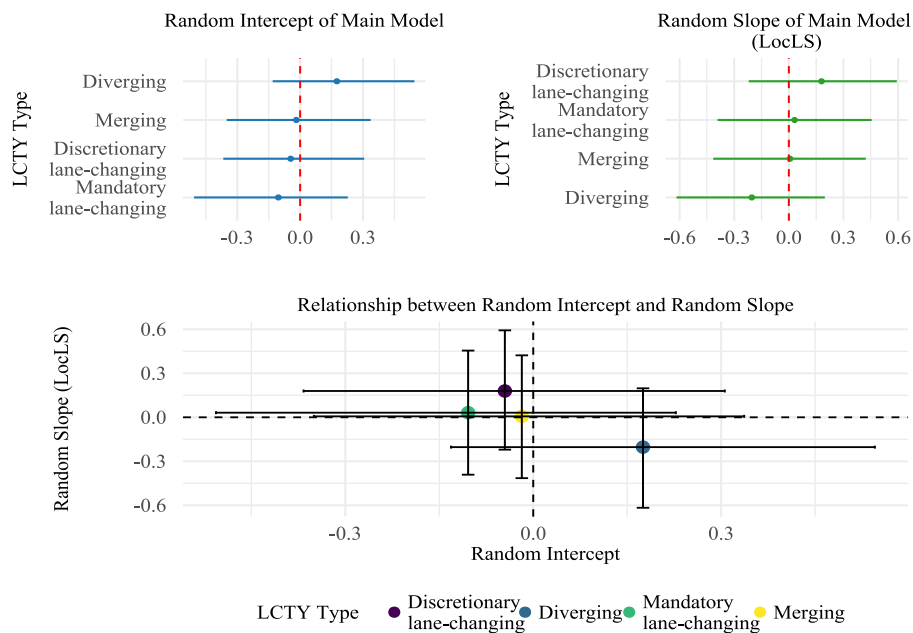


Figure 4.13 Visualisation of random effects of main model at the lane-changing type level for accepted target lane lag gap decision (variable LocLS).

Table 4.8. Results of accepted target lane lag gap decision model (Hierarchical Bayesian Double-Hurdle Null Model (HBDHNM)).

Variables		Mean	Standard error	95% confidence interval
Standard deviation (Lane-changing event level)		1.11	0.02	(1.07, 1.15)
Hurdle model	Intercept	-1.54	0.74	(-2.70, 0.36)
	Standard deviation (Data type level)	0.65	0.88	(0.01, 3.12)
	Standard deviation (Lane-changing type level)	0.93	0.58	(0.34, 2.46)
Main Model	Intercept	0.78	1.54	(-2.37, 3.82)
	Standard deviation (Data type level)	1.95	1.37	(0.55, 5.65)
	Standard deviation (Lane-changing type level)	0.16	0.18	(0.02, 0.60)

Table 4.9. Comparison of model performance metrics of accepted target lane lag gap decision models.

Model	$elpd_{loo}$	Standard error	LOOIC
Generalised Linear Model (GLM)	-4800.2	263.1	9600.4
Hierarchical Linear Model (HLM)	-4851.8	259.8	9703.5
Hierarchical Bayesian Double-Hurdle Null Model (HBDHNM)	-2844.7	48.1	5689.5
Hierarchical Bayesian Double-Hurdle Basic Model (HBDHBM)	-2629.5	50.1	5259.0
Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM)	-2575.8	51.3	5151.6

Table 4.10. Results of accepted target lane lag gap decision model (Hierarchical Bayesian Double-Hurdle Full Model (HBDHFM)).

Variable		Mean	Standard error	95% confidence interval
Standard deviation (Lane-changing event level)		0.92	0.02	(0.89, 0.96)
Hurdle Model	Intercept	-1.64	0.98	(-3.29, 0.65)
	Len_TF (The length of the following vehicle in the target lane.)	0.19	0.08	(0.02, 0.34)
	V_CF (The speed of the following vehicle in the current lane when the vehicle initiates a lane change.)	-0.19	0.08	(-0.35, -0.02)
	GD_TF (The gap distance between the lane-changing vehicle and the following vehicle in the target lane when the vehicle initiates a lane change.)	-1.28	1.13	(-3.64, 0.97)
	LocLS (The distance from the starting point of the weaving section to the lane-changing start position.)	0.06	1.51	(-3.00, 3.05)
	Standard deviation (Data type level)	1.04	1.11	(0.04, 4.18)
	Random slope LocLS (Data type level)	1.63	1.38	(0.34, 5.43)
	Cor (Random intercept, Random slope LocLS) (Data type level)	0.17	0.56	(-0.88, 0.97)
	Standard deviation (Lane-changing type level)	1.42	0.74	(0.56, 3.39)
	Random slope GD_TF (Lane-changing type level)	1.88	1.00	(0.60, 4.41)
Main Model	Cor (Random intercept, Random slope GD_TF) (Lane-changing type level)	-0.21	0.54	(-0.98, 0.83)
	Intercept	0.54	1.29	(-2.19, 3.06)
	LocLS (The distance from the starting point of the weaving section to the lane-changing start position.)	0.14	0.22	(-0.27, 0.56)
	Wid_CL (The width of the leading vehicle in the current lane.)	-0.06	0.03	(-0.12, -0.00)

Wid_CF (The width of the following vehicle in the current lane.)	0.09	0.03	(0.04, 0.15)
GD_TF (The gap distance between the lane-changing vehicle and the following vehicle in the target lane when the vehicle initiates a lane change.)	0.82	1.19	(-1.71, 3.11)
VT_TF (The type of the following vehicle in the target lane: 0-passenger car, 1-van.)	0.21	0.10	(0.02, 0.41)
V_CF (The speed of the following vehicle in the current lane when the vehicle initiates a lane change.)	-0.09	0.03	(-0.15, -0.03)
Standard deviation (Data type level)	1.35	1.21	(0.26, 4.66)
Random slope GD_TF (Data type level)	1.21	1.18	(0.20, 4.55)
Cor (Random intercept, Random slope GD_TF) (Data type level)	-0.21	0.54	(-0.98, 0.83)
Standard deviation (Lane-changing type level)	0.26	0.24	(0.06, 0.87)
Random slope LocLS (Lane-changing type level)	0.33	0.28	(0.10, 1.05)
Cor (Random intercept, Random slope LocLS) (Lane-changing type level)	-0.39	0.48	(-0.98, 0.70)
Maximum of potential scale reduction factor ($\hat{R}$)		1.00	
Minimum of Bulk effective sample size (Bulk- <i>ESS</i>)		6401	
Minimum of Tail effective sample size (Tail- <i>ESS</i>)		5397	
Sum of logarithmic probability densities ($elpd_{loo}$)		-2575.8	
Leave-one-out cross-validation (LOOIC)		5151.6	
Pareto k shape parameter		<0.7	

4.5 Conclusions

Based on the video trajectory data of the weaving section collected by drones in Chapter 2 and the simulation behaviour data obtained from the driving simulation experiment in Chapter 3, this chapter systematically extracts the metrics of the three key decision-making stages of lane-changing behaviour: the lane-changing start position, accepted target lane lead gap (AG_TLead), and accepted target lane lag gap (AG_TLag), and filters out the key variables that affect lane-changing decisions. In response to the unique three-level nested structure (data type – lane-changing type – lane-changing event) of the weaving section lane-changing data, one Hierarchical Bayesian Model and two Hierarchical Bayesian Double-Hurdle models were constructed to deeply identify the risk factors in the lane change decision-making process through this multi-level modelling framework. The system reveals the mechanism by which different traffic environment variables affect lane-changing behaviour and the heterogeneity characteristics at the individual, scenario, and behaviour type levels. The model results showed significant between-to-group variations in the Hierarchical Bayesian Double-Hurdle Null Model (HBDHNM), fully verifying the scientific rigor and necessity of the hierarchical Bayesian modelling framework.

The results of the hierarchical Bayesian model show that lane-changing to the left within the weaving section requires a longer weaving length compared to lane-changing to the right. The physical size and type of surrounding vehicles have a significant impact on lane-changing start position decisions. An increase in the speed of the following vehicle in the current lane will enhance the time pressure on the vehicles changing lanes, thereby prompting drivers to choose a more backward starting position for the lane change. It is notable that this speed pressure effect has a distinct heterogeneous feature, that is, the lane-changing start position in the simulation environment is less sensitive to the speed change of the following vehicle, and the discretionary lane-changing behaviour shows a higher sensitivity compared to other types of lane-changing. The results of the hierarchical Bayesian double-hurdle model further reveal the two-stage independence characteristics of lane-changing decisions. The binary decision of whether to choose a positive accepted target lane lead/lag gap and the continuous decision of how much the value of accepted target lane lead/lag gap are respectively dominated by different factors, a finding that economically validates the rationality of using the double-hurdle model to characterise the two decision-making stages respectively. An in-depth analysis shows that dynamic factors such as the gap distance of the target lane and the relative speed difference significantly influence the driver's decision on whether to accept the positive accepted target lane gaps. In determining the size of the specific gaps, in addition to the above factors, it is also affected by multiple factors such as the size characteristics and speed status of the vehicle itself and the surrounding vehicles. By analysing the random effects within the Bayesian framework, this study also found systematic heterogeneity in the degree of variable influence between data types and lane-changing types. This heterogeneous feature reveals the differences in driving decision-making mechanisms in different data

collection environments and lane-changing scenarios, providing a new perspective for understanding the complexity of lane-changing behaviour in weaving sections.

In summary, this chapter, from the perspective of risk factor identification and based on the three-level data structure features, establishes an adaptive Bayesian modelling framework to identify the key risk factors comprehensively and systematically in lane-changing decisions in weaving sections and clarify the intrinsic mechanism of interaction between micro-traffic environment variables and lane-changing decisions. The study in this chapter also found that different decision-making models may lead to differentiated risk tendencies, which lays an important theoretical foundation and methodological support for the next chapter to explore the risk levels and influencing factors under different lane-changing decision-making models.

Chapter 5

5. Analysis of the causes of lane-changing collision risk in the weaving section considering unobserved heterogeneity

5.1 Background

Compared with basic sections, lane-changing behaviour in weaving section shows a higher level of risk exposure due to strict spatiotemporal constraints and dense multi-vehicle interactions. Conducting specialised risk causation analysis for lane-changing behaviour in weaving section has significant theoretical value and practical significance. In Chapter 4 of the study, by constructing a hierarchical Bayesian model and its double-hurdle model extension, the key influencing factors of lane-changing decisions in weaving section were analysed, the heterogeneous characteristics in the variable effects were revealed, and the driver lane-changing decision-making mechanism was deeply explained from the perspective of micro-traffic behaviour. Including the intrinsic mechanisms of decision-making mechanisms such as lane change start position selection and accepted target lane gaps. However, Chapter 4 does not establish a direct association between lane-changing decision variables and vehicle collision risk, nor does it intuitively quantify the actual risk state during the execution of lane-changing behaviour. The study in this chapter will approach the quantitative assessment of the risk state of lane-changing, focusing on the mechanism by which the risk decision factors identified in Chapter 4 affect the level of lane-changing risk. By establishing a direct link between decision-making behaviour and safety consequences, the study will deepen and expand from understanding behavioural mechanisms to identifying risk elements. This chapter develops a comprehensive lane-changing risk indicator that captures both the duration of collision risk exposure and expected collision severity.

By integrating key variables of lane-changing decision-making behaviour identified in Chapter 4, a direct link between decision-making behaviour and risk assessment is established, and finally a causal analysis model for lane-changing collision risk in weaving sections that accommodates unobserved heterogeneity is constructed.

Based on the above research objective, this chapter will integrate the vehicle lane-changing behaviour data obtained from field observations and driving simulation experiments, extract complete lane-changing behaviour samples from multi-source trajectory data, and construct a representative analysis dataset. Furthermore, based on risk exposure theory and collision dynamics theory, the risk level of lane-changing events is quantified from two dimensions: duration of risk exposure and expected severity of collision, and the scientific classification of lane-changing risk levels is achieved through cluster analysis methods. Subsequently, key variables affecting the lane-changing risk in weaving section were screened, variable correlation analysis and collinearity diagnosis were carried out, and random-parameter ordered Probit models and extended models considering mean and variance heterogeneity were respectively established to effectively capture the effects of unobserved heterogeneity. Finally, by evaluating the fitting performance and interpretive ability of the model, the formation mechanism of lane-changing risk is deeply analysed from the perspective of heterogeneity, revealing the key risk factors of lane-changing behaviour in the weaving section and their pathways of action, providing theoretical basis and practical guidance for the safety design and operation management of the weaving section.

5.2 Data collection and processing

5.2.1 Extraction of the trajectories of lane-changing vehicles and key lane-changing participants

Based on the research in the previous chapters, this chapter constructs a dataset containing 2,061 valid lane-changing behaviour by fusing the field observation data of the weaving section extracted in Chapter 2 with the driving simulation data obtained in Chapter 3. The wavelet transform method effectively identified the start and end times of lane-changing behaviour and further extracted the complete trajectory data of LCV and key lane-changing participants during the lane-changing process, including the movement trajectories of CLV, CFV, TLV and TFV. Consistent with the data processing method in Section 4.2.1 of Chapter 4, all data were systematically organised and rigorously screened to construct a high-quality analysis sample set, providing a reliable empirical basis for the study of the lane-changing collision risk in the weaving section.

5.2.2 Lane-changing risk assessment index

(1) Indicator definitions

To quantify lane-changing risk in weaving section, this thesis constructs a comprehensive Lane Change Risk Assessment Index (LCRAI) based on two

dimensions: duration of risk exposure and expected severity of collision (Zhang et al., 2023). In terms of the duration of risk exposure, the GTTC concept proposed in Section 2.3.2 is introduced to assess the interaction risk between vehicles during lane-changing. The GTTC considers the differences in vehicle size and driving direction, which can more accurately depict the risk state faced in lane-changing behaviour. The spatiotemporal overlap analysis method is used to identify whether the vehicle trajectories overlap simultaneously in time and space, thereby determining whether there are objective conditions for the actual conflict to occur. On this basis, the risk exposure duration of the lane-changing behaviour is calculated in combination with GTTC. In terms of the expected severity of the collision, calculate the speed loss caused by the potential collision based on the momentum theorem to quantify the possible severity of the conflict. By fusing the two dimensions of risk exposure duration and expected collision severity through the fault tree analysis method, a comprehensive lane-changing risk assessment index LCRAI was constructed.

①Duration of risk exposure

To quantify the duration of risk exposure, first introduce the GTTC concept presented in Section 2.3.2. The method first identifies the closest point between vehicles as a potential collision point, and then solves the GTTC based on the standard kinematic equation to assess the interaction risk of vehicles during lane-changing. According to the definition of traffic conflict techniques in Section 2.3.1, the condition for two vehicles to have a conflict is that their trajectories intersect simultaneously in time and space, that is, the two vehicles arrive at the same location at the same time and thus may have a collision. When analysing lane-changing behaviour conflicts, the actual size of the vehicles needs to be considered. Since the trajectories of the vehicles on the two-dimensional plane do not intersect in a point-like manner but form an overlapping area, this area is the potential conflict area.

In a following scenario, the two vehicles are travelling in the same lane, and there is always a spatial overlap in their trajectories. As long as the collision time index is below the set threshold, there is a possibility of collision. In a lane-changing scenario, the conflict involves vehicles in different lanes, and the trajectory of the lane-changing vehicle may not overlap with that of the other vehicle in time and space while performing the lane-changing action. Figure 5.1 shows two cases where the trajectories overlap spatially but not temporally. In Figure 5.1(a), the vehicle V_2 has left the conflict area before V_1 entering it, while in Figure 5.1(b), the vehicle V_1 has left before V_2 entering the conflict area. There is no temporal overlap in either of these cases, and no actual collision occurs, thus there is no risk of collision. Therefore, to accurately quantify the duration of risk exposure, GTTC and spatiotemporal overlap analysis should be used in conjunction. The former considers the impact of vehicle size and driving direction to assess instantaneous risk, while the latter comprehensively identifies real conflicts on the two-dimensional plane from both temporal and spatial dimensions. Together, they form a precise framework for assessing the duration of risk exposure.

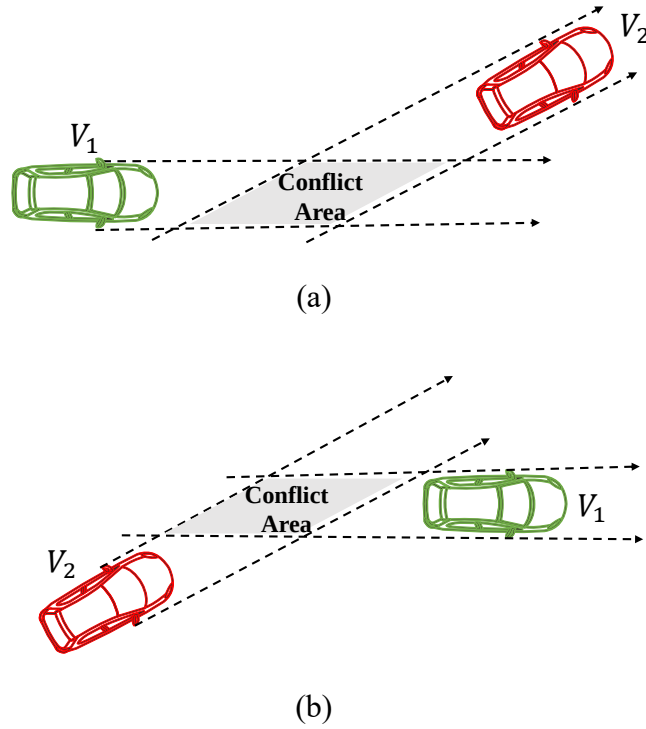


Figure 5.1 Two cases where vehicle travel trajectories overlap in space but not in time.

When there is a potential risk of collision, there must be a pair of collision points that first come into contact. Simplify the external profile of the vehicle into a rectangle and set 12 representative points along the rectangular boundary as potential collision points, as shown in Figure 5.2. These points include the four vertices of the rectangle, one second-order division point on each short side, and three fourth-order division points on each long side. By this layout, the distance between any two adjacent points is less than the width of the vehicle, ensuring that all potential conflict contacts are covered geometrically.

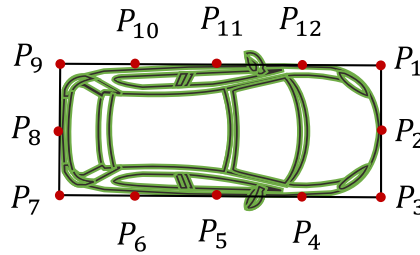


Figure 5.2 Schematic diagram of 12 representative points on the vehicle's rectangular boundary.

By analysing the 12 representative points on the profile to determine the first contact collision point pairs, when judging whether there is a potential collision risk between the vehicle V_1 and a certain point on the vehicle V_2 (denoted as the point P), it can be divided into three cases as shown in Figure 5.3 based on the spatial position relationship of the point P relative to the expected driving trajectory of the vehicle. That is, the point P is located on the left, inside or right side of the vehicle's expected trajectory area. The red dots in Figure 5.3 indicate the positions of the dots, and the dashed arrows indicate the expected direction of the vehicle's trajectory.

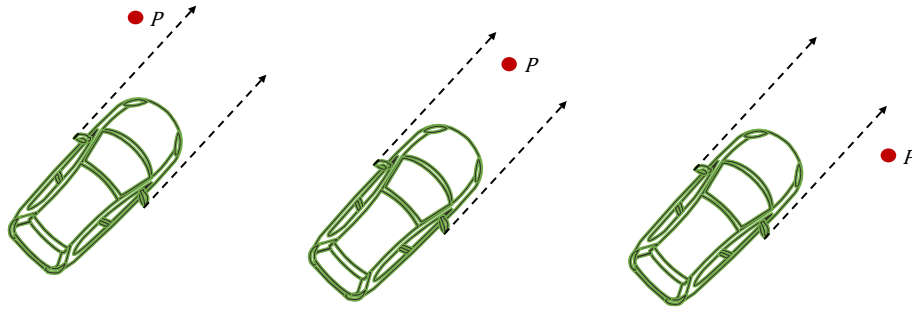


Figure 5.3 The positional relationship between point P and the direction of vehicle expected direction of trajectory.

As shown in Figure 5.4, this thesis takes the situation where the point P is located within the spatial region of the vehicle's expected trajectory as an example to illustrate the specific process of conflict spatiotemporal overlap analysis. The blue arrow in Figure 5.4 represents the relative speed between the vehicle V_1 and V_2 , which is calculated by Equation (5.1). α_1 and α_2 respectively represent the angles between the representative points P_1 and P_3 on the rectangular boundary of the vehicle V_1 and the horizontal direction, measured relative to the direction of the relative velocity of V_1 with respect to V_2 . Since the calculation is based on relative velocity, the point P is relatively stationary in the reference frame. β_1 and β_2 respectively represent the angles between the relative position vectors of P_1 and P_3 with respect to point P and the horizontal direction. To determine whether there is a risk of collision between point P_1 and P_3 on the rectangular boundary of vehicle V_1 and point P on vehicle V_2 , it is necessary to compare the consistency of the magnitude relationship between the relative velocity direction and the relative position direction. For this purpose, the indicator h_i is defined as the difference α_i between β_i , as shown in Equations (5.2) and (5.3). If $h_i=0$, it indicates that there is a risk of collision between points P_i and P . Otherwise, there is no risk of collision between these points.

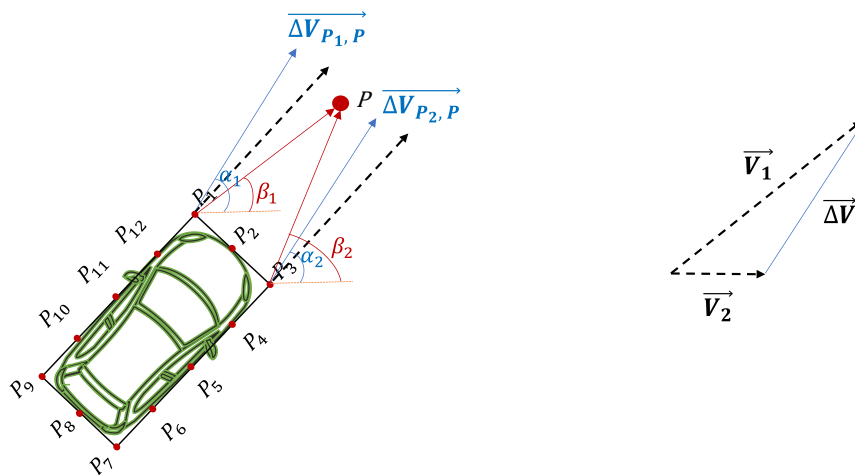


Figure 5.4 Example of spatiotemporal overlap analysis.

$$\overrightarrow{\Delta V} = \overrightarrow{V_1} - \overrightarrow{V_2} \quad (\text{Eq5.1})$$

where, $\overrightarrow{V_1}$ and $\overrightarrow{V_2}$ respectively represent the velocity vectors of the vehicle V_1 and V_2 in the global coordinate system, $\overrightarrow{\Delta V}$ represents the relative velocity vector of vehicle V_2 with respect to vehicle V_1 in the reference frame of vehicle V_1 .

$$h_1 = \alpha_1 - \beta_1 \quad (\text{Eq5.2})$$

$$h_2 = \alpha_2 - \beta_2 \quad (\text{Eq5.3})$$

Since the spatiotemporal overlap analysis is restricted to 12 discrete representative points on the rectangular boundary of the vehicle, the intermediate value theorem is introduced to guarantee that all potential collision point pairs are captured.

$$h_1 < 0 \wedge h_2 > 0 \Rightarrow \exists h_j : h_1 < h_j < h_2 \wedge h_j = 0 \quad (\text{Eq5.4})$$

In the example shown in Figure 5.4, since $h_1 > 0$, and $h_2 < 0$, according to the intermediate value theorem, there must be some point P_j on the vehicle V_1 between P_1 and P_3 such that $h_j = 0$. If the vehicle travels along the current expected trajectory, the point P_j will overlap with P , which indicates a potential risk of collision between the vehicle V_1 and V_2 .

Spatiotemporal overlap analysis is used to determine whether there is spatiotemporal overlap in vehicle trajectories, thereby identifying whether a conflict constitutes a collision risk, while GTTC is used to assess the likelihood of a conflict occurring. To comprehensively determine whether a conflict has a potential collision risk, the fault tree analysis method is introduced to integrate the logical relationship between the two. The fault tree analysis method uses logical reasoning to identify and assess the potential dangers of each system, which can not only reveal the direct cause of the fault but also dig deep into its potential inducement. The fault tree is composed of event symbols and logic gates, among which the most basic logic gates include the “and” gate and the “or” gate: The “and” gate indicates that the output event A will occur only when all input events (such as B_1 and B_2) occur simultaneously, as a logical “and” relationship. The “or” gate indicates that the occurrence of any input event (or) leads to the occurrence of the output event A , which is represented by the logical “or” relationship.

“and” gate: $A = B_1 \cap B_2$;

“or” gate: $A = B_1 \cup B_2$.

The fault tree analysis method commences with an undesired top event. Through logical reasoning, it conducts a layer-by-layer analysis of all the direct, indirect, and root causes that gave rise to that event until the root event cannot be further decomposed. The entire process employs logic gates to depict the causal relationships among events, ultimately shaping an inverted tree like logic diagram. Its basic analysis process primarily encompasses the following four steps.

Step 1: Define the top event. Identify the specific unwanted event (i.e., system failure or collision) that requires study.

Step 2: Build the fault tree. Commencing from the top event, systematically explore all possible cause events in a downward manner and connect them using specified logic gate symbols to construct a complete fault tree.

Step 3: Conduct qualitative analysis. By resolving the minimum cut-set of the fault tree, all the most fundamental and indivisible event combinations that lead to the occurrence of the top event are identified.

Step 4: Conduct quantitative analysis. Given the probabilities of each basic event, quantitatively evaluate the probability of the top event through Boolean algebra and probability calculation, and compute the importance of each basic event.

In this thesis, “conflicts with potential collision risks” are defined as the top event of the fault tree. It consists of two basic events: X_1 (GTTC between vehicles is less than the safety threshold) and X_2 (there is spatiotemporal overlap between vehicles). The event X_2 is determined by extracting 12 representative points on the rectangular boundary between two vehicles. If there is spatiotemporal overlap between any pair of these points, it can be concluded that there is spatio-temporal overlap between the vehicles. Therefore, the overlapping relationship between these 12 points is integrated via the “or” gate logic to form the event X_2 . The occurrence of the top event requires the simultaneous establishment of the basic events X_1 and X_2 . Therefore, the two are logically connected through the “and” gate, which jointly leads to the occurrence of the top event. Based on the above analysis, the constructed fault tree structure is shown in Figure 5.5.

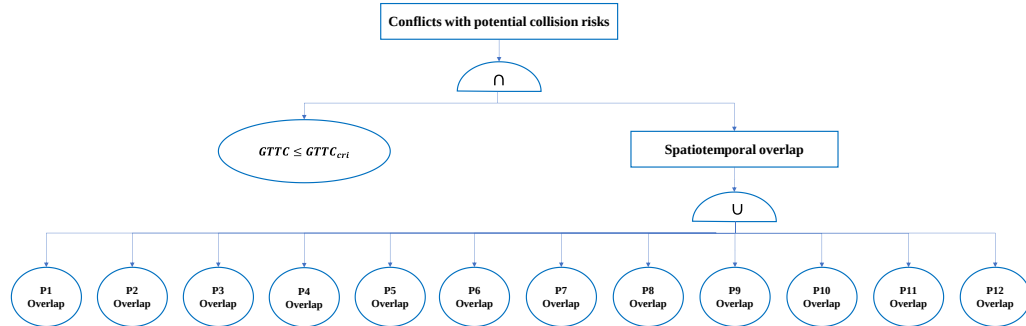


Figure 5.5 Fault tree model of spatiotemporal overlap analysis.

Based on the above fault tree analysis, this thesis combines the spatiotemporal overlap analysis with the GTTC concept to reconstruct the original Equation (2.8), resulting in the Equation (5.5) as shown below:

$$GTTC = \begin{cases} \frac{-D_{i,j}}{\dot{D}_{i,j}}, & \dot{D}_{i,j} < 0 \text{ and there is spatiotemporal overlap.} \\ +\infty, & \dot{D}_{i,j} \geq 0 \text{ or there is spatiotemporal overlap.} \end{cases} \quad (\text{Eq5.5})$$

Based on this, an Exposure-to-Risk (*ERI*) is defined, which represents the proportion of the time a vehicle is in a risky state to the total time it takes to change lanes. The equation is as follows:

$$ERI = \frac{t_{GTT C \leq GTT C_{cri}}}{t_{LC}} \quad (\text{Eq5.6})$$

$GTT C_{cri}$ is the safety threshold for $GTT C$. $t_{GTT C \leq GTT C_{cri}}$ represents the cumulative duration of $GTT C$ below the safety threshold. Additionally, t_{LC} is the duration of the vehicle lane-changing process. Figure 5.6 shows a schematic diagram of the ERI calculation.

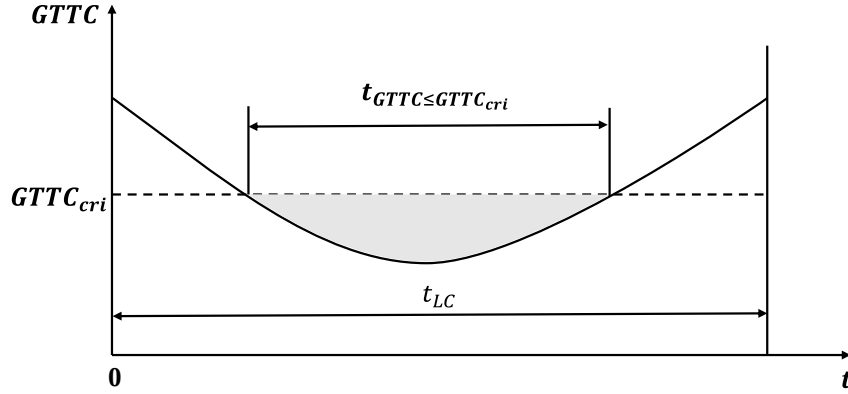


Figure 5.6 Schematic diagram of the ERI calculation.

Regarding the value of $GTT C_{cri}$, the study by Hooper and McGee found that the 85th percentile of driver perception-reaction time is 1.5 seconds (Hooper & McGee, 1983). However, given that the remaining 15% of drivers may exhibit longer reaction times (Naylor & Graham, 1997), existing studies have adopted a more conservative threshold. Overall, $GTT C_{cri}$ is typically defined to range between 1.5 and 5.5 seconds (Minderhoud & Bovy, 2001). To fully capture risky lane-changing behaviours, this study sets the $GTT C_{cri}$ safety threshold at 4 seconds.

② Expected severity of the collision

When analysing traffic conflicts, in addition to considering the duration of risk exposure, the severity of the conflict should also be included in the assessment. Several indicators for assessing the severity of conflicts have been proposed in existing studies (Bagdadi, 2013; Laureshyn et al., 2017; Park et al., 2018; Jiang et al., 2020). This thesis uses the change in velocity based on the momentum theorem (Delta-V) as the basis for evaluating the severity of the conflict. Delta-V refers to the change in speed of a vehicle during a collision (Laureshyn et al., 2017). Studies have explored the relationship between Delta-V and the probability of serious injury to occupants in a vehicle and found that Delta-v is the best single indicator for predicting the severity of a vehicle collision (Shelby, 2011; Laureshyn et al., 2017). When a vehicle experiences a significant change in speed during a collision, it indicates that it has been subjected to a strong external force. In addition, the weight of the vehicle also has a significant impact on speed changes. Vehicles of smaller mass are more sensitive to collisions and usually produce more significant Delta-V. Another key factor that affects Delta-V is the amount of energy absorbed by the vehicle during the collision, that is, the elasticity of the collision. To simplify the analysis, this thesis assumes that the collision is a completely inelastic collision,

that is, the two vehicles move together at the same speed after the collision, which can be further deduced based on the law of conservation of momentum.

$$m_1 \vec{v}_1 + m_2 \vec{v}_2 = (m_1 + m_2) \vec{v}_{after} \quad (\text{Eq5.7})$$

where, m_1 and m_2 are the masses of vehicles V_1 and V_2 , respectively; $\vec{v}_1$ and $\vec{v}_2$ are the velocity vectors of vehicles V_1 and V_2 before the collision; and $\vec{v}_{after}$ denotes the common velocity vector of vehicles V_1 and V_2 after the collision. Based on Equation (5.7), the magnitudes of the velocity changes experienced by vehicles V_1 and V_2 during the collision can be further derived, denoted as Δv_1 and Δv_2 , respectively. The detailed calculation procedure is provided in Equations (5.8) and (5.9).

$$\Delta v_1 = \frac{m_2}{m_1 + m_2} \times \sqrt{v_1^2 + v_2^2 - 2v_1 v_2 \cos \theta} \quad (\text{Eq5.8})$$

$$\Delta v_2 = \frac{m_1}{m_1 + m_2} \times \sqrt{v_1^2 + v_2^2 - 2v_1 v_2 \cos \theta} \quad (\text{Eq5.9})$$

where, v_1 and v_2 denote the magnitudes of the velocities of vehicles V_1 and V_2 , respectively, while θ represents the angle between the directions of motion of vehicles V_1 and V_2 .

Given that the speed change values of vehicles V_1 and V_2 , denoted as Δv_1 and Δv_2 , are unequal, this study defines Δv as the maximum of the two values to evaluate the potential severity of the conflict, as expressed in Equation (5.10). A higher Δv value indicates a more severe anticipated collision outcome, whereas a lower value suggests a less severe one.

$$\Delta v = \max\{\Delta v_1, \Delta v_2\} \quad (\text{Eq5.10})$$

Since the conflict did not involve an actual collision, the speed of the vehicles at the moment of the supposed collision cannot be determined. Therefore, it is necessary to make assumptions about the movement behaviour of the vehicles. Specifically, assume that both vehicles maintain their current speed magnitudes and directions while staying close to each other to estimate the Delta-V value.

Furthermore, it can be inferred from Equations (5.8) and (5.9) that the values of Δv_1 and Δv_2 are affected by the vehicle mass. The driving simulation data used in this thesis contains a complete vehicle model to acquire the precise mass. However, the trajectory data from field observations lacks this information. Generally, vehicle length is positively correlated with mass. For an approximate estimation, the vehicle mass is calculated using Equations (5.11) to (5.13) based on the correlation between vehicle length and mass (Lu et al., 2014).

$$L_i = 3 \times (1 - \mu) + 23\mu \quad (\text{Eq5.11})$$

$$\mu = \frac{m_i - m_{min}}{m_{max} - m_{min}} \quad (\text{Eq5.12})$$

$$m_i = \frac{L_i - 3}{20} \times (m_{max} - m_{min}) + m_{min} \quad (\text{Eq5.13})$$

where, L_i represents the length of the vehicle i extracted from the field observation data, and m_i is the estimated mass of the vehicle i . The lower limit m_{min} and upper limit m_{max} of the mass estimates set in this thesis are 1,000 kg and 15,000 kg respectively, which represent the typical mass of a car and a half-load heavy truck.

Severity Risk Index (SRI) is defined as the ratio of the actual speed change value, Δv , observed during a conflict event to its critical threshold, Δv_{cri} , and serves as an indicator for assessing the potential severity of a collision. The computation of SRI is expressed in Equation (5.14). A higher SRI value indicates that the observed Δv approaches the critical threshold, thereby reflecting an increased level of risk associated with the conflict.

$$SRI = \frac{\Delta v}{\Delta v_{cri}} \quad (\text{Eq5.14})$$

where, Δv_{cri} represents the maximum speed change that could be achieved in the event of a vehicle collision. To determine this value, parameters such as the vehicle's mass, maximum speed, and collision angle need to be further determined based on Equations (5.8) and (5.9). When the masses of the two vehicles, m_1 and m_2 , are greater than their difference, the maximum value of Δv_{cri} is taken. Based on the maximum speed limit of the weaving section where the trajectory data was collected, the vehicle speed is set to 100 km/h, and then Δv_{cri} is further increased. Additionally, since the weaving section is located on a section with a central green divider, oncoming vehicles do not need to be considered. Therefore, the range of collision angles between vehicles is limited to 0° to 90° . The maximum value of Δv_{cri} is achieved when the collision angle between vehicles is 90° . Based on the above assumptions, $\Delta v_{cri} = 141.42$ km/h was calculated.

③ Lane Change Risk Assessment Index (LCRAI)

Based on the ERI defined above and the severity risk index SRI , this thesis constructs the Lane-Changing Risk Assessment Index (LCRAI) by integrating these two indices. Methodologically, the fault tree analysis framework is continuously employed. Taking the overall risk of a single lane-changing event as the top event, the interaction between the LCV and its four surrounding vehicles (CLV, CFV, TLV, and TFV) is considered. As long as there is a conflict with any one of these vehicles, it is regarded as a lane-changing risk. Thus, there are four intermediate events in the system, and their logical relationship is an “or” gate. The occurrence of each intermediate event necessitates the simultaneous presence of ERI and SRI . Therefore, the relationship between its subordinate basic events is an “and” gate. Based on the above logic, the structure model of the lane-changing risk fault tree constructed is presented in Figure 5.7.

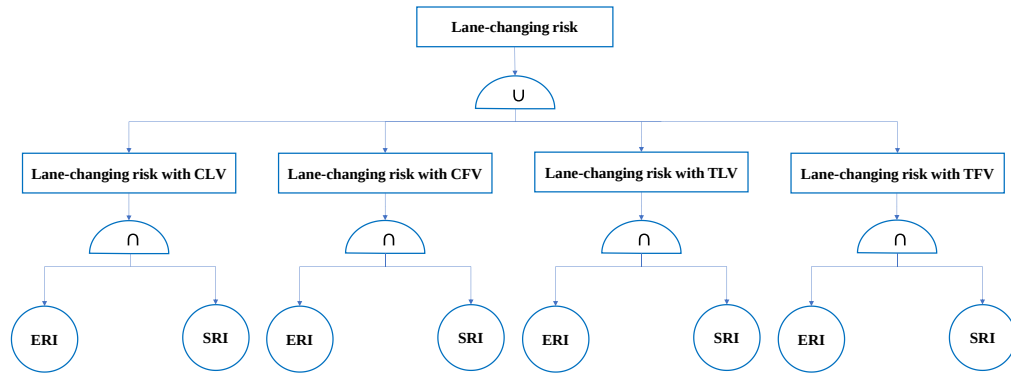


Figure 5.7 Fault tree model of lane-changing risk.

Based on this, the $LCRAI_k$ is defined as the natural logarithm of the product of the corresponding ERI_k and SRI_k between the LCV and the surrounding vehicle k , as shown in Equation (5.15). During a lane-changing, the LCV may be affected by four key lane-changing participants around it. Therefore, the overall risk of the lane-change event is defined as the sum of the risk indicators between the LCV and these four vehicles, as shown in Equation (5.16).

$$LCRAI_k = \ln (ERI_k \times SRI_k) \quad (\text{Eq5.15})$$

$$LCRAI = \sum_{k=1}^4 LCRAI_k \quad (\text{Eq5.16})$$

The constructed LCRAI comprehensively reflects the risk level of lane-changing events from two dimensions of the duration of risk exposure and the expected severity of collision. A higher LCRAI value indicates a greater risk of lane-changing. Conversely, a lower value implies a safer lane-changing situation.

(2) Results of indicator calculation

LCRAI values were computed for the 2,061 lane-changing behaviour samples extracted in Section 5.2.1, and the results are summarised in Table 5.1. By its definition, the LCRAI of certain samples is invalid, as depicted in Figure 5.7. If neither the LCV nor the four surrounding vehicles satisfy the conditions for lane-changing risk, the “lane-changing risk” top event does not take place, and the corresponding sample cannot be included in the final descriptive statistics. Although the “lane-changing risk” does not occur, it does not imply that the actual lane-changing events are devoid of lane-changing risk. This is because this is based on the threshold selected by the GTTC and only indicates that the lane-changing risk of these lane-changing events is relatively low. The range of effective LCRAI is $(-\infty, 0]$, and the larger the value, the greater the risk of a lane-changing collision. It can be observed from the table that the proportion of valid samples of all lane-changing types in the field observation data is 60.86%, which is higher than 49.11% in the driving simulation data, suggesting a higher incidence of lane-changing risk in the field observation samples. However, regarding the statistical characteristics of the effective samples, the mean, minimum, and maximum values of LCRAI in the field observation data were all lower than those in the simulation data. Since the

magnitude of the LCRAI values reflects the degree of risk, the results imply that although the probability of lane-changing risk is lower in the driving simulation data, the risk level is higher. Moreover, in terms of lane-changing types, diverging manoeuvres exhibited the highest proportion of lane-changing risk and risk level in both types of data. In conclusion, both the data source and the type of lane-changing can influence the probability and severity of lane-changing collisions in weaving sections.

Table 5.1. Descriptive statistics of the LCRAI calculation results.

Data type	LC ^a Type	Effective sample ratio	Mean	S.D.	Min.	Max.
Field	DLC ^b	58.33%	-9.88	4.66	-26.93	-2.69
Field	MLC ^c	50.15%	-6.75	3.10	-17.40	-2.36
Field	Merging	56.86%	-7.79	5.21	-22.51	-1.88
Field	Diverging	71.12%	-8.70	4.56	-24.88	-1.52
Field	Total	60.86%	-8.76	4.55	-26.93	-1.52
Simulation	DLC ^b	41.18%	-5.62	3.24	-15.05	-2.35
Simulation	MLC ^c	43.08%	-4.87	1.53	-7.13	-1.24
Simulation	Merging	49.59%	-5.64	2.72	-15.93	2.27
Simulation	Diverging	57.38%	-5.89	2.08	-10.74	-1.17
Simulation	Total	49.11%	-5.62	2.47	-15.93	-1.17

Note: ^a: lane change; ^b: discretionary lane change; ^c: mandatory lane change.

(3) Categorisation of the indicator results

To differentiate the risk levels during the lane-changing process, this thesis employs an enhanced K-means clustering algorithm to categorise the LCRAI results calculated in Table 5.1 into distinct risk levels. The enhanced K-means clustering algorithm represents an optimisation of the conventional K-means method. The primary enhancement lies in the optimisation of the selection of the initial cluster centres via the probability sampling strategy, thus diminishing the algorithm's sensitivity to the initial values. Although the conventional K-means algorithm is straightforward and efficient, its initial cluster centres are typically randomly generated, which can readily cause the clustering results to reach a local optimum. Selecting the appropriate initial cluster centres emerge as the key to enhancing the clustering effect. The enhanced K-means algorithm effectively boosts the stability and quality of the clustering results by dispersing the initial cluster centres as widely as possible across various regions of the data distribution. The specific procedure for classifying LCRAI into risk levels based on the enhanced K-means clustering algorithm is as follows.

Step 1: Input LCRAI samples at risk of lane-change collision ($N=2,061$), label LCRAI samples with an extremely low risk of lane change collision ($n=853$), and determine the optimal cluster number K and the maximum number of iterations by integrating the elbow method and the silhouette coefficient method.

Step 2: Randomly select the first cluster centre from the LCRAI samples at lane-change collision risk.

Step 3: For subsequent centres $c_k (k = 2, 3, \dots, K)$, calculate the probability that the point is selected as the next clustering centre.

$$P(x_i) = \frac{D(x_i)^2}{\sum_{j=1}^{N-n} D(x_j)^2} \quad (\text{Eq5.17})$$

where, $D(x_i) = \min_{c \in C} |x_i - C|$ is the shortest distance from the sample to the existing cluster centre.

Step 4: Repeat Step 2 until an initial centre k is selected.

Step 5: Assign each sample to the nearest cluster centre.

$$\text{Cluster}(x_i) = \arg \min_k \|x_i - c_k\| \quad (\text{Eq5.18})$$

Step 6: Recalculating the centre of each cluster.

$$C_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i \quad (\text{Eq5.19})$$

Step 7: The algorithm terminates when the change in the centre is less than the threshold or when the maximum number of iterations is attained.

Step 8: Output the cluster assignment, cluster centre, and classification decision boundary of the lane-changing collision risk LCRAI sample.

Since the LCRAI samples with an extremely low lane-changing risk ($n=853$) account for a relatively high proportion (41.39%) in the overall sample ($N=2,061$), to avoid the interference of these invalid values on the clustering process and prevent the imbalance of category division caused by distance calculation deviation, this thesis pre-excludes the extremely low risk samples before clustering.

Cluster analysis is then conducted only for valid LCRAI samples. To determine the optimal number of clusters, this thesis combines the elbow method and the silhouette coefficient method for evaluation. As shown in Figure 5.8, when the number of clusters is 3, the elbow feature is distinct, and subsequently, the rate of decrease in the sum of squares within the clusters slows down significantly. Meanwhile, as shown in Figure 5.9, the average silhouette coefficient reaches a relatively high level when the number of clusters is 3. A further comparison of the intra-group variance interpretation ratio between 2 and 3 reveals that the latter is 17% higher. Finally, the number of clusters is determined to be 3, and based on this, the valid LCRAI samples are clustered.

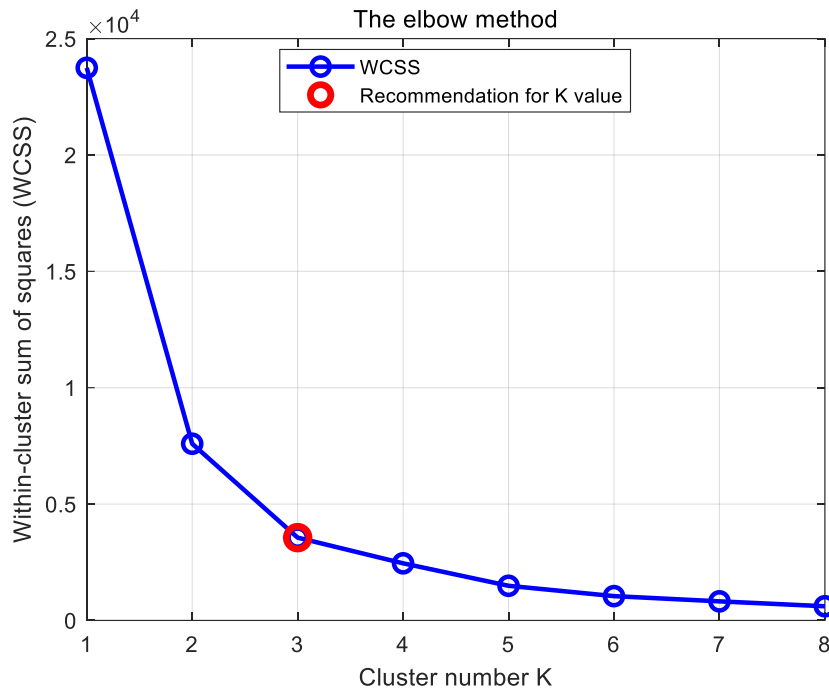


Figure 5.8 Elbow plot of the enhanced K-means clustering for LCRAI samples associated with lane-changing risk.

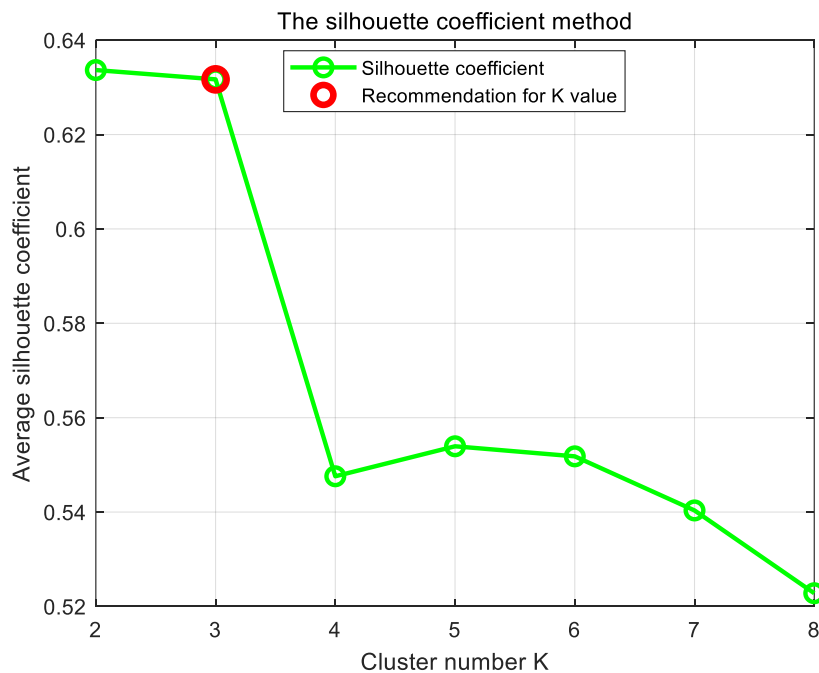


Figure 5.9 Average silhouette coefficient for the enhanced K-means clustering of LCRAI samples with lane-changing risk.

The distribution of data coloured by cluster labels is presented in Figure 5.10. From left to right, it ranges from Cluster 3, Cluster 1 and Cluster 2. The corresponding LCRAI values increase successively, and so do the corresponding lane-changing risk levels. Regarding the degree of distribution overlap, there is only a slight overlap among the clusters, which indicates that the boundaries between

different risk levels are relatively distinct. Based on the actual meaning, Cluster 3, Cluster 1, and Cluster 2 are named low lane-changing risk, moderate lane-changing risk, and high lane-changing risk respectively. It should be noted that the risk levels defined here are relative concepts based on the clustering results. A higher risk does not necessarily imply an extremely high absolute risk; instead, it indicates a significantly higher risk level than the other two types of samples.

As mentioned previously, LCRAI samples with extremely low lane-changing risk did not participate in the clustering process. Although the LCRAI values of these samples are invalid, by definition, they represent a situation with extremely low lane-changing collision risk, and thus they are uniformly classified as extremely low lane-changing risk.

The number of samples and LCRAI values for each risk level are presented in Table 5.2. Regarding sample composition, samples with extremely low lane-changing risk constitute 41.39%, which is the highest proportion among all risk levels. Meanwhile, samples with high lane-changing risk account for 35.08%, ranking second. This distribution suggests that there is a polarisation in the risk of lane-change collision in the weaving section, which is in line with the assessment of lane-changing risk in the weaving section in Chapter 2. Field observations reveal that the weaving ratio in the weaving section surpasses 30%, and over 30% of the traffic flow experiences conflicts on the driving path, a proportion notably higher than that of the basic section. Among the 2,061 lane-changing behaviour samples collected, the proportion of lane-changing behaviour with strong spatiotemporal constraints (including mandatory lane-changing, merging, and diverging) was approximately 64%. Mandatory lane-changing often has a higher collision risk level. These factors jointly account for the relatively high proportion of samples with a high lane-changing risk.

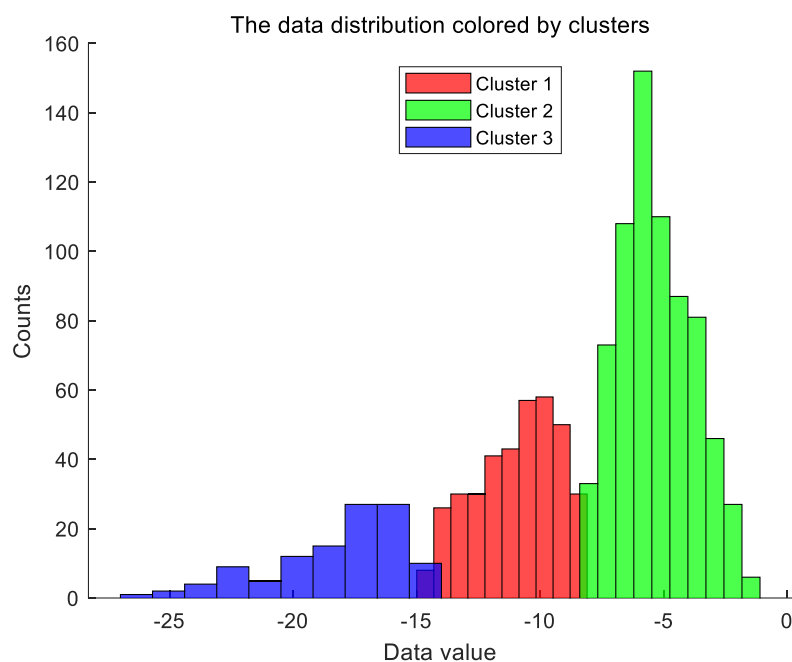


Figure 5.10 The distribution of data is presented through the cluster colouring of the lane-changing risk LCRAI sample clustering results.

Table 5.2. Characteristics of LCRAI in each category under varying risk levels.

Category	Counts (%)	LCRAI Min.	LCRAI Max.
Extremely low lane-changing risk (Not included in the clustering process)	853 (41.39%)	/	/
Low lane-changing risk (Cluster 3)	112 (5.43%)	-26.93	-14.64
Moderate lane-changing risk (Cluster 1)	373 (18.10%)	-14.55	-8.16
High lane-changing risk (Cluster 2)	723 (35.08%)	-8.12	-1.17

The silhouette coefficient is a crucial indicator for assessing the quality of cluster analysis. To evaluate the clustering effect, silhouette coefficient analysis is employed to quantify the degree of sample aggregation within each cluster. The specific steps are as follows.

Step 1: Calculate the average distance between the sample x_i and all other samples within the same cluster, and use this value as the within-cluster cohesion $a^{(i)}$ of the sample.

Step 2: Calculate the average distance from the sample x_i to all other samples within its assigned cluster, then compute the average minimum distance from x_i to all samples in every other cluster; the minimum value of these distances is defined as the separation degree $b^{(i)}$ of x_i with respect to its nearest neighboring cluster.

Step 3: The silhouette coefficient $S^{(i)}$ of sample x_i is calculated based on cohesion and separation as follows:

$$S^{(i)} = \frac{b^{(i)} - a^{(i)}}{\max\{b^{(i)}, a^{(i)}\}} \quad (\text{Eq5.20})$$

The range of silhouette coefficients is $[-1, 1]$. When $a^{(i)} = b^{(i)}$, the silhouette coefficient is 0, indicating that the clustering attribution of the sample is not clear enough. When $b^{(i)} \gg a^{(i)}$, the silhouette coefficient is close to 1, indicating that the sample is correctly assigned into clusters with high density and good separation, and at this point, the clustering performance is optimal.

Figure 5.11 shows the distribution characteristics of the sample silhouette coefficients in the clustering results. The silhouette coefficients of all samples are evenly distributed in the positive semi-axis interval, and the mean silhouette coefficients of each cluster are between 0.6 and 0.8. This distribution is statistically significant: first, the silhouette coefficients of all sample points are positive, indicating that the overall clustering structure is reasonable; second, the silhouette coefficients of each cluster exceed the baseline of 0.5, and some clusters even approach the excellent level of 0.8, reflecting a high degree of similarity among the samples within the clusters while maintaining significant differences between the

clusters. According to the evaluation criteria proposed by Kaufman and Rousseeuw, when the silhouette coefficient is greater than 0.5, the clustering effect can be considered good (Kaufman & Rousseeuw, 2009), and the results of this thesis are significantly better than this benchmark.

This quantitative evidence fully demonstrates that the clustering algorithm employed in this thesis can effectively identify the inherent patterns in the data, and the clustering structure formed has high internal consistency and external discrimination. This reliable clustering result provides sufficient scientific basis and credibility for the risk classification system on which the subsequent modelling analysis is based.

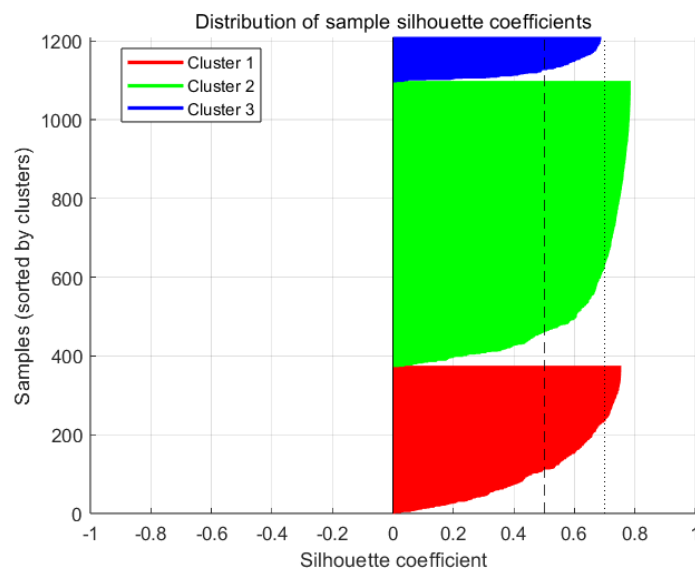


Figure 5.11 Distribution of sample profile coefficients for lane-changing risk LCRAI sample clustering results.

5.2.3 Variable screening and description

There are substantial differences in the variable screening strategy between this chapter and Chapter 4. Chapter 4 centres on the analysis of the lane-changing decision-making mechanism in the weaving section and selects three crucial decision variables, namely the lane-changing start position, AG_Lead, and AG_Lag, as the research objects. Given that these decision variables are instantaneous indicators representing the state at the start of the lane change, to maintain the simplicity of the model, the variables listed in Table 4.1 reflect the static characteristics of the lane-changing vehicles and the key lane-changing participants at the beginning of the lane change. This chapter broadens the research perspective to the risk assessment of the entire lane-changing process, which is the complete process from the initiation to the completion of the lane-changing. The continuous dynamic interaction between the lane-changing vehicle and the surrounding traffic environment has a significant impact on the final lane-changing risk level. Hence, relevant factors throughout the lane-changing execution process are screened as variables.

To conduct a causative analysis of lane-changing risk at weaving sections, this chapter builds upon the variable framework in Table 4.1. Through a systematic literature review, it ultimately integrates 53 potential risk-influencing factors to construct a more comprehensive variable system. The expanded variable system encompasses the following four dimensions: (1) Basic characteristics of lane-changing behaviour, such as lane-changing type, lane-changing direction, lane-changing spatial position, and lane-changing duration; (2) Physical attributes of the vehicles, including size parameters and type classifications of the lane-changing vehicle and the key lane-changing participants; (3) Motion state characteristics, including dynamic indicators like vehicle speed and its rate of change; (4) Relative motion characteristics, including interaction indicators such as gap distances and relative speeds between the lane-changing vehicle and the key lane-changing participants. The complete definitions and descriptive statistical characteristics of all variables are presented in Table 5.3.

Considering the continuity of the variable system in this chapter with that in Chapter 4, this section conducts a preliminary analysis of the statistical characteristics of the new variables in comparison with Table 4.1. The analysis of spatial characteristics reveals that the standard deviation at the end of the lane-change is similar to that at the start of the lane-change, and both values are relatively large. This indicates significant heterogeneity in the choice of the lane-change end position for different types of lane changes. The statistical distribution characteristics of the effective start/end positions of the lane-change are basically consistent with those of the start/end positions of the lane-change. In terms of time characteristics, the mean duration of the lane-change (6.25 s) is significantly longer than the mean duration of the effective lane-change (0.48 s), which implies that the effective lane-change operation time is short. This might be because the lane-changing vehicle spends most of its time searching for an appropriate moment to initiate the lane-change operation and only conducts substantial lane-change operations when specific conditions are met. The analysis of the longitudinal trajectory characteristics of the vehicles shows that there is a wide range of longitudinal distances for lane changes, which reveals significant differences in spatial requirements among different types of lane changes within the weaving section. The analysis of the speed dynamics features shows that the speed of the lane-changing vehicle fluctuates by up to 7.69 m/s during the lane-change. This suggests that the lane-changing vehicle needs significant speed regulation behaviour to obtain the optimal lane-changing timing, which may elevate the potential collision risk. The speed distribution features indicated that the average speed of the lane-changing vehicles and the key lane-changing participants was maintained at approximately 15 m/s, which was not significantly different from the average speed of the field observation data. Moreover, the standard deviation of each vehicle's speed was controlled within 2 m/s, demonstrating a relatively stable speed characteristic during the lane-change process. The descriptive statistics of the average gap distance showed that the average gap distance between the LCV and the TLV was notably smaller than that of other vehicles, which might reflect the special following strategy during the lane-changing process. The descriptive

statistics of the relative speed mode imply that the LCV maintains only a negative speed difference relative to the CLV and a positive speed difference with all other key lane-changing participants. This feature may originate from a specific conflict-avoidance strategy for following.

In the modelling preparation stage of this thesis, all variables were pre-processed. Firstly, a rigorous collinearity diagnosis was carried out to guarantee that the variance inflation factor (VIF) of all variables was below the threshold of 10. Subsequently, the continuous variables were standardised to eliminate the dimensional effect. The specific variable pre-processing methods adhered to the norms established in Section 4.2.3 of Chapter 4. After the standardised data pre-processing, the final set of constructed variables provided a solid data foundation for the subsequent risk causation analysis modelling work.

Table 5.3. Variable definitions and descriptive statistics of lane-changing risk.

Variable definitions	Unit	Mean	SD	Min.	Max.
LocLS: The distance from the starting point of the weaving section to the lane-changing start position.	m	122.52	84.61	4.18	396.54
LocLE: The distance from the starting point of the weaving section to the lane-changing end position.	m	224.38	88.56	28.79	398.67
LocEffLS: The distance from the starting point of the weaving section to the lane-changing effectively start position.	m	167.57	80.47	6.18	389.18
LocEffLE: The distance from the starting point of the weaving section to the lane-changing effectively end position.	m	174.82	82.44	6.82	393.08
AG_Lead: The accepted target lane lead gap when the vehicle initiates a lane change.	s	20.52	23.93	-2.24	194.71
AG_Lag: The accepted target lane lag gap when the vehicle initiates a lane change.	s	2.66	8.30	-37.77	160.24
LCTY: Lane-changing type: 0-Discretionary lane change, 1-Mandatory lane change, 2-Merging, 3-Diverging.	/	1.43	1.28	0	3
DT: Data type: 0-Field data, 1-Simulation data.	/	0.18	0.38	0	1
LCdir: Lane-changing direction: 0- Change lanes to the right, 1- Change lanes to the left.	/	0.20	0.40	0	1
LCD: Duration of the lane change process.	s	6.25	3.41	0.50	20.3
ELCD: Duration of the effective lane change process.	s	0.48	0.85	0.16	5.51
LCDis: The longitudinal distance travelled by the LCV during lane-changing.	m	100.86	58.94	1.93	327.74
Len_Ego: The length of the lane-changing vehicle.	m	3.70	0.83	2.27	11.43
Len_CL: The length of the leading vehicle in the current lane.	m	3.81	0.95	2.27	11.43
Len_CF: The length of the following vehicle in the current lane.	m	3.76	0.82	2.27	9.36
Len_TL: The length of the leading vehicle in the target lane.	m	3.98	0.84	2.27	10.34
Len_TF: The length of the following vehicle in the target lane.	m	3.89	1.10	2.27	13.97
Wid_Ego: The width of the lane-changing vehicle.	m	1.85	0.23	1.71	2.60
Wid_CL: The width of the leading vehicle in the current lane.	m	1.86	0.26	1.71	2.61
Wid_CF: The width of the following vehicle in the current lane.	m	1.84	0.25	1.71	2.80
Wid_TL: The width of the leading vehicle in the target lane.	m	1.87	0.22	1.73	2.54
Wid_TF: The width of the following vehicle in the target lane.	m	1.85	0.28	1.76	3.03
VT_CL: The type of the leading vehicle in the current lane: 0-passenger car, 1-van.	/	0.05	0.21	0	1
VT_CF: The type of the following vehicle in the current lane: 0-passenger car, 1-van.	/	0.04	0.20	0	1
VT_TL: The type of the leading vehicle in the target lane: 0-passenger car, 1-van.	/	0.04	0.19	0	1
VT_TF: The type of the following vehicle in the target lane: 0-passenger car, 1-van.	/	0.07	0.25	0	1

Table 5.3. Variable definitions and descriptive statistics of lane-changing risk (continued).

Variable definitions	Unit	Mean	SD	Min.	Max.
VVar_Ego : The difference between the maximum and minimum speeds of the LCV during lane-changing.	m/s	7.69	6.24	0.02	41.28
aveV_Ego : The average speed of LCV during lane-changing.	m/s	16.67	3.58	5.75	36.06
aveV_CL : The average speed of CLV during lane-changing.	m/s	17.10	4.48	5.72	37.40
aveV_CF : The average speed of CFV during lane-changing.	m/s	15.61	3.72	0.23	35.81
aveV_TL : The average speed of the TLV during lane-changing.	m/s	16.23	3.97	7.57	36.97
aveV_TF : The average speed of TFV during lane-changing.	m/s	14.87	3.75	4.98	33.46
sdV_Ego : The standard deviation of speed of LCV during lane-changing.	m/s	1.35	1.08	0.01	9.64
sdV_CL : The standard deviation of speed of CLV during lane-changing.	m/s	1.70	1.38	0.05	10.57
sdV_CF : The standard deviation of speed of CFV during lane-changing.	m/s	1.47	2.10	0.03	64.80
sdV_TL : The standard deviation of speed of TLV during lane-changing.	m/s	1.78	1.58	0.06	13.74
sdV_TF : The standard deviation of speed of TFV during lane-changing.	m/s	1.49	2.02	0.02	53.34
aveGD_CL : The average gap distance between LCV and CLV during lane-changing.	m	42.54	34.25	-0.10	342.97
aveGD_CF : The average gap distance between LCV and CFV during lane-changing.	m	48.95	73.42	-2.57	385.49
aveGD_TL : The average gap distance between LCV and TLV during lane-changing.	m	21.41	32.49	-1.89	331.91
aveGD_TF : The average gap distance between LCV and TFV during lane-changing.	m	41.10	66.19	-3.04	393.56
sdGD_CL : The standard deviation of the gap distance between LCV and CLV during lane-changing.	m	4.72	2.08	0.04	7.26
sdGD_CF : The standard deviation of the gap distance between LCV and CFV during lane-changing.	m	4.85	2.31	0.05	8.87
sdGD_TL : The standard deviation of the gap distance between LCV and TLV during lane-changing.	m	2.13	1.57	0.03	4.12
sdGD_TF : The standard deviation of the gap distance between LCV and TFV during lane-changing.	m	4.49	1.86	0.01	6.96
aveVDif_CL : The average speed difference between LCV and CLV during lane-changing.	m/s	-0.76	3.12	-19.11	9.73
aveVDif_CF : The average speed difference between LCV and CFV during lane-changing.	m/s	0.82	2.95	-10.95	19.21
aveVDif_TL : The average speed difference between LCV and TLV during lane-changing.	m/s	0.19	3.23	-17.90	15.45
aveVDif_TF : The average speed difference between LCV and TFV during lane-changing.	m/s	1.48	3.60	-11.56	19.23
sdVDif_CL : The standard deviation of the speed difference between LCV and CLV during lane-changing.	m/s	1.93	1.27	0.04	10.47
sdVDif_CF : The standard deviation of the speed difference between LCV and CFV during lane-changing.	m/s	1.91	2.20	0.07	10.65
sdVDif_TL : The standard deviation of the speed difference between LCV and TLV during lane-changing.	m/s	1.99	1.47	0.02	13.19
sdVDif_TF : The standard deviation of the speed difference between LCV and TFV during lane-changing.	m/s	1.89	2.06	0.05	9.46

5.3 Methods

According to the LCRAI classification system established in Table 5.2, the lane-changing risk levels are divided into four ordered categories: extremely low lane-changing risk, low lane-changing risk, moderate lane-changing risk, and high lane-changing risk. These risk levels exhibit a strictly ascending order relationship, which is in line with the mathematical characteristics of ordered categorical variables. Thus, the ordered Probit model is employed as the basic modelling framework. To assess the adaptability of different modelling strategies, this thesis constructs three models with progressive relationships, namely the fixed-parameter ordered Probit model (M_1), the random-parameter ordered Probit model (M_2), and the random-parameter ordered Probit model considering the heterogeneity of mean and variance (M_3). By comparing these three models, not only can the optimal modelling scheme be selected, but also valuable insights into the data generation process can be gained from the model evolution process, laying a methodological foundation for subsequent risk factor identification and heterogeneity analysis.

5.3.1 Fixed-parameter ordered Probit model

First, a fixed-parameter ordered Probit model needs to be established. Assume that the risk level of lane-changing behaviour (y) can be represented by latent variables (y_i^*). Then, establish the relationship between the lane-changing collision risk level i and the related influencing factors as follows:

$$y_i^* = \beta x_i + \varepsilon_i \quad (\text{Eq5.21})$$

where, β is the independent variable parameter vector, x_i is the independent variable vector of the lane-changing behaviour i , and ε_i is the random error term, which is independent of covariates x_i and represents the influence of unobserved factors on the collision risk level other than the observed covariates.

The ordered Probit model maps the potential and difficult-to-observe continuous variables y_i^* to observable ordered variables y_i , where y_i represents the risk level of lane-changing collisions. These observable variables y_i can be linked to the hidden variables y_i^* by Equation (5.22).

$$y_i = \begin{cases} 0 & \text{if } y_i^* \leq \mu_0 \\ 1 & \text{if } \mu_0 < y_i^* \leq \mu_1 \\ 2 & \text{if } \mu_1 < y_i^* \leq \mu_2 \\ 3 & \text{if } y_i^* > \mu_2 \end{cases} \quad (\text{Eq5.22})$$

where, $I = (\mu_0, \mu_1 \dots \mu_j)$ is the set of lane-changing collision risk level cut-off points, which satisfies $\mu_0 < \mu_1 \dots < \mu_j$, and $\mu_0 = -\infty, \mu_j = +\infty$.

Assume that the random error term ε_i follows the standard normal distribution, that is $\varepsilon_i | x_i \sim N(0,1)$. Its probability density function is denoted as $f(\varepsilon_i) = \phi(\varepsilon_i)$,

and its cumulative distribution function is denoted as $F(\varepsilon_i) = \Phi(\varepsilon_i)$. The probability that lane-changing collision risk level i is j can be expressed as:

$$P(y_i = j | \mathbf{x}_i) = P(u_{j-1} < y_i^* < u_j) \quad (\text{Eq5.23})$$

Substituting Equation (5.21) into Equation (5.23) gives:

$$P(u_{j-1} < y_i^* < u_j) = P(u_{j-1} - \boldsymbol{\beta} \mathbf{x}_i < \varepsilon_i < u_j - \boldsymbol{\beta} \mathbf{x}_i) \quad (\text{Eq5.24})$$

$$P(u_{j-1} - \boldsymbol{\beta} \mathbf{x}_i < \varepsilon_i < u_j - \boldsymbol{\beta} \mathbf{x}_i) = \Phi(u_j - \boldsymbol{\beta} \mathbf{x}_i) - \Phi(u_{j-1} - \boldsymbol{\beta} \mathbf{x}_i) \quad (\text{Eq5.25})$$

5.3.2 Random-parameter ordered Probit model considering the heterogeneity of mean and variance

Heterogeneity arising from data sources and individual differences is a crucial issue in statistical analysis. Ignoring this heterogeneity can result in bias in parameter estimation and distortion of research inferences. Therefore, researchers are increasingly adopting random-parameter models to address the limitations of traditional modelling methods (Mannering et al., 2016; Seraneeprakarn et al., 2017). Fixed-parameter ordered Probit models assume that the parameters $\boldsymbol{\beta}$ are fixed values. However, certain factors may influence the risk level of lane-changing collisions with individual differences. To comprehensively capture the unobserved heterogeneity, this thesis employs a random-parameter ordered Probit model. In this model, the characteristic parameters exhibit random effects, and the parameters of different lane-changing behaviour events may vary. This is accomplished by incorporating random terms into the original model's terms $\boldsymbol{\beta}$.

$$\boldsymbol{\beta}_i = u_i + \boldsymbol{\theta} \mathbf{Z}_i + \varphi_i \quad (\text{Eq5.26})$$

where, u_i represents the mean of all observations, $\boldsymbol{\theta}$ denotes the vector of parameters to be estimated, $\mathbf{Z}_i$ is the vector of explanatory variables that affect the mean of $\boldsymbol{\beta}_i$, and φ_i is the random distribution term employed to capture the unobserved heterogeneity among the observations, assuming it follows a normal distribution.

The Halton sampling method is employed to solve the model. When both the mean and standard deviation of the parameter estimation coefficients are significant at the 0.05 significance level, the variable is regarded as a random-parameter. Otherwise, it is reduced to a fixed parameter. To conduct a further analysis of the unobserved heterogeneity, the heterogeneity in the mean and variance of the random-parameters was modeled (Seraneeprakarn et al., 2017).

$$\boldsymbol{\beta}_{in} = u_i + \boldsymbol{\theta}_{in} \mathbf{Z}_{in} + \sigma_{in} \exp(\boldsymbol{\omega}_{in} \mathbf{W}_{in}) \nu_{in} \quad (\text{Eq5.27})$$

where, $\mathbf{Z}_{in}$ is used to capture the interpretation vector of mean heterogeneity, and its estimation parameter is the vector $\boldsymbol{\theta}_{in}$; σ_{in} is the standard deviation of the random-parameter; $\mathbf{W}_{in}$ is used to capture the interpretation vector of variance heterogeneity, and its estimation parameter is the vector $\boldsymbol{\omega}_{in}$; v_{in} is a perturbation term. If the vectors $\mathbf{Z}_{in}$ and $\mathbf{W}_{in}$ are not significant, it is considered that there is no significant mean and variance heterogeneity in the model.

In ordered Probit models, it is often difficult to directly explain the specific relationship between each factor and the risk level using the coefficients $\boldsymbol{\beta}$. The signs of these coefficients only indicate the direction of influence on extreme categories. Therefore, after the model estimation, the marginal effect of each variable needs to be calculated. Specifically, the marginal effect refers to the change in the probability that a unit change of a certain variable causes the risk level to fall into a specific category while other variables remain at the average level. Calculating the marginal effect helps to gain a deeper understanding of the model results and provides a basis for the formulation of risk management policies. The calculation equation is as follows.

$$\frac{\partial_p(y_i = j | \mathbf{x}_i)}{\partial_{x_k}} = \hat{\beta}_k [\phi(u_{j-1} - \bar{\mathbf{X}}\hat{\mathbf{B}}) - (u_j - \bar{\mathbf{X}}\hat{\mathbf{B}})] \quad (\text{Eq5.28})$$

where, $\hat{\beta}_k$ is the k th component of the coefficient vector $\boldsymbol{\beta}$, $\bar{\mathbf{X}}$ is the mean of the vector of the observation vector of the influencing factor, and $\hat{\mathbf{B}}$ is the vector of parameter estimates.

5.3.3 Model parameter estimation methods

In this thesis, the maximum likelihood estimation method is employed for parameter estimation, which is accomplished by optimising the likelihood function. Based on the provided conditional probability equation, the likelihood function is constructed as follows using the set of observational data N (Bhat, 2001).

$$L(\boldsymbol{\beta}, \boldsymbol{\mu} | y_i, \mathbf{x}_i) = \sum_{i=1}^N \sum_{j=1}^J \delta(y_i = j) \ln[\phi(u_j - \boldsymbol{\beta}_i \mathbf{x}_i) - \phi(u_{j-1} - \boldsymbol{\beta}_i \mathbf{x}_i)] \quad (\text{Eq5.29})$$

where, N represents the total sample size, $\delta(y_i = j)$ is the indicator function that characterises the weight of samples with a lane-changing collision risk level j in the group data i , and the parameter estimates are as follows:

$$\hat{\boldsymbol{\Gamma}} = (\hat{\mu}_0, \hat{\mu}_1, \dots, \hat{\mu}_{j-1}), \quad \hat{\mathbf{B}} = (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_k)^T \quad (\text{Eq5.30})$$

$$\delta(y_i = j) = \begin{cases} 1, & \text{if } y_i = j \\ 0, & \text{others} \end{cases} \quad (\text{Eq5.31})$$

In this thesis, the NLOGIT6 statistical software was employed for model parameter estimation. To achieve the optimal model goodness-of-fit, various random-parameter distribution functions were tested, such as the normal distribution, the uniform distribution, the student's distribution, and the log-normal distribution. The results indicated that the model with a normal distribution exhibited the best performance, which was consistent with the conclusions of existing studies (Yu et al., 2015; Azimi et al., 2020). During parameter estimation, a maximum likelihood estimation with 1,000 Halton samples was utilised to guarantee the stability and validity of the results (Bhat, 2001; Train, 2009).

5.3.4 Model performance evaluation metrics

To evaluate the performance of different models, the minimum Akaike Information Criterion (*AIC*) and Log-likelihood Ratio (*LR*) were used as two performance indicators for model fitting.

$$AIC = -2\ln(L) + 2K \quad (\text{Eq5.32})$$

where, L represents the likelihood function, and K represents the number of parameters. Smaller values of K imply that the model is more concise, whereas larger values of L indicate better goodness of fit. The smaller the AIC value, the better the balance between simplicity and goodness of fit of the model. An AIC difference exceeding 5 indicates a statistically significant difference between the models.

Since there exists a nesting relationship between the random-parameter ordered Probit model considering heterogeneity of mean and variance and the fixed parameter and random-parameter ordered Probit model, the random-parameter ordered Probit model considering heterogeneity of mean and variance can be regarded as a constrained version of the latter. Therefore, this thesis evaluates its goodness of fit to the data by comparing the log-likelihood ratio. The statistics of the contrastive likelihood ratio test typically follow a chi-square distribution, where the degrees of freedom are the difference in the number of parameters of the two models. Chi-square statistics are used to test whether there is a significant difference between the models.

$$\chi^2 = -2[LL(\beta_{M_1}) - LL(\beta_{M_2})] \quad (\text{Eq5.33})$$

where, $LL(\beta_{M_1})$ and $LL(\beta_{M_2})$ represent the log-likelihood values of the constrained model M_1 and the unconstrained model M_2 , respectively, when the parameters converge. If the chi-square statistic exceeds the critical value of the chi-square distribution, the unconstrained model M_2 is considered to have a better fit.

5.4 Model results and analysis

In this thesis, a fixed-parameter ordered Probit model, a random-parameter ordered Probit model, and a random-parameter ordered Probit model considering heterogeneity of mean and variance were established respectively to explore the risk factors influencing the level of lane-changing collision risk. Based on the fixed-parameter ordered Probit model, the possible random effects of all variables in the model were examined to construct the random-parameter ordered Probit model. By looking for possible heterogeneity in the mean and variance of significant random-parameters in the random-parameter ordered Probit model, the results showed that none of the random-parameters exhibited significant variance heterogeneity. Table 5.4 presents the comparison of fitting performance indicators among the above three groups of models for the lane-changing risk level. Table 5.5 presents the estimation results of the model for the lane-changing risk level (the random-parameter ordered Probit model considering heterogeneity of mean and variance) after model comparison, and Table 5.6 presents the average marginal effect of the variables in the model for the lane-changing risk level.

Table 5.4. Comparison of model performance metrics of lane-changing risk level causation models.

Model	Fixed-parameter ordered Probit model (M_1)	Random-parameter ordered Probit model (M_2)	Random-parameter ordered Probit model considering mean and variance heterogeneity (M_3)
Sample size	2,061	2,061	2,061
Estimate the number of parameters K	21	30	40
LL_c (log-likelihood values at model convergence)	-2329.75	-2283.13	-2265.97
LL_0 (log-likelihood of the null model)	-2473.66	-2473.66	-2473.66
Log-likelihood ratio χ^2	$-2[LL(\beta_{M_1}) - LL(\beta_{M_3})] = 127.56^{***}$	$-2[LL(\beta_{M_1}) - LL(\beta_{M_2})] = 93.24^{***}$	$-2[LL(\beta_{M_2}) - LL(\beta_{M_3})] = 34.32^{***}$
AIC	4701.5	4626.3	4611.9

Note: *** indicates $p < 0.001$.

Table 5.5. Results of lane-changing risk level causation model (M_3).

Variable	Coef.	S.E.	Z-stat	p-value
Constant	-0.042	0.059	-0.700	0.482
LCTY=3 (Lane-changing type is diverging.)	0.196	0.080	2.430	0.015
VT_TL (The vehicle type of TLV is van.)	-0.714	0.189	-3.790	< 0.001
Len_TF (The length of the following vehicle in the target lane.)	0.306	0.054	5.700	< 0.001
Wid_CL (The width of the leading vehicle in the current lane.)	0.123	0.044	2.790	0.005

Table 5.5. Results of lane-changing risk level causation model (M_3) (continued).

Variable		Coef.	S.E.	Z-stat	p-value
Wid_TF (The width of the following vehicle in the target lane.)		-0.256	0.054	-4.710	< 0.001
aveV_TL (The average speed of the TLV during lane-changing.)		-0.353	0.049	-7.220	< 0.001
sdV_TF (The standard deviation of speed of TFV during lane-changing.)		0.188	0.051	3.690	< 0.001
AG_Lag (The accepted target lane lag gap when the vehicle initiates a lane change.)		-0.137	0.048	-2.880	0.004
aveGD_TL (The average gap distance between LCV and TLV during lane-changing.)		-0.184	0.042	-4.420	<0.001
aveGD_TF (The average gap distance between LCV and TFV during lane-changing.)		0.186	0.046	4.040	<0.001
sdGD_CL (The standard deviation of the gap distance between LCV and CLV during lane-changing.)		-0.184	0.040	-4.600	<0.001
aveVDif_CL (The average speed difference between LCV and CLV during lane-changing.)		0.416	0.052	7.960	<0.001
aveVDif_CF (The average speed difference between LCV and CFV during lane-changing.)		-0.330	0.045	-7.280	<0.001
aveVDif_TL (The average speed difference between LCV and TLV during lane-changing.)		-0.259	0.058	-4.500	<0.001
sdVDif_CL (The standard deviation of the speed difference between LCV and CLV during lane-changing.)		0.539	0.041	13.19	<0.001
Random Parameters	ELCD (Duration of the effective lane change process.)	0.299	0.056	5.340	<0.001
	LocLS (The distance from the starting point of the weaving section to the lane-changing start position.)	-0.322	0.053	-6.030	<0.001
	Wid_TL (The width of the leading vehicle in the target lane.)	0.155	0.051	3.030	0.003
	sdV_CF (The standard deviation of speed of CFV during lane-changing.)	0.690	0.077	8.960	<0.001

Table 5.5. Results of lane-changing risk level causation model (M_3) (continued).

Variable		Coef.	S.E.	Z-stat	p-value
Random Parameters	aveGD_CF (The average gap distance between LCV and CFV during lane-changing.)	0.137	0.056	2.430	0.015
	sdGD_CF (The standard deviation of the gap distance between LCV and CFV during lane-changing.)	-0.268	0.093	-2.870	0.004
	ELCD (Duration of the effective lane change process.): Wid_CL (The width of the leading vehicle in the current lane.)	0.124	0.038	3.250	0.001
	ELCD (Duration of the effective lane change process.): AG_Lag (The accepted target lane lag gap when the vehicle initiates a lane change.)	0.269	0.064	4.210	<0.001
	LocLS (The distance from the starting point of the weaving section to the lane-changing start position.): Wid_TF (The width of the following vehicle in the target lane.)	-0.254	0.042	-6.110	<0.001
Heterogeneity in the means	Wid_TL (The width of the leading vehicle in the target lane.): Wid_TF (The width of the following vehicle in the target lane.)	0.092	0.033	2.750	0.006
	Wid_TL (The width of the leading vehicle in the target lane.): DT (Data type is driving simulation data)	-0.458	0.164	-2.790	0.005
	Wid_TL (The width of the leading vehicle in the target lane.): AG_Lag (The accepted target lane lag gap when the vehicle initiates a lane change.)	-0.109	0.043	-2.500	0.012
	sdV_CF (The standard deviation of speed of CFV during lane-changing.): DT (Data type is driving simulation data)	-0.438	0.172	-2.540	0.011
	sdV_CF (The standard deviation of speed of CFV during lane-changing.): AG_Lag (The accepted target lane lag gap when the vehicle initiates a lane change.)	0.172	0.057	3.000	0.003
	aveGD_CF (The average gap distance between LCV and CFV during lane-changing.): Wid_TF (The width of the following vehicle in the target lane.)	0.188	0.060	3.110	0.002
	sdGD_CF (The standard deviation of the gap distance between LCV and CFV during lane-changing.): Wid_CL (The width of the leading vehicle in the current lane.)	0.477	0.103	4.640	<0.001

Table 5.6. Mean marginal effects of variables in the lane-changing collision risk causation model (M_3).

Variable	Extremely low lane-changing risk	Low lane-changing risk	Moderate lane-changing risk	High lane-changing risk
LCTY=3 (Lane-changing type is diverging.)	-0.072**	0.003**	0.032**	0.037**
VT_TL (The vehicle type of TLV is van.)	0.247***	-0.029***	-0.115***	-0.103***
Len_TF (The length of the following vehicle in the target lane.)	-0.112***	0.006***	0.050***	0.057***
Wid_CL (The width of the leading vehicle in the current lane.)	-0.045***	0.002**	0.020***	0.023***
Wid_TF (The width of the vehicle behind the target lane.)	0.094***	-0.005***	-0.042***	-0.048***
aveV_TL (The average speed of the TLV during lane-changing.)	0.130***	-0.007***	-0.058***	-0.066***
sdV_TF (The standard deviation of speed of TFV during lane-changing.)	-0.069***	0.003**	0.031***	0.035***
AG_Lag (The accepted target lane lag gap when the vehicle initiates a lane change.)	0.050***	-0.003**	-0.022***	-0.025***
aveGD_TL (The average gap distance between LCV and TLV during lane-changing.)	0.068***	-0.003***	-0.030***	-0.034***
aveGD_TF (The average gap distance between LCV and TFV during lane-changing.)	-0.069***	0.003***	0.031***	0.035***
sdGD_CL (The standard deviation of the gap distance between LCV and CLV during lane-changing.)	0.068***	-0.003***	-0.030***	-0.034***
aveVDif_CL (The average speed difference between LCV and CLV during lane-changing.)	-0.153***	0.008***	0.068***	0.077***
aveVDif_CF (The average speed difference between LCV and CFV during lane-changing.)	0.122***	-0.006***	-0.054***	-0.061***

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.001$.

Table 5.6. Mean marginal effects of variables in the lane-changing collision risk causation model (M_3) (continued).

Variable	Extremely low lane-changing risk	Low lane- changing risk	Moderate lane- changing risk	High lane- changing risk
aveVDif_TL (The average speed difference between LCV and TLV during lane-changing.)	0.095***	-0.005***	-0.042***	-0.048***
sdVDif_CL (The standard deviation of the speed difference between LCV and CLV during lane-changing.)	-0.198***	0.010***	0.088***	0.100***
ELCD (Duration of the effective lane change process.)	-0.110***	0.006***	0.049***	0.055***
LocLS (The distance from the starting point of the weaving section to the lane-changing start position.)	0.118***	-0.006***	-0.053***	-0.060***
Wid_TL (The width of the leading vehicle in the target lane.)	-0.057***	0.003**	0.025***	0.029***
sdV_CF (The standard deviation of speed of CFV during lane-changing.)	-0.254***	0.013***	0.113***	0.128***
aveGD_CF (The average gap distance between LCV and CFV during lane-changing.)	-0.050**	0.003*	0.022**	0.025**
sdGD_CF (The standard deviation of the gap distance between LCV and CFV during lane-changing.)	0.098***	-0.005**	-0.044***	-0.050***

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.001$.

5.4.1 Model evaluation

Based on the model fitting results presented in Table 5.4, a comparison is made among the fitting performances of the fixed-parameter ordered Probit model, the random-parameter ordered Probit model, and the random-parameter ordered Probit model considering heterogeneity of mean and variance. The random-parameter ordered Probit model considering heterogeneity of mean and variance exhibits the smallest AIC value, which confirms that this model attains the best fitting accuracy while controlling complexity. The log-likelihood chi-square test statistic χ^2 rejects the null hypothesis at a confidence level exceeding 99.99%, indicating that the random-parameter ordered Probit model considering heterogeneity of mean and variance fits better than the other two groups of models. This model not only effectively captures the unobserved heterogeneity in the data but also strikes a balance between model simplicity and goodness of fit. Therefore, this thesis selects this model as the final analysis model, and its parameter estimation results will serve as a basis for the risk guidance analysis of lane-changing collisions.

5.4.2 Analysis of parameter estimation results

(1) Analysis of the effects of fixed parameters

The regression results of the stochastic parametric ordered Probit model considering heterogeneity of mean and variance as shown in Table 5.5, have identified multiple factors that significantly impact the propensity for lane-changing risk. The fixed parameters of the model reflect the average direction of each variable's influence on the propensity for the level of lane-changing risk. When the value is $p < 0.05$, the direction of influence is consistent across all samples, indicating that the effect is statistically significant.

Lane-changing type is one of the key factors influencing lane-changing risk. When the lane-changing type is diverging (LCTY=3), it significantly increases the likelihood of lane-changing risk compared to other lane-changing types. A diverging manoeuvre typically occurs in the exit area of the weaving section, where drivers take more aggressive driving actions because they are afraid of missing the exit due to time pressure (Hao et al., 2020b). From the perspective of vehicle movement characteristics, a diverging manoeuvre means changing lanes to the right, and there is a large visual blind spot on the right rear of the vehicle. Drivers typically glance at the right blind spot less frequently during lane-changing than at the left, which increases perceptual uncertainty (Olsen et al., 2005). In addition, vehicles need to leave the main road of the highway and slow down to enter the ramp, which can cause sudden deceleration and increase the risk of rear-end or side collisions.

The type and size of the key lane-changing participants exert a substantial influence on the lane-changing risk. When the vehicle type of TLV is van (VT_TL), the risk tendency is notably diminished. This could be attributed to the fact that vans possess a regular shape and a relatively stable driving pattern, enabling drivers to perceive and predict their behaviour more easily, which in turn encourages drivers to adopt a more cautious lane-changing strategy (Guo et al., 2025). Regarding

vehicle size, an increase in length of the following vehicle in the target lane (Len_TF) significantly heightens the risk propensity, which aligns with the perspective that large vehicles augment the difficulty of distance judgement and speed estimation. An increase in the width of the leading vehicle in the current lane (Wid_CL) also elevates the risk, as wider vehicles may partially obstruct the field of view necessary for lane-changing, thus increasing the complexity of lane-changing. Remarkably, an increase in width of the following vehicle in the target lane (Wid_TF) decreases the risk propensity. This might be because wider rear vehicles are detected earlier by drivers, offering them more reaction time to adjust and adopt a more conservative lane-changing strategy (Moridpour et al., 2012; Peng & Yang, 2012).

The impact of vehicle speed characteristics on lane-changing risk is more intricate. An increase in the average speed of the TLV during lane-changing (aveV_TL) substantially reduces the risk propensity, which supports the view that lane-changing is more easily accomplished in a smooth traffic flow. The greater the aveV_TL, the lower the probability of a collision between the lane-changing vehicle and the target lane leading vehicle (Chen et al., 2021). Conversely, an increase in the standard deviation of speed of TFV during lane-changing (sdV_TF) elevates the risk, indicating that the instability of the speed of the following vehicle increases the difficulty for the LCV to predict the safe distance. This is consistent with the argument in traffic flow theory that speed fluctuations increase decision-making uncertainty (Chen et al., 2021).

Regarding the time and distance gaps, an increase in accepted target lane lag gap when the vehicle initiates a lane change (AG_Lag) significantly reduces the risk propensity, which is consistent with the common understanding that a larger time gap offers a more sufficient safety buffer. Concerning the distance gap, an increase in the average gap distance between LCV and TLV during lane-changing (aveGD_TL) significantly reduces the risk. Conversely, an increase in the average gap distance between LCV and TLV during lane-changing (aveGD_TF) unexpectedly elevates the risk (Toledo & Zohar, 2007). This counter-intuitive phenomenon may imply that drivers tend to adopt a riskier lane-changing strategy when they perceive a greater distance from the vehicle behind. For example, more rapid deceleration or cutting, this partly validates the applicability of the risk compensation theory in lane-changing behaviour. Additionally, an increase in the standard deviation of the gap distance between LCV and CLV during lane-changing (sdGD_CL) reduces the risk, and distance fluctuations may act as a risk warning signal to prompt drivers to be more prudent.

The disparity in speed among vehicles also exerts a significant influence on the lane-changing risk. An elevation in the average speed difference between LCV and CLV during lane-changing (aveVDif_CL) notably heightens the risk (Zhou et al., 2020). A larger positive speed disparity may lead the LCV to encounter greater relative speed adjustment pressure when merging into the lane and may even prompt emergency braking. Conversely, an increase in the average speed difference between LCV and CFV during lane-changing (aveVDif_CF) mitigates the risk, as vehicles behind generally have more reaction time when the LCV is moving faster.

An increase in the average speed difference between LCV and TLV during lane-changing (aveVDif_TL) also lessens the risk, suggesting that maintaining a positive speed disparity with the TLV facilitates a smoother merge into the traffic flow (Chen et al., 2021). It is especially crucial to note that the standard deviation of the speed difference between LCV and CLV during lane-changing (sdVDif_CL) is the most significant among all variables. Abrupt fluctuations in the speed disparity often signify unstable following behaviour or potential conflicts, which substantially augment the lane-changing risk (Chen et al., 2021).

(2) Analysis of the effects of random-parameters

Random-parameters are employed to depict the heterogeneity of the impact of corresponding variables on lane-changing risk across diverse driving behaviours or scenarios. Through conducting goodness-of-fit tests on multiple distribution forms, the normal distribution is finally determined as the prior distribution form of the random-parameters. The coefficients of these variables mirror their average impact on the propensity for lane-changing risk, whereas the actual impact varies according to the individual driver or the specific situation.

On average, an increase in the duration of the effective lane change process (ELCD) significantly elevates the likelihood of lane-changing risk, a conclusion that aligns with existing research findings (Mwesige et al., 2016; Karimi et al., 2021). Random-parameters further disclose significant inter-individual variations. Some drivers may employ more risky strategies when the lane-changing time is extended, whereas others may adopt more cautious driving behaviour, which leads to an increase in lane-changing duration. In this case, their risk propensity may decline.

Overall, an increase in the distance from the starting point of the weaving section to the lane-changing start position (LocLS) contributes to reducing the lane-changing risk, yet the effect is also heterogeneous. Research has indicated that traffic conflicts in the common type of weaving sections are primarily concentrated near the triangle of the on-ramp and in the latter half of the weaving section (Zhang et al., 2023). This is frequently associated with local traffic congestion induced by concentrated vehicle lane changes. In the direction of vehicle travel, the risk of lane-changing is higher at the beginning of the weaving section, then gradually declines. Near the end of the weaving section, due to the potential resurgence of exit traffic pressure, this spatial distribution can help explain the heterogeneous distribution of the impact of LocLS on the lane-changing risk.

An increase in the width of the leading vehicle in the target lane (Wid_TL) is positively correlated with the overall tendency of high lane-changing risk, but this effect is not consistent. Wider leading vehicles can increase operational risk in specific scenarios by inducing visual occlusion, while some drivers will actively adjust their behaviour and adopt a more cautious lane-changing strategy after perceiving this potential hazard. This compensatory behaviour reduces the negative impact of this variable to a certain extent (Peng & Yang, 2012).

An increase in the standard deviation of speed of CFV during lane-changing (sdV_CF) generally heightens the driver's propensity to initiate lane changes, as greater speed fluctuations in the following vehicle impair the lead driver's ability

to anticipate traffic dynamics. However, this relationship is context-dependent: for example, when the following vehicle detects the lane-changing vehicle's manoeuvre intention and proactively decelerates to facilitate the manoeuvre, elevated speed variability may instead contribute to conflict mitigation.

An increase in the average gap distance between LCV and CFV during lane-changing (aveGD_CF) is associated with a statistically significant increase in the likelihood of high lane-changing risk, a finding that is somewhat counterintuitive. The underlying mechanism can be explained by risk compensation theory: when drivers perceive a larger available space behind their vehicle during the lane-changing process, some drivers are more inclined to adopt aggressive lane-changing strategies, which ultimately increases the operational risk of the manoeuvre.

An increase in the standard deviation of the gap distance between LCV and CFV during lane-changing (sdGD_CF) is found to reduce the overall lane-changing risk propensity. This indicates that distance fluctuations can act as an implicit risk warning signal to a certain extent, which enhances drivers' situational vigilance. Nevertheless, in specific lane-changing scenarios, such fluctuations can also disturb the accuracy of drivers' estimation of safe gap distance, which in turn increases the probability of misjudgement in lane-changing decision-making. This result reflects the bidirectional nature of this variable's influence across different scenarios.

(3) Analysis of the effects of mean heterogeneity in random-parameters

By introducing an interaction term to examine the moderating effect of various situational factors on the relationship between the core variable and lane-changing risk, specifically the moderating influence on the mean of the random-parameter, a positive coefficient indicates that the moderating variable strengthens the positive association between the random-parameter and lane-changing risk (or attenuates its negative association), while a negative coefficient indicates the opposite moderating effect.

For the interaction effects involving the duration of the effective lane change process (ELCD), an increase in the width of the leading vehicle in the current lane (Wid_CL) strengthens the positive effect of ELCD on lane-change risk tendency. Wider leading vehicles exacerbate the occlusion of drivers' forward and lateral visual fields. If the effective lane change process is further prolonged under this condition, the information uncertainty perceived by the driver will accumulate substantially, which in turn amplifies the overall risk perception. Similarly, if the accepted target lane lag gap when the vehicle initiates a lane change (AG_Lag) is large, the positive effect of ELCD on lane-change risk is also more pronounced. The underlying mechanism is that a large accepted lag gap may induce driver decision delay, leading to further extension of the lane change duration, and ultimately increasing the interaction complexity and potential conflicts with the dynamic traffic flow.

The width of the following vehicle in the target lane (Wid_TF), a key moderating variable, exhibits multiple synergistic effects. On one hand, an increase in Wid_TF amplifies the negative impact of the distance from the starting point of the weaving section to the lane-changing start position (LocLS) on lane-changing risk. Wider following vehicles are more easily detectable by surrounding drivers,

which strengthens drivers' cautious motivation when initiating lane changes away from the weaving section starting point, making the risk-reduction effect associated with increased distance more pronounced. On the other hand, Wid_TF also amplifies the positive impact of the width of the leading vehicle in the target lane (Wid_TL) on lane-changing risk. This reflects the width superposition effect that emerges when both the leading and following vehicles are wide: multiple visual obstructions and spatial constraints collectively increase drivers' psychological load and operational burden, which further elevates the overall lane-changing risk level.

The accepted target lane lag gap when the vehicle initiates a lane change (AG_Lag) and the driving simulation data type (DT) both exert a significant moderating effect on the relationship between the width of the leading vehicle in the target lane (Wid_TL) and lane-changing risk. When AG_Lag increases, the effect of Wid_TL on risk weakens, indicating that a sufficient safety time gap can partially offset the visual obstruction and pressure perception caused by a wider TLV, and reduce its risk amplification effect. For the simulated driving data scenario, the positive impact of Wid_TL on risk is also generally weaker, which may be attributed to the insufficient fidelity of simulation platforms in depth perception and motion feedback, making it difficult to fully reproduce drivers' sensitivity to the width of leading vehicles under real driving conditions (Kemeny & Panerai, 2003; Baumberger et al., 2005). Similarly, in the simulated environment, the standard deviation of speed of CFV during lane-changing (sdV_CF) also has a weaker positive impact on risk, reflecting the limitations of simulation software in characterizing dynamic vehicle-to-vehicle interactions, especially the propagation and feedback mechanisms of speed fluctuations (Wan et al., 2014). In real on-road driving, when AG_Lag is large, the positive impact of sdV_CF on risk is stronger. A possible explanation is that a large safety gap reduces drivers' alertness to rear speed fluctuations; once such fluctuations propagate to the lane-changing vehicle, the adjustment time window is compressed, ultimately leading to increased risk.

Several interaction effects further illustrate the regulatory role of the risk compensation mechanism. An increase in Wid_TF amplifies the positive correlation between the average gap distance between the average gap distance between LCV and CFV during lane-changing (aveGD_CF) and lane-changing risk, which is consistent with the core proposition of risk compensation theory: when a driver may adopt a more aggressive lane-changing strategy when there is sufficient gap distance behind the LCV and the size of the following vehicle is large. For instance, more aggressive cut-ins and intentional deceleration further increase actual lane-changing risk. In addition, when Wid_CL is large, the negative effect of the standard deviation of the gap distance between LCV and CFV during lane-changing (sdGD_CF) on lane-changing risk is attenuated. This indicates that the continuous visual obstruction caused by a wide leading vehicle weakens the function of gap distance fluctuation as a risk warning signal, thereby reducing its early warning effectiveness for drivers.

(4) Analysis of the mean marginal effect

In the ordered Probit model, the average marginal effect is employed to quantify the marginal impact of independent variables on the probability of each category of

the dependent variable. The value of the average marginal effect indicates the magnitude of change in the probability that an individual observation is classified into a specific risk level when a given independent variable increases by one unit. The estimates of the average marginal effect reported in Table 5.6 reveal that different influencing factors differ significantly in both the direction and magnitude of their effects on lane-changing risk across all risk levels. The following analysis separately discusses the top five key variables ranked by impact size from the two dimensions of risk intensification and risk mitigation.

Among all factors contributing to elevated lane-changing risk, the standard deviation of speed of CFV during lane-changing (sdV_CF) has the most significant impact. Specifically, a one-unit increase in sdV_CF is associated with a 12.8% rise in the probability of a vehicle transitioning to a higher risk level. This result indicates that CFV speed fluctuations can substantially interfere with drivers' judgement of safe lane-changing timing, and this variable is closely linked to the uncertainty induced by speed instability in car-following behaviour. In real-world driving scenarios, abrupt speed changes of the following vehicle disrupt the lane-changing vehicle's estimation of the minimum safe distance, thereby significantly increasing the likelihood of traffic conflicts. The standard deviation of the speed difference between LCV and CLV during lane-changing ($sdVDif_CL$) ranks second in terms of risk-increasing effect: a one-unit increase in $sdVDif_CL$ corresponds to a 10.0% increase in the probability of higher risk. This indicator captures the fluctuation characteristics of the relative speed between the LCV and the CLV, and its instability directly reflects the unpredictability of the car-following state, which tends to induce dangerous manoeuvres such as emergency braking or abnormal acceleration, consequently significantly increasing the lane-changing risk level (Hu et al., 2022). The average speed difference between LCV and CLV during lane-changing ($aveVDif_CL$) also has a significant positive effect on the lane-changing risk level, with a one-unit increase leading to a 7.7% rise in the probability of higher risk. This suggests that when the LCV travels at a higher speed than the CLV, the risk of potential conflict increases. The underlying mechanism may be that a larger positive speed difference reduces the effective decision-making time available to the lane-changing driver, thereby increasing the potential for lateral collisions. For the effective lane change process (ELCD), a one-unit extension is associated with a 5.5% increase in the probability of higher risk. Longer lane-changing duration typically reflects that the driver is indecisive or lacks operational proficiency. This uncertainty prolongs the vehicle's transition period between lanes, which in turn increases the likelihood of interaction conflicts with surrounding vehicles (Mwesige et al., 2016; Karimi et al., 2021). Finally, a one-unit increase in the length of the following vehicle in the target lane (Len_TF) is correlated with a 5.7% increase in the probability of higher risk. Owing to the larger size of vehicles, lane-changing drivers often experience more prominent visual blind spots and distance judgement errors, which reduces the accuracy of their safety gap assessment and ultimately elevates the overall lane-changing risk level.

Among the factors that suppress lane-changing risk, the average speed of the TLV during lane-changing ($aveV_TL$) has the strongest impact: a one-unit increase

in aveV_TL reduces the probability of high lane-changing risk by 6.6% and increases the probability of an extremely low risk level by 13.0%. This finding is consistent with the core proposition of traffic flow theory that smooth traffic flow facilitates safe lane-changing. Specifically, higher average TLV speeds generally indicate more stable and sparser traffic flow conditions, which creates a more favourable operating environment for lane-changing manoeuvres. A one-unit increase in the average speed difference between LCV and CFV during lane-changing (aveVDif_CF) is associated with a 6.1% decrease in the probability of high risk. This suggests that when the LCV maintains a larger positive speed difference relative to the CFV, the overall lane-changing risk can be effectively reduced: a higher relative speed lowers the risk of rear-end collisions from behind during the lane-changing process, and creates a larger rear safety buffer for the manoeuvre. Additionally, an increase in the distance from the starting point of the weaving section to the lane-changing start position (LocLS) also significantly reduces lane-changing risk, with each additional unit corresponding to a 6.0% decrease in the probability of high risk. This conclusion is consistent with existing research showing that most lane-changing manoeuvres are concentrated in the first half of weaving sections, leading to elevated vehicle interaction and conflict risks in this region (Van Beinum et al., 2018; Van Beinum & Wegman, 2019; Van Beinum et al., 2020). As LocLS increases, the space in the second half of the weaving section is more fully utilised, the spatial distribution of vehicles becomes more dispersed, and the overall risk level decreases accordingly. An increase in the average speed difference between LCV and TLV during lane-changing (aveVDif_TL) also exhibits a risk-mitigating effect: each one-unit increase reduces the probability of high risk by 4.8%, indicating that maintaining an appropriate positive speed difference relative to the TLV helps the lane-changing vehicle merge into the target lane more smoothly and establish a safer following state. Finally, an increase in the width of the vehicle behind the target lane (Wid_TF) reduces the probability of high risk by 4.8%. This may be explained by the fact that wider vehicles are more easily detected by lane-changing drivers, leaving drivers more reaction time to adjust their lane-changing strategies, a phenomenon consistent with the significance effect in visual perception theory.

By analysing the results of the mean marginal effect, this thesis demonstrates that the uncertainty of vehicle motion states (e.g., the standard deviation of speed, and the standard deviation of speed difference) exerts a significantly stronger effect on lane-changing risk than static vehicle attributes (e.g., vehicle length and width). This finding strongly corroborates the core proposition of dynamic traffic risk theory, which holds that motion uncertainty is the primary source of traffic conflicts. The results further highlight the key role of relative motion relationships in the risk formation mechanism, indicating that reasonable regulation of speed differences can be an effective approach to improving lane-changing safety. Based on the above analysis, this study proposes that the design of intelligent driving systems should strengthen real-time monitoring of speed fluctuations of surrounding vehicles, and incorporate such fluctuations as a core indicator for risk early warning. At the traffic engineering level, optimising the geometric layout and length configuration of

weaving sections can guide vehicles to use weaving sections more evenly across the spatiotemporal dimension. For driver behaviour guidance, priority should be given to training on speed difference management strategies, to improve drivers' awareness and ability to create safe lane-changing conditions through active speed adjustment.

5.5 Conclusions

This chapter systematically conducts a causal analysis of lane-changing collision risk in weaving sections while accounting for unobserved heterogeneity. By integrating multi-source lane-changing behaviour data, this chapter extracts samples of valid lane-changing manoeuvre and constructs a sample database containing complete lane-changing events. Furthermore, by incorporating both risk exposure duration and expected collision severity, this study develops a comprehensive lane-changing risk assessment index, LCRAI, which enables accurate quantification of lane-changing collision risk levels. To achieve clear classification of risk levels, an enhanced K-means clustering algorithm is adopted to partition lane-changing events into distinctly distinguishable risk categories based on risk characteristics. By establishing a random-parameter ordered Probit model considering heterogeneity of mean and variance, this study not only effectively identifies the key factors influencing lane-changing collision risk, but also reveals the unobserved heterogeneity across different influencing factors in depth. Based on the assessment of model fit and interpretability, this thesis reveals the formation mechanism of lane-changing collision risk in weaving sections from the perspective of heterogeneity. Vehicle physical attributes (e.g., type, size), motion state characteristics (e.g., average speed, speed fluctuation, relative speed), relative motion characteristics (e.g., gap distance, time gap), lane-changing decision outcomes (e.g., lane-changing start position, accepted target lane lag gap, effective lane-changing duration), and lane-changing contextual elements (e.g., lane-changing type, spatial position) together constitute the complete set of key variables that affect lane-changing collision risk. This thesis further analyses the action mechanisms, heterogeneity sources, and complex interactions among these factors, and finds that the impacts of vehicle dynamic state characteristics and relative motion characteristics on lane-changing collision risk are significantly stronger than those of static attribute parameters. This finding provides critical guidance for intervention targeting lane-changing collision risk in weaving sections. Based on an in-depth analysis of the action mechanisms of various factors and their interaction effects, this thesis further proposes targeted risk management strategies. At the methodological level, the analytical framework constructed in this chapter not only provides a measurement tool for assessing lane-changing collision risk levels in weaving sections, but also offers a novel theoretical perspective for exploring the causal mechanism of lane-changing collisions in this facility type. At the practical level, the research conclusions provide a scientific foundation for developing targeted traffic safety intervention measures for weaving sections. The analysis of the contributing factors to lane-changing collision risk conducted in this

chapter also lays a solid foundation for the lane-changing collision risk prediction research presented in the subsequent Chapter 6.

Chapter 6

6. Lane-changing collision risk prediction for the weaving section based on spatio-temporal representation decoupling

6.1 Background

Chapter 5 builds a random-parameter ordered Probit model considering heterogeneity of mean and variance to analyse the fundamental causes of lane-changing collision risk. However, this approach focuses on post-hoc attribution analysis and suffers from temporal lag. Conventional statistical models typically rely on kinematic characteristics collected during the lane-changing execution phase for model development, which makes them incapable of processing high-dimensional, large-sample temporal trajectories and unable to meet the requirements of pre-emptive real-time risk warning. Existing risk prediction studies mostly adopt a single machine learning or deep learning framework. Nevertheless, lane-changing data collected at weaving sections exhibits high heterogeneity, containing both static spatial topological information (e.g., basic information and decision-making features such as vehicle dimensions and lane-changing position) and dynamic kinematic sequences (e.g., vehicle motion and relative motion features such as absolute speed and relative speed difference). Machine learning models excel at fine partitioning of static boundaries but lack the capacity to capture causal recursion in time series, while deep learning models are skilled at capturing transient dynamic evolution. When processing mixed structured data, low-dimensional static features are easily masked by high-frequency fluctuating dynamic features during backpropagation. When dealing with imbalanced samples, deep learning models are also prone to lacking ordinal awareness for minority classes and falling into gradient collapse. To date, there is a dearth of academic

research investigating the complementarity of these two underlying spatiotemporal representation mechanisms in the context of lane-changing collision risk prediction.

To address these limitations, this chapter proposes a prediction architecture based on decoupled spatiotemporal representation. A static candidate feature set covering higher-order statistical distributions and a dynamic candidate feature set that preserves the original physical temporal evolution law are constructed separately, and then a feature engineering method integrating spatial clustering enhancement and boundary cleaning resampling to address the class imbalance problem are developed. Machine learning models are integrated to extract static discrete feature boundaries, applied deep learning models to capture high-frequency temporal patterns, and adopted Bayesian optimisation and cross-validation recursive feature elimination to escape the local optimum trap caused by feature space and hyperparameter coupling. By constructing an information fusion mechanism based on decoupled spatiotemporal representation, the static decision field and dynamic time series field complement each other's advantages, which enhances the consistency of risk level estimation while ensuring macroscopic discriminative performance. To overcome the limitations of complex black-box models and validate the risk causation analysis conclusions presented in Chapter 5, interpretable machine learning methods and high-frequency temporal evolution inversion methods are introduced to identify the influencing factors of lane-changing collision risk level.

6.2 Feature engineering

Based on the research presented in the preceding section, a dataset containing 2,061 valid lane-changing behaviour samples was constructed. First, wavelet transform was applied to identify the start time of lane-changing behaviour T_s . Then, four distinct prediction time windows Δ_t (i.e., 0.5 s, 1.0 s, 1.5 s, and 2.0 s) were defined by backward extension from the baseline T_s . Finally, the complete trajectory data of lane-changing vehicles and surrounding related vehicles under different prediction time windows $[T_s - \Delta_t, T_s]$ were extracted, and the filtered trajectory sample set was used as the data foundation for feature space construction and prediction model training.

6.2.1 Candidate feature set

The lane-changing collisions risk exhibits sporadicity, nonlinearity, and spatiotemporal coupling, which imposes strict requirements on the characterisation of underlying risk feature mechanisms. Due to the differences in feature capture mechanisms between classical machine learning methods and deep learning methods, static and dynamic candidate feature sets are constructed respectively, and the construction process is shown in Figure 6.1. For machine learning models that rely on explicit feature inputs, statistical feature sets covering multiple time slices are established. While for deep learning models adept at capturing long short-term

dependencies, sequential feature sets that retain the original temporal evolution pattern are constructed.

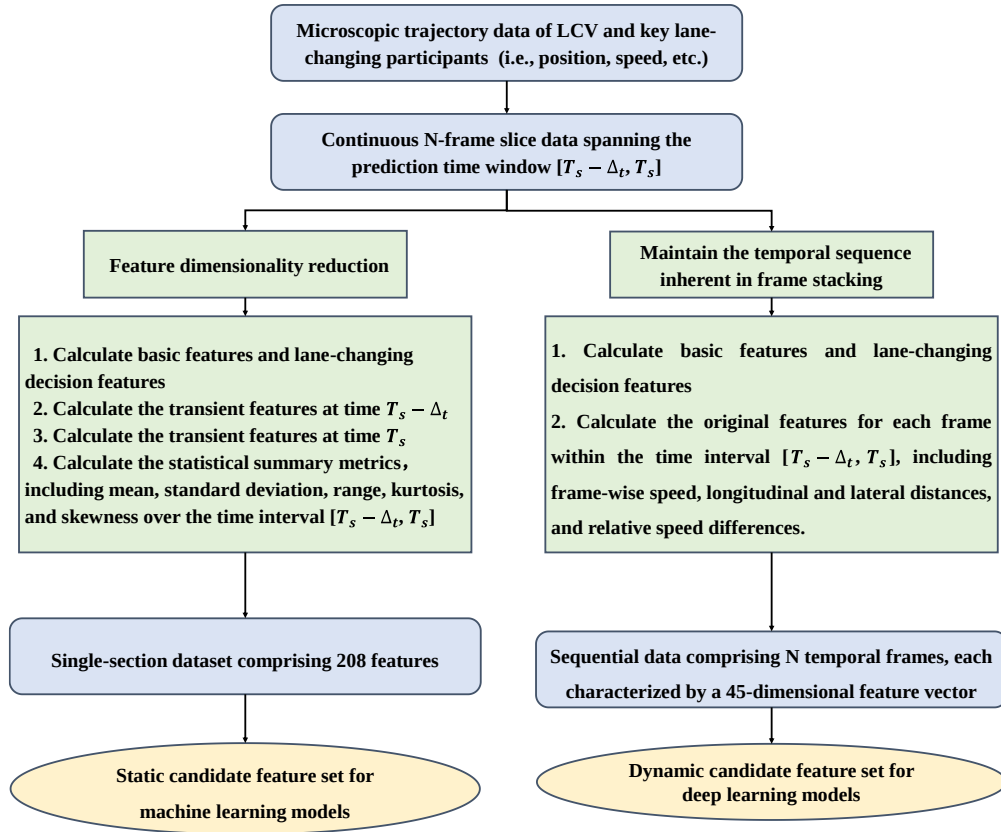


Figure 6.1 Construction of candidate feature sets for a lane-changing collision risk prediction model.

Based on the analysis of the contributing factors of lane-changing collision risk in Chapter 5, this study summarised and condensed a static candidate feature dataset that influences lane-changing collision risk prediction. The dataset contains a total of 208 candidate features, as presented in Table 6.1. These static candidate features are categorised into five main groups: basic features, lane-changing decision features, transient features at time $T_s - \Delta_t$, aggregated features within the time interval $[T_s - \Delta_t, T_s]$, and transient features at time T_s . Basic features cover information on lane-changing type, data type, lane-changing direction, as well as vehicle type and dimensions. Lane-changing decision features reflect the spatial position of the vehicle and the accepted time gap at the initiation of the lane-changing, including the longitudinal distance from the starting point of the weaving section, AG_Lead, and AG_Lag. Transient features at $T_s - \Delta_t$ and T_s respectively capture the motion state characteristics of vehicles (e.g., speed, lateral spacing) at the start and end of the time window, as well as the relative motion characteristics between vehicles (e.g., longitudinal/lateral distance, speed difference, gap distance). Aggregated features for the interval $[T_s - \Delta_t, T_s]$ are obtained via statistical dimension reduction of the continuous information extracted within the time window. Specifically, this step calculates the mean, standard deviation, maximum, minimum, range, kurtosis, and skewness of the motion state features and relative motion features of the lane-changing vehicle and key lane-changing participants

during the interval. This process compresses the complex spatiotemporal process into high-order statistical distribution features to align with the spatial partitioning logic of machine learning models.

The evolution of lane-changing collision risk is a continuous vehicle dynamics process. Leveraging the superior strengths of deep learning models in temporal modelling and causal inference, this study constructs a dynamic candidate feature set tailored for deep learning-based prediction. By retaining the high-dimensional original kinematic states within the prediction time window $[T_s - \Delta_t, T_s]$, and integrating them with basic features and lane-changing decision features, a 45-dimensional dynamic candidate feature set is obtained, as presented in Table 6.2. When the deep learning model is applied, the feature vectors are input in the form of time series, enabling the model to autonomously extract implicit dynamic representations. The dynamic candidate features are categorised into three main classes: basic features, lane-changing decision features, and frame-by-frame original dynamic features within the period $[T_s - \Delta_t, T_s]$. Specifically, the frame-by-frame dynamic features provide a complete record of the speed, lateral spacing, relative distance, speed difference, and time gap between the lane-changing vehicle and its interacting vehicles throughout the time window.

Table 6.1. Static candidate feature sets for machine learning models.

Categories	Candidate feature description	Number
Basic Features	Lane-changing type: 0-Discretionary lane change, 1-Mandatory lane change, 2-Merging, 3-Diverging.	1
	Data type: 0-Field data, 1-Simulation data.	1
	LCdir: Lane-changing direction: 0- Change lanes to the right, 1- Change lanes to the left.	1
	Vehicle length and width for LCV, CLV, CFV, TLV, TFV.	5 * 2
	Vehicle types for LCV, CLV, CFV, TLV, TFV.	5
Lane-changing decision features	LocLS: The distance from the starting point of the weaving section to the lane-changing start position.	1
	AG_Lead: The accepted target lane lead gap when the vehicle initiates a lane change.	1
	AG_Lag: The accepted target lane lag gap when the vehicle initiates a lane change.	1
	The time gap between LCV and CLV when the vehicle initiates a lane change.	1
	The time gap between LCV and CFV when the vehicle initiates a lane change.	1
Transient features at time $T_s - \Delta_t$	Speed for LCV, CLV, CFV, TLV, TFV.	5
	Lane gap for LCV.	1
	The longitudinal distances between LCV and CLV, CFV, TLV, TFV, respectively.	4
	The lateral distances between LCV and CLV, CFV, TLV and TFV, respectively.	4
	The speed differences between LCV and CLV, CFV, TLV, TFV, respectively.	4
	The time gap between LCV and CLV, CFV, TLV, TFV, respectively.	4
Aggregated features within the time interval $[T_s - \Delta_t, T_s]$	The longitudinal travel distance, lateral travel distance, and the ratio of longitudinal distance to lateral distance for LCV.	3
	The mean, standard deviation, maximum, minimum, range, kurtosis, and skewness for the speed of LCV, CLV, CFV, TLV, and TFV.	5 * 7
	The mean, standard deviation, maximum, minimum, range, kurtosis, and skewness for the longitudinal distances between LCV and CLV, CFV, TLV and TFV, respectively.	4 * 7
	The mean, standard deviation, maximum, minimum, range, kurtosis, skewness for the lateral distance between LCV and CLV, CFV, TLV, TFV, respectively.	4 * 7
	The mean, standard deviation, maximum, minimum, range, kurtosis, skewness for the speed difference between LCV and CLV, CFV, TLV, TFV, respectively.	4 * 7
	The mean, standard deviation, maximum, minimum, range, kurtosis, and skewness for the time gap between LCV and CLV, CFV,	4 * 7

Transient features at time T_s	TLV and TFV, respectively	
	The speed for LCV, CLV, CFV, TLV, TFV ($V_Ego, V_CL, V_CF, V_TL, V_TF$).	5
	The gap distance between LCV and CLV, CFV, TLV, TFV when the vehicle initiates a lane change ($GD_CL, GD_CF, GD_TL, GD_TF$).	4
	The speed difference between LCV and CLV, CFV, TLV, TFV when the vehicle initiates a lane change ($VDif_CL, VDif_CF, VDif_TL, VDif_TF$).	4

Table 6.2. Dynamic candidate feature sets for deep learning models.

Categories	Candidate feature description	Number
Basic Features	Lane-changing type: 0-Discretionary lane change, 1-Mandatory lane change, 2-Merging, 3-Diverging.	1
	Data type: 0-Field data, 1-Simulation data.	1
	LCdir: Lane-changing direction: 0- Change lanes to the right, 1- Change lanes to the left.	1
	Vehicle length and width for LCV, CLV, CFV, TLV, TFV.	5 * 2
	Vehicle types for LCV, CLV, CFV, TLV, TFV.	5
Lane-changing decision features	LocLS: The distance from the starting point of the weaving section to the lane-changing start position.	1
	AG_Lead: The accepted target lane lead gap when the vehicle initiates a lane change.	1
	AG_Lag: The accepted target lane lag gap when the vehicle initiates a lane change.	1
	The time gap between LCV and CLV when the vehicle initiates a lane change.	1
	The time gap between LCV and CFV when the vehicle initiates a lane change.	1
Original dynamic characteristics of time interval $[T_s - \Delta_t, T_s]$	Speed for LCV, CLV, CFV, TLV, TFV.	5
	Lane gap for LCV.	1
	The longitudinal distances between LCV and CLV, CFV, TLV, TFV, respectively.	4
	The lateral distances between LCV and CLV, CFV, TLV and TFV, respectively.	4
	The speed differences between LCV and CLV, CFV, TLV, TFV, respectively.	4
	The time gap between LCV and CLV, CFV, TLV, TFV, respectively.	4

6.2.2 Data processing

(1) Data interpolation and normalisation

During the feature construction process, for missing trajectory data, this Chapter follows the processing principles proposed in Chapters 4 and 5: samples are directly excluded if the LCV exhibits missing trajectories in the critical execution stage; samples are retained if only partial trajectory segments of key vehicles are missing. For static candidate feature sets designed for machine learning, this thesis adopts mean interpolation to impute missing entries. This method preserves the expected value of the overall feature distribution, while maximising the number of valid samples retained. For dynamic candidate feature sets oriented to deep learning, where inputs are kinematic features that follow strict temporal causality, this thesis uses linear interpolation for missing value imputation. This method aligns with the assumption that dynamic vehicle trajectories evolve smoothly, and avoids introducing high-frequency temporal noise. Furthermore, to eliminate discrepancies in physical dimensions across features, accelerate the convergence of gradient descent, and suppress singular value interference, this thesis implements standardisation for all continuous features, and adopts one-hot encoding for nominal categorical features.

(2) Data equalisation processing

Directly feeding extracted 208-dimensional static aggregated features into machine learning models poses notable challenges: conventional models struggle to disentangle the potentially complex nonlinear manifold structures inherent in high-dimensional feature spaces. Additionally, microscopic lane-changing collision risk datasets typically exhibit class imbalance, which drives models to converge toward biased decision boundaries that favour majority classes, resulting in poor generalisation performance for minority class recognition. To address these two key challenges, this study integrates spatial topological feature derivation and hybrid sampling into the machine learning framework to construct physically interpretable high-dimensional decision boundaries.

① Spatial topological feature derivation based on K-means clustering

To compensate for the limitation of machine learning models in perceiving global spatial distribution, this study introduces the unsupervised K-means clustering algorithm to conduct topological mapping on the original high-dimensional static feature space, and extract spatial distance features from a global perspective. The algorithm partitions the high-dimensional feature space into k clusters via iterative optimisation, and identifies the centroid of each cluster $C_k (k = 2, 3, \dots, K)$. Based on prior hyperparameter optimisation and pre-experimental exploration, this study sets the number of clusters k to 6. After fitting the clustering algorithm, the Euclidean distance between any sample vector x_i in the training set and test set and the six cluster centroids is calculated, and six new spatial distance features are generated for each original sample. These six-dimensional derived features are directly concatenated and fused into the original feature matrix as implicit spatial constraints. This method enriches the data representation dimension

without altering the physical meaning of the original features, and enables the model to refer to the relative positions of samples in the global topological space when constructing and optimising decision boundaries, thereby significantly improving the model's ability to perceive and segment complex, ambiguous non-linear risk boundaries.

②Hybrid sampling method based on SMOTE-Tomek

To address the class imbalance problem in datasets, existing studies typically resolve this issue via resampling, which can be categorised into three types: over-sampling, under-sampling, and hybrid methods combining the two strategies. Over-sampling balances class distributions by generating and adding synthetic minority-class samples, enabling the model to better identify and learn feature patterns from minority classes, improve the recognition accuracy of minority classes, and ultimately boost the overall predictive performance of the model. Currently, the most widely applied over-sampling method is the Synthetic Minority Over-sampling Technique (SMOTE) (Adeel et al., 2024; Mo et al., 2024). Under-sampling is another mainstream approach for mitigating data class imbalance. In contrast to over-sampling, under-sampling balances class distribution by removing redundant majority-class samples, which allows the model to allocate more attention to minority-class samples and thus improves the model's predictive performance. To date, Tomek Links is the most widely adopted under-sampling method in existing research (Mehranian et al., 2023).

To address the class imbalance problem, this thesis does not adopt a standalone over-sampling or under-sampling approach, but instead introduces the SMOTE-Tomek hybrid sampling method (Khleel & Nehéz, 2023). This method combines the synthetic sample generation capacity of SMOTE with the boundary cleaning mechanism of Tomek Links. The working principle of the SMOTE-Tomek hybrid sampling method is illustrated in Figure 6.2. First, the SMOTE method is applied to conduct spatial interpolation-based expansion for minority classes. For existing minority class samples, SMOTE identifies the k nearest neighbors in the feature space, then performs linear interpolation along the line segment connecting each original sample and its nearest neighbors to synthesize new minority samples. This process continues until the number of samples across all classes reaches a balanced state. However, the unconstrained linear interpolation of standard SMOTE tends to generate many overlapping ambiguous samples at the junctions of different risk level classes, leading to reduced discriminability at the classifier's decision boundary. The Tomek Links-based decision boundary cleaning step is introduced to resolve this issue. If two samples from different risk level classes are each other's nearest neighbor in the feature space, this indicates that the two samples lie on an ambiguous decision boundary or are inherent noise points, so the algorithm removes this sample pair. After processing with the SMOTE-Tomek hybrid sampling method, we obtain not only a dataset with balanced sample counts across all risk levels, but also a high-quality training set with clear inter-class boundaries. It should be emphasised that, to prevent data leakage, both the spatial topological feature derivation based on K-means clustering and the SMOTE-Tomek hybrid

sampling were strictly performed exclusively within the training set. The test set was only mapped and evaluated using the fitting rules derived from the training set.

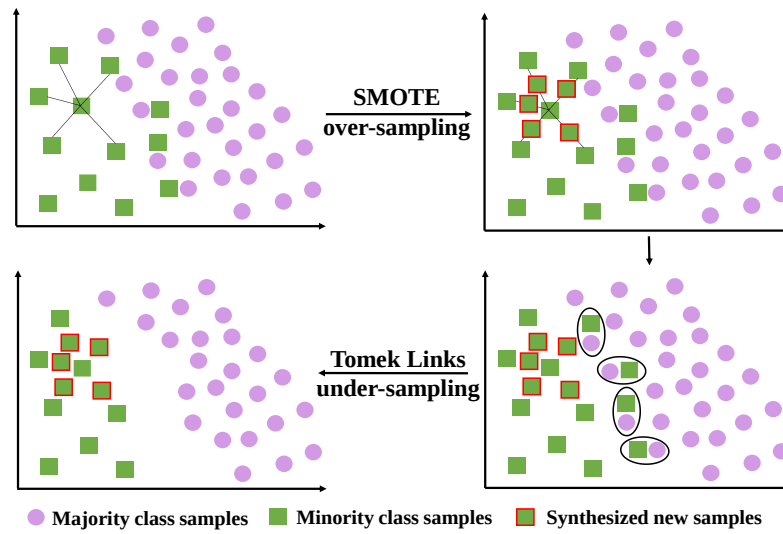


Figure 6.2 Schematic illustration of the SMOTE-Tomek hybrid sampling approach.

6.3 Methods

After the feature space is constructed, this section presents a lane-changing collision risk prediction architecture based on spatiotemporal representation decoupling to avoid feature flooding in a single model with mixed structured data. First, the machine learning model and the deep learning model are selected respectively to construct the evaluation baseline. Among them, the machine learning model receives a static feature matrix purified by spatial clustering enhancement, boundary cleaning, and recursive feature elimination, with a focus on finding the optimal decision boundary in a high-dimensional static space. Deep temporal networks, on the other hand, receive the original three-dimensional high-frequency temporal features and focus on mining dynamic evolution and local mutation patterns of microscopic kinematic metrics. Based on this, an information fusion mechanism based on spatiotemporal representation decoupling is introduced to achieve complementary advantages of static feature modelling and dynamic time series modelling in a continuous probability space, thereby constructing a prediction model that considers both macroscopic statistical characteristics and microscopic evolution laws.

6.3.1 Machine learning models

(1) Support Vector Machine (SVM)

First proposed by Cortes and Vapnik (1995), Support Vector Machine (SVM) is a statistical learning algorithm that performs classification by constructing an optimal decision hyperplane in a high-dimensional feature space. In this thesis, the core objective of the SVM is to maximise the geometric margin between lane change samples categorised into different risk levels. This optimisation objective is achieved through reliance on “support vectors” — the critical sample points that lie

closest to the classification boundary. Since most practical datasets are not perfectly linearly separable, the SVM introduces penalty factors and slack variables to tolerate a certain proportion of misclassification, while maintaining a robust decision boundary. Furthermore, to address complex non-linear classification tasks, the SVM leverages the kernel trick. Specifically, this thesis adopts the Radial Basis Function (RBF) kernel to implicitly project the original input features into an infinite-dimensional feature space. This mapping transforms non-linear classification problems into linearly solvable problems in the high-dimensional space, enabling the SVM to effectively separate samples of different risk levels while resisting interference from local high-order noise. Figure 6.3 presents the schematic diagram of the classification decision boundary for SVM.

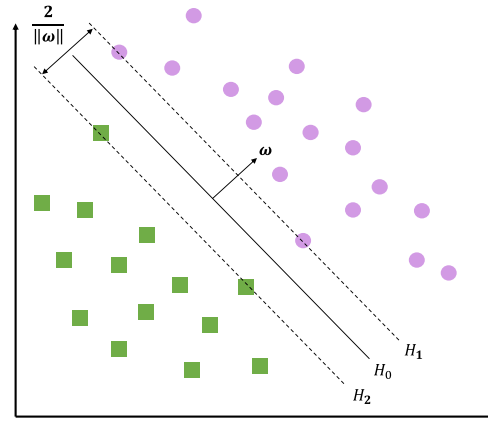


Figure 6.3 Schematic of SVM classification decision boundary.

(2) Random Forest (RF)

Proposed by Breiman (2001), Random Forest (RF) is a robust ensemble learning algorithm based on the bootstrap aggregating (Bagging) framework that integrates multiple decision trees as weak learners to improve overall predictive performance. The implementation workflow begins with bootstrap sampling, where multiple independent training subsets are drawn with replacement from the original dataset to train each decision tree independently. During tree construction, the algorithm uses Gini impurity as the primary criterion for node splitting. By evaluating candidate features and splitting thresholds, it selects the split that maximises node purity (i.e., reduces prediction uncertainty the most), enabling each tree to recursively split nodes based on locally optimal features. After all individual decision trees generate independent predictions, RF aggregates these results to produce the final overall output: majority voting is typically applied for classification tasks, while weighted averaging is used for regression tasks. This ensemble mechanism endows the model with excellent parallelizability and high prediction accuracy, while effectively mitigating the adverse impact of noise and outliers. However, the overall performance of RF remains sensitive to hyperparameter configurations, and the algorithm may face challenges such as non-smooth decision boundaries and suboptimal generalisation performance when processing high-dimensional sparse data. Figure 6.4 illustrates the complete framework of the RF algorithm.

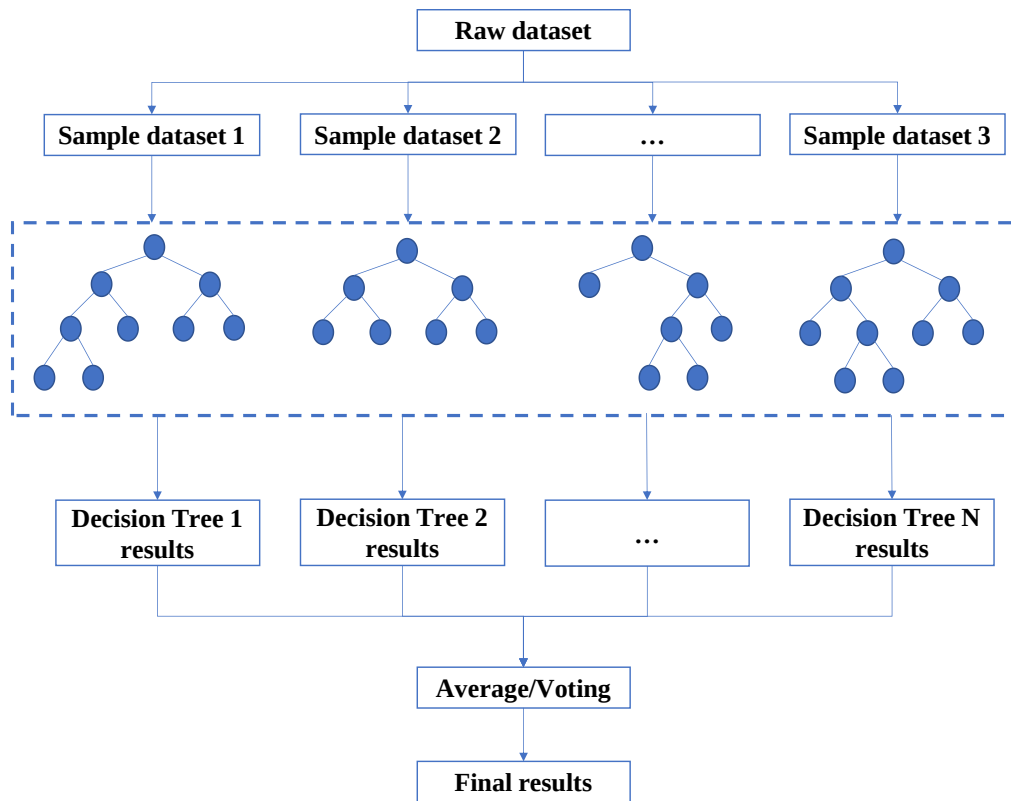


Figure 6.4 The algorithm framework of RF.

(3) Extreme Gradient Boosting (XGBoost)

XGBoost is an ensemble learning algorithm derived from the Gradient Boosting Decision Tree (GBDT), which was proposed by Chen & Guestrin (2016). In contrast to the parallel Bagging strategy adopted by RF, XGBoost employs the Boosting framework, which effectively captures complex nonlinear relationships by iteratively adding new decision tree weak learners to fit the residuals of the previous generation model. Compared with conventional GBDT, XGBoost incorporates both first-order and second-order gradient information into the loss function and introduces an additional structural regularisation term. The inclusion of gradient information enables XGBoost to estimate and optimise residuals more accurately in each iteration, while the structural regularisation term constrains model complexity, allowing the balance of the model's fitting performance and generalisation ability via tuning regularisation parameters. The algorithmic framework of XGBoost is presented in Figure 6.5.

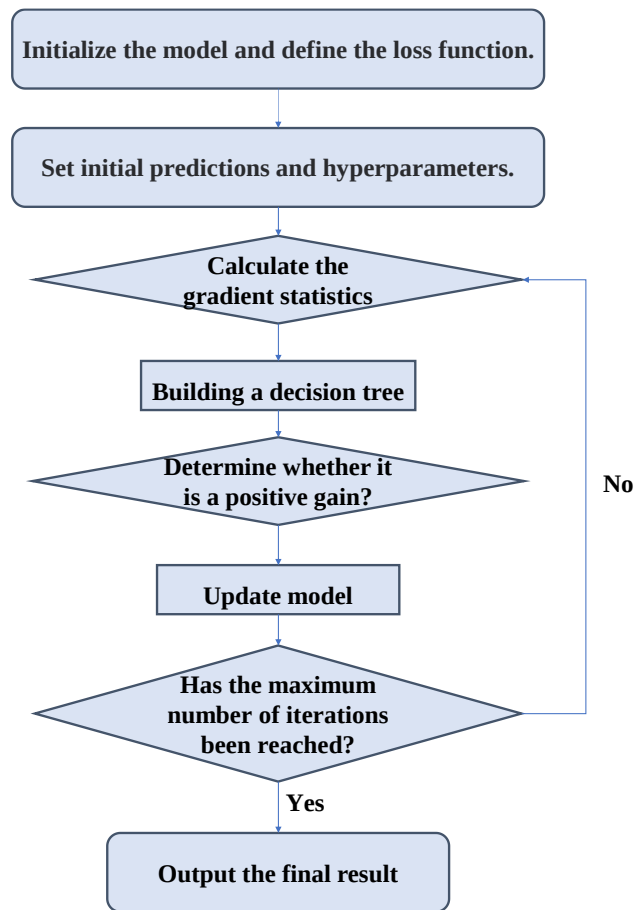


Figure 6.5 The algorithm framework of XGBoost.

Extreme Gradient Boosting (XGBoost) operates via a systematic iterative procedure consisting of five core steps: model initialisation, gradient computation, decision tree induction, model update, and final prediction aggregation. To begin, the algorithm initialises baseline predictions and configures key hyperparameters, including maximum tree depth, learning rate, and regularisation terms. In each iteration, the algorithm computes both the first-order and second-order gradients of the loss function, leveraging a second-order Taylor approximation to approximate the objective loss more accurately. A new decision tree is then constructed to fit the pseudo-residuals obtained from the previous iteration, by evaluating candidate splits across all input features. The optimal split is selected by maximising the split gain, which is calculated based on the gradient statistics of samples within the child nodes and incorporates structural regularisation terms to explicitly penalise overfitting. Tree growth terminates when any predefined stopping criterion is satisfied, including reaching the maximum depth, falling below the minimum leaf sample size, or obtaining a non-positive split gain. After stopping, optimal weights are assigned to the leaf nodes. The newly induced tree is then added to the ensemble, with its output scaled by the learning rate to dampen its contribution and improve the overall generalisation ability of the model. This iterative procedure repeats until either the predefined number of trees is reached or the model performance converges. Finally, XGBoost aggregates the scaled predictions from all induced trees to generate the final model output. While XGBoost is widely acknowledged

for its highly optimised implementation, robust regularisation framework, and strong predictive performance, it still faces two key limitations: the complexity of hyperparameter tuning, and reduced computational efficiency when processing ultra-high-dimensional sparse data.

(4) Hyperparameter optimisation and feature screening methods

The predictive performance of machine learning models is highly dependent on the purity of the feature space and the optimal configuration of hyperparameters. To achieve this, this thesis adopts a joint optimisation scheme comprising prior hyperparameter calibration and Recursive Feature Elimination (RFE).

Initially, Bayesian global optimisation based on the Tree-structured Parzen Estimator (TPE) is executed within the full-dimensional feature space (Bergstra et al., 2011). By setting a quantile threshold based on validation loss, TPE divides historical observations into superior and inferior performance groups, constructing their respective probability density distributions, $l(x)$ and $g(x)$. The algorithm then identifies the optimal hyperparameter combination by maximising the Expected Improvement (EI), which is mathematically equivalent to maximising the likelihood ratio:

$$x^* = \arg \max_x \frac{l(x)}{g(x)} \quad (\text{Eq6.1})$$

where, x^* denotes the optimal hyperparameter configuration that maximises this likelihood ratio, representing the robust, globally optimal parameter set identified within the search space.

This highly efficient sampling mechanism yields a robust, globally optimal parameter set. These prior parameters are subsequently injected into a baseline model to initiate RFE (Guyon et al., 2002). In each iteration, the algorithm calculates the global importance score of every feature based on node splitting gains, employing greedy backward culling to systematically strip away the least informative noise features.

To rigorously monitor model performance during this feature reduction process, a hierarchical cross-validation mechanism is introduced, utilising the cross-validated mean of the Quadratic Weighted Kappa (QWK) as the generalised evaluation function (Cohen, 1968). QWK evaluates the ordinal consistency between predicted and true labels on a scale from 0 to 1, where values closer to 1 indicate higher predictive agreement across progressive grades. The formulation is defined as:

$$QWK = 1 - \frac{\sum_{i,j} W_{i,j} O_{i,j}}{\sum_{i,j} W_{i,j} E_{i,j}} \quad (\text{Eq6.2})$$

where, $O_{i,j}$ represents the observed frequency within the multi-class confusion matrix, and $E_{i,j}$ denotes the expected frequency assuming that predictions and true

labels are independent. To heavily penalise larger misclassifications, the penalty matrix $W_{i,j}$ applies a squared mapping based on the class index difference:

$$W_{i,j} = \frac{(i-j)^2}{(K-1)^2} \quad (\text{Eq6.3})$$

By iteratively traversing the feature space and dynamically dropping features to maximise this cross-validated QWK objective function, the algorithm ultimately locks in the most streamlined and optimal feature subset.

6.3.2 Deep learning models

To construct deep learning models for the multi-dimensional analysis of the transient dynamic evolution characteristics of vehicle lane-changing collision risk, this study selects three representative time-series architectures with distinct underlying mathematical processing mechanisms: Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN), and Transformer network. Furthermore, given the high nonlinearity and complex physical phase transition boundaries of microscopic traffic flow data, traditional Multi-Layer Perceptrons (MLPs) are prone to encountering representation bottlenecks during fitting. Therefore, this study introduces the Kolmogorov-Arnold Network (KAN) to reconstruct the three baseline architectures. By feeding the output features of the three temporal architectures into the KAN layer, this study constructs three novel deep learning models, namely GRU-KAN, TCN-KAN, and Transformer-KAN.

(1) KAN

This thesis introduces the cutting-edge Kolmogorov-Arnold Network (KAN) (Liu et al., 2024) as an advanced alternative to the traditional Multi-Layer Perceptron (MLP). The theoretical foundation of KAN stems from the Kolmogorov-Arnold representation theorem, which posits that any multivariate continuous function can be precisely decomposed into a finite composition of univariate continuous functions:

$$f(x) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^n \phi_{q,p}(x_p) \right) \quad (\text{Eq6.4})$$

Inspired by this theorem, KAN fundamentally shifts the network paradigm by deploying learnable one-dimensional nonlinear functions on the network's "edges" (weights), while the "nodes" (neurons) strictly perform simple summation operations. For a single-layer KAN mapping an input vector $\mathbf{x} \in \mathbb{R}^{N_{in}}$ to an output vector $\mathbf{y} \in \mathbb{R}^{N_{out}}$, this mechanism is mathematically expressed as:

$$y_i = \sum_{j=1}^{N_{in}} \phi_{i,j}(x_j), \quad i \in \{1, 2, \dots, N_{out}\} \quad (\text{Eq6.5})$$

where, $\phi_{i,j}(\cdot)$ denotes the learnable activation function parameterised on each specific edge. To guarantee both fitting accuracy and precise local control over complex nonlinear manifolds, this research adopts a composite activation function structured around basis functions and B-Splines:

$$\phi(x) = \omega_b b(x) + \omega_s \text{spline}(x) \quad (\text{Eq6.6})$$

where, $b(x)$ acts as a base residual activation function dedicated to maintaining global gradient stability, while $\text{spline}(x)$ represents a higher-order local spline expansion parameterised by a finite set of control points, with ω_b and ω_s serving as their respective weights.

The primary advantage of employing local spline functions on KAN edges is their robust local control capability. Traditional MLPs are notoriously susceptible to global “catastrophic forgetting” during parameter updates. In contrast, when physical traffic characteristics fluctuate within a specific interval, KAN only requires localised adjustments to the spline control points near that interval, thereby seamlessly adapting to new patterns without disrupting the global manifold.

(2) GRU-KAN

The Gated Recurrent Unit (GRU) is an advanced variant of traditional Recurrent Neural Networks (RNNs), specifically designed to mitigate the vanishing and exploding gradient problems commonly encountered in time series processing (Cho et al., 2014). Compared to Long Short-Term Memory (LSTM) networks, GRU streamlines the architecture by integrating the input and forget gates into a single update gate, and merging the cell state with the hidden state. This structural optimisation significantly enhances computational efficiency while preserving the model’s capacity to capture long-term temporal dependencies.

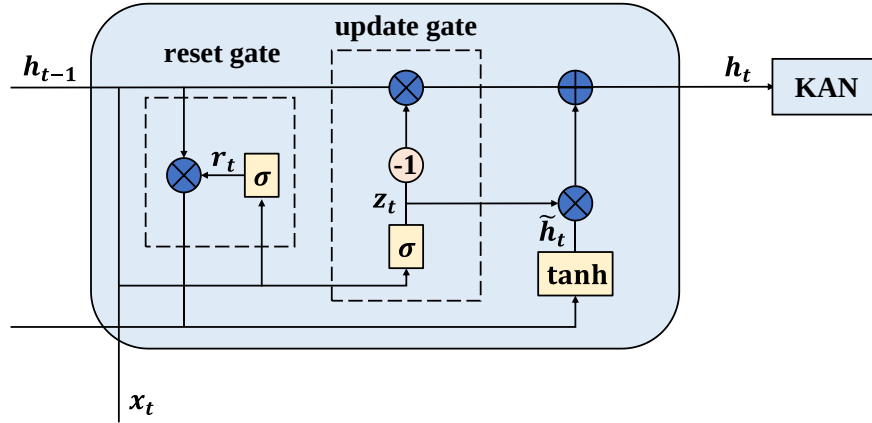


Figure 6.6 The algorithm framework of GRU-KAN.

Given the input vector $x_t \in \mathbb{R}^d$ and the previous hidden state $h_{t-1} \in \mathbb{R}^h$ at time step t , the forward propagation mechanism of the GRU is defined by the following formulations:

The reset gate (r_t) controls the extent to which the historical hidden state is ignored:

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (\text{Eq6.7})$$

The update gate (z_t) determines the fusion ratio between the previous hidden state and the newly generated candidate state:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (\text{Eq6.8})$$

The candidate hidden state ($\tilde{h}_t$) integrates the current input with the historical information moderated by the reset gate:

$$\tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \quad (\text{Eq6.9})$$

Finally, the current hidden state (h_t) is obtained via linear interpolation through the update gate:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (\text{Eq6.10})$$

where, $\sigma(\cdot)$ and $\tanh(\cdot)$ denote the Sigmoid and hyperbolic tangent activation functions, respectively, while $\odot$ represents the Hadamard (element-wise) product. The matrices W and U are the learnable weight parameters, and b denotes the corresponding bias terms. In the proposed GRU-KAN framework, once the final hidden state of the temporal sequence is extracted, it is fed into the KAN module. The KAN subsequently performs advanced non-linear feature mapping and dimensionality reduction to yield the final predictive logic value.

(3) TCN-KAN

To overcome the inherent limitations of Recurrent Neural Networks (RNNs), their inability to perform parallel computation and the memory decay associated with long sequences, the Temporal Convolutional Network (TCN) is introduced for time series modelling (Bai et al., 2018). TCN employs a one-dimensional fully convolutional network architecture that fundamentally relies on two mechanisms: causal convolution and dilated convolution. Causal convolution strictly restricts information flow to prevent the leakage of future data into past predictions, while dilated convolution allows the kernel to sample the input sequence with intermittent gaps.

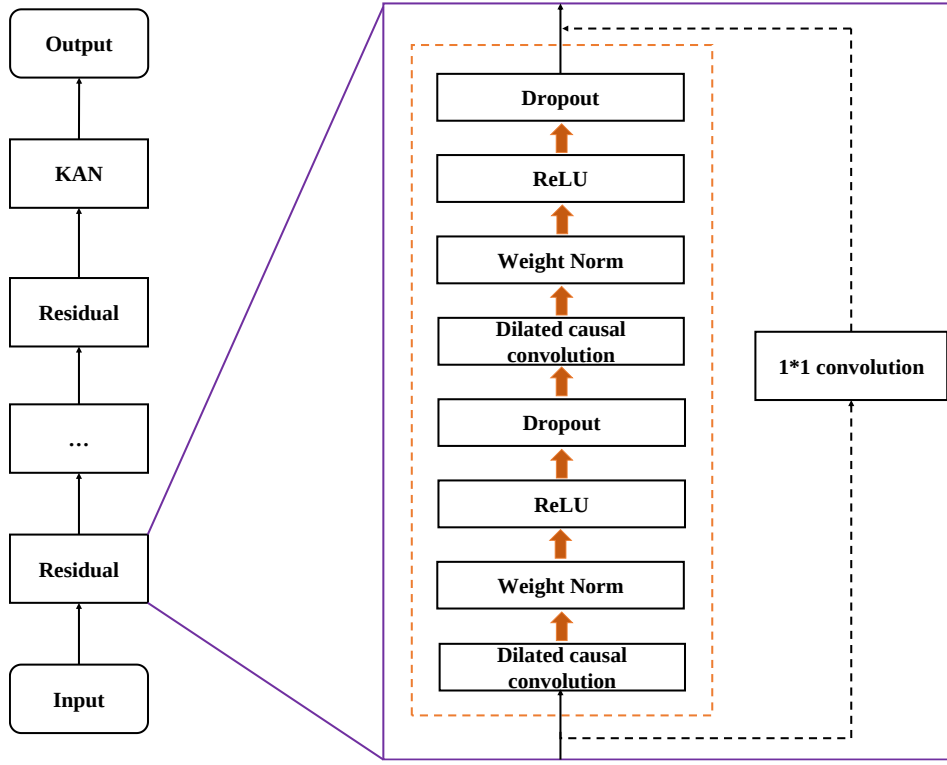


Figure 6.7 The algorithm framework of TCN-KAN.

where, the input sequence is $X \in \mathbb{R}^{T \times d}$, T is the time step and d is the feature dimension. A convolution kernel $w \in \mathbb{R}^{k \times d}$ (k for the size of the convolution kernel) slides over the timeline and performs the causal dilation convolution operation at the position i :

$$s_i = \phi \left(\sum_{t=0}^{k-1} \sum_{m=1}^d w_{t,m} \cdot x_{i-d_r \cdot t, m} + b \right) \quad (\text{Eq6.11})$$

where, s_i is the convolution output, d_r is the dilation coefficient, the index term $i - d_r \cdot t$ ensures that the operation strictly adheres to causal constraints (without revealing future information), and $\phi(\cdot)$ is the nonlinear activation function. To reduce gradient decay in the deep network, TCN introduces residual blocks whose internal convolutional feature variations $\mathcal{F}(x_i)$ are added to the input through cross-layer identity mapping:

$$o_i = \phi(x_i + \mathcal{F}(x_i)) \quad (\text{Eq6.12})$$

where, o_i refers to the output value of the residual block at the i th time step, x_i is the original feature vector passed over from the previous layer of the network at the i th time step. By exponentially increasing the coefficient of expansion between network layers, TCN can obtain local receptive fields covering the entire prediction time window at shallower network layers, effectively extracting high-frequency

distortion modes such as step signals or spike pulses, and the resulting time series features are also connected to KAN for subsequent regression.

(4) Transformer-KAN

The Transformer architecture performs global parallel computing of sequences by completely discarding recursion and convolution operations and relying on the Self-Attention Mechanism (Vaswani et al., 2017). When processing the data, the self-attention mechanism can break the time step limit and directly calculate the correlation weights between any two-time frames, thereby capturing key time-dependent features.

The equation for its Multi-Head Self-Attention is:

$$Attention(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = softmax\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (\text{Eq6.13})$$

$$MultiHead(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = concat(head_1, \dots, head_h)W^0 \quad (\text{Eq6.14})$$

where, $\mathbf{Q}$, $\mathbf{K}$ and, $\mathbf{V}$ respectively represent the Query, Key, and Value matrices derived from the linear mapping of the input sequence, and d_k are the feature dimension scaling factors. To prevent vanishing gradients in the deep network, the model introduces residual connections and layer normalisation, and the output x' is denoted as:

$$x' = LayerNorm(x + MultiHead(x, x, x)) \quad (\text{Eq6.15})$$

Then x' is fed into the next module of the encoder, namely the Feed Forward Neural Network (FFNN). The fully connected network consists of two layers. The first layer has an activation function called ReLU, and the second layer has a linear activation function, mathematically expressed as:

$$FFN(x') = \max(0, x'W_1 + b_1)W_2 + b_2 \quad (\text{Eq6.16})$$

where, W_1 , b_1 , W_2 and b_2 denote the learnable weights and biases of the two fully connected layers, respectively. The FFNN module performs the same nonlinear spatial transformation independently on the position of each time step, further enhancing the model's ability to express complex temporal features. The module's output will again undergo residual join and layer normalisation processing.

The final high-order temporal representation vector of the output is extracted and fed into KAN at the end of the network, where the edge spline function is used for nonlinear feature approximation and ordered regression.

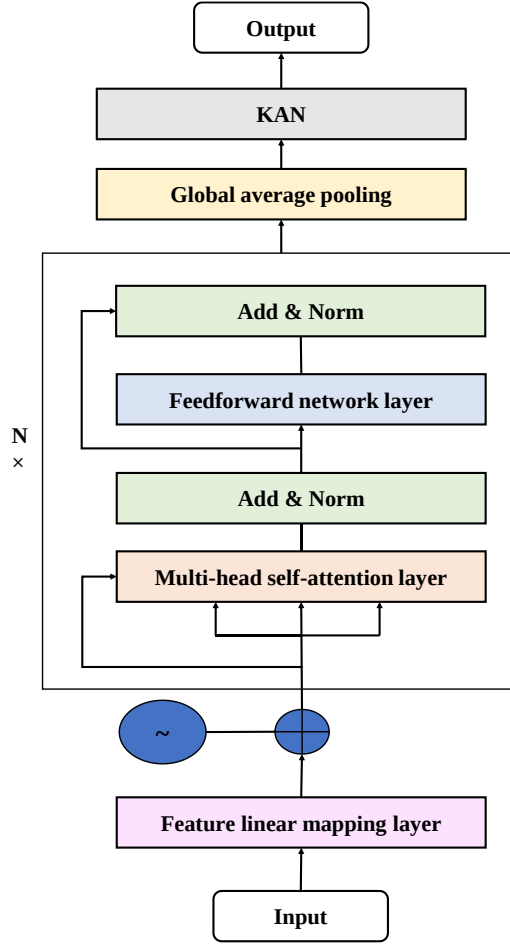


Figure 6.8 The algorithm framework of Transformer-KAN.

(5) Ordered regression structures based on risk progressive constraints

In view of the progressive attribute of the risk level of lane-changing collision, the traditional classification cross-entropy loss function has serious order blindness and ignores the progressive severity among risk categories. For this reason, instead of blindly expanding the capacity of the deep network, this thesis performs ordered regression reconstruction on the topology of the output layer of the temporal architecture. Introducing the Frank & Hall ordered expansion paradigm (Frank & Hall, 2001), the original 4-classification task is dimensionally reduced and decoupled into 3 parallel binary classification tasks, and the prediction target is transformed from a single discrete label to 3 progressive conditional thresholds:

$$P(y > k|x), \quad k \in \{0,1,2\} \quad (\text{Eq6.17})$$

The output dimension of the network is then reduced to 3 dimensions and jointly optimised by a multi-label binary cross-entropy loss function (BCEWithLogitsLoss):

$$L_{ordinal} = \sum_{k=0}^2 BCE(\hat{p}_k, I(y > k)) \quad (\text{Eq6.18})$$

where, $I(\cdot)$ denotes the indicator function, and $\hat{p}_k$ denotes the output probability of the k th binary classification node. During the inference stage, the standard four-class classification probabilities can be recovered via differential reconstruction as follows:

$$P(y = k|x) = P(y > k - 1|x) - P(y > k|x) \quad (\text{Eq6.19})$$

The boundary conditions are defined as $P(y = 0|x) = 1 - P(y > 0|x)$, and $P(y > 3|x) = 0$. This architecture endows the model with a bottom-up penalty mechanism for cross-level misjudgements, which is logically consistent with the QWK evaluation metric.

(6) Early stop circuit breaker mechanism

As the number of training epochs increases, the model tends to rote-memorise the random noise present in training samples, leading to a substantial increase in structural risk, this corresponds to the occurrence of severe overfitting (Prechelt, 1998). To mitigate this degradation process, this thesis introduces an early stopping mechanism, where p_{es} is defined as the tolerance threshold for early stopping, and the mathematical condition for triggering the mechanism is given by:

$$\mathcal{L}_{val}^{(t-i)} > \mathcal{L}_{val}^*, \quad \forall i \in \{0, 1, \dots, p_{es} - 1\} \quad (\text{Eq6.20})$$

where, $\mathcal{L}_{val}^{(t-i)}$ represents the validation loss value from the current round t , going back consecutively over the past p_{es} rounds. $\mathcal{L}_{val}^*$, represents the loss of the historical optimal validation set. When this condition is triggered, the system forces training truncation and performs weight rollback, which extracts the network parameters θ_{t^*} at the historically optimal generalisation point t^* as the final model parameters θ_{final} :

$$\theta_{final} = \theta_{t^*}, \quad t^* = \arg \min_t \mathcal{L}_{val}^{(t)} \quad (\text{Eq6.21})$$

By adopting an early stopping fusion mechanism, the proposed model maintains a stable search space on nonlinear physical manifolds, and effectively mitigates overfitting on complex high-frequency traffic dynamics data.

6.3.3 Information fusion mechanism based on decoupled spatiotemporal representation

In microscopic traffic flow data mining tasks, collected data exhibit significant heterogeneity, containing both discrete static spatial attributes and dynamic high-frequency fluctuating time series. When a single model is applied to directly model heterogeneous mixed data in an end-to-end manner, it is prone to the issue of feature flooding. To address this problem, this thesis proposes an information fusion mechanism based on decoupled spatiotemporal representation. The proposed

architecture decouples the prediction task into two components: a static spatial topological baseline model that adopts a machine learning algorithm to process tabular features, and a dynamic temporal evolution baseline model that leverages a deep learning model to capture continuous kinematic transient patterns. After independently completing risk probability mapping in the feature space, this thesis constructs a decision-level prior fusion mechanism. For an input sample x , assume there exist $M = 2$ heterogeneous baseline model branches, and the m th probability distribution vector output by the baseline model is defined as:

$$\mathbf{P}_m(x) = [p_{m,1}(x), p_{m,2}(x), \dots, p_{m,k}(x)]^T \quad (\text{Eq6.22})$$

where, $p_{m,k}(x)$ denotes the probability that the baseline model m predicts sample x belongs to the category k , and $p_{m,k}(x)$ satisfies the normalisation constraint $\sum_{k=1}^K p_{m,k}(x) = 1$. The final weighted output probability vector $\mathbf{P}_f(x)$ of the heterogeneous fusion framework is defined via linear combination as follows:

$$\mathbf{P}_f(x) = \sum_{m=1}^M \omega_m \cdot \mathbf{P}_m(x) \quad (\text{Eq6.23})$$

To maintain mathematical rigor of the probability space, the weight coefficients ω_m must satisfy the following strict linear constraints:

$$\sum_{m=1}^M \omega_m = 1, \quad \omega_m \in [0,1] \quad (\text{Eq6.24})$$

Specifically, the prediction category $\hat{y}$ of the fusion model is determined by the maximum a posteriori probability criterion:

$$\hat{y} = \arg \max_{k \in \{1, \dots, K\}} \left(\sum_{m=1}^M \omega_m \cdot p_{m,k}(x) \right) \quad (\text{Eq6.25})$$

Given the class imbalance inherent in vehicle lane-changing collision risk datasets, this study introduces the quadratic weighted kappa (QWK) as the global objective function to calibrate the weight coefficients ω_m . The calculation equation of QWK is presented in Equation (6.2). Under this constraint, the calibration of the fusion weights ω_m is transformed into a single-objective optimisation problem with a linear constraint:

$$W^* = \arg \max_W \left(\kappa \left(Y_{true}, \arg \max \left(\mathbf{P}_f(x; \mathbf{W}) \right) \right) \right) \quad (\text{Eq6.26})$$

$$s. t. \quad \sum_{m=1}^M \omega_m = 1, \quad \omega_m \geq 0 \quad (\text{Eq6.27})$$

Given the non-differentiability and discrete-step characteristics of the objective function, this study adopts an adaptive high-frequency grid search combined with

a cross-validation strategy to explore the solution space. To identify the global maximum on the QWK response surface, an exhaustive search with a step size of 0.05 over the interval [0,1] is conducted, which enables adaptive allocation of weight coefficients for each baseline model.

After introducing the basic theory of baseline models and reviewing existing model optimisation methods, a heterogeneous fusion framework is constructed based on the information fusion mechanism of decoupled spatiotemporal representation, as illustrated in Figure 6.9.

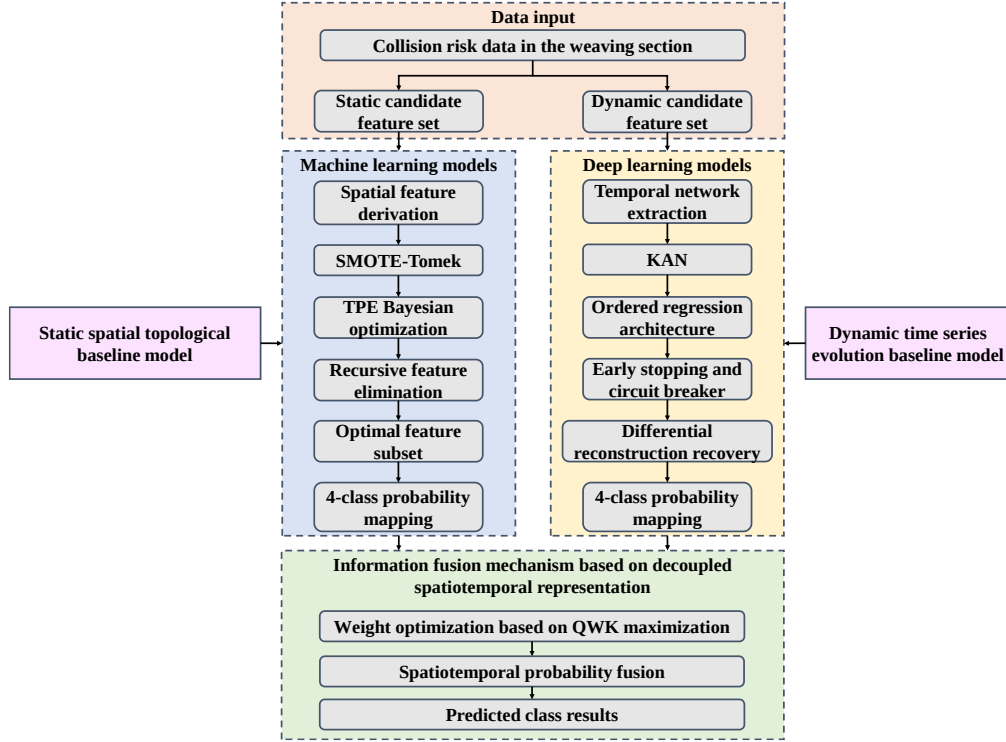


Figure 6.9 Schematic diagram of heterogeneous fusion framework.

6.3.4 Model performance evaluation metrics

Consistent with the setting in Chapter 5, the lane-changing risk categories in this study are divided into four classes: “extremely low lane-changing risk”, “low lane-changing risk”, “moderate lane-changing risk”, and “high lane-changing risk”, which are assigned values of 0, 1, 2, and 3 respectively. For lane-changing collision risk warning tasks, datasets typically exhibit class imbalance, and risk categories have an inherent strictly progressive severity order in real-world engineering applications. When overall accuracy is adopted as the sole evaluation metric, the optimised model tends to prioritise prediction accuracy for majority classes to obtain a spuriously high overall score. Therefore, this study adopts a multi-dimensional evaluation metric system that covers overall accuracy, class balance, and ordinal consistency of risk grades.

Given that the lane-changing collision risk investigated in this study exhibits clear hierarchical ordering constraints, and misclassifying high-risk instances as low-risk can lead to severe safety consequences in real-world scenarios, the QWK, a metric for evaluating ordinal classification consistency, is selected as a key

performance indicator for the model. The definition and calculation of QWK have been presented in Section 6.3.1. Per convention, a QWK value in the interval [0.4, 0.6) indicates moderate consistency between model predictions and ground truth, a value in [0.6, 0.8) indicates high consistency, and a value in [0.8, 1.0] indicates very strong consistency between model predictions and actual risk levels. In addition to QWK, the model is also evaluated with the following indicators:

(1) Accuracy

Accuracy is the most fundamental evaluation metric for classification tasks, which quantifies the proportion of correctly classified samples among all test samples. Let N denote the total number of test set samples, $C_{i,j}$ denote the number of samples with true label i that are predicted as label j , and K denote the total number of classes. The overall accuracy is defined as the ratio of the sum of the main diagonal elements of the confusion matrix to the total number of samples. Specifically, it represents the proportion of correctly predicted samples (sum of $C_{k,k}$) relative to the total number of test samples $C_{i,j}$, and is calculated as follows:

$$Accuracy = \frac{\sum_{k=1}^K C_{k,k}}{\sum_{i=1}^K \sum_{j=1}^K C_{i,j}} \quad (\text{Eq6.28})$$

(2) Precision (P_k), recall (R_k) and F1 score ($F1_k$)

First calculate the true positive (TP_k), false positive (FP_k), and false negative (FN_k) for each category k , followed by the calculation of category-specific precision (P_k) and recall (R_k), as formalised below:

$$P_k = \frac{TP_k}{TP_k + FP_k} \quad (\text{Eq6.29})$$

$$R_k = \frac{TP_k}{TP_k + FN_k} \quad (\text{Eq6.30})$$

Precision quantifies the false positive rate of the early warning system, whereas recall quantifies the false negative rate for high-risk events. Based on this definition, the harmonic mean $F1_k$ is adopted to jointly balance precision and recall, as expressed below:

$$F1_k = \frac{2 \cdot P_k \cdot R_k}{P_k + R_k} \quad (\text{Eq6.31})$$

To evaluate the model's capability against class imbalance, the macro-average metric is adopted, which is calculated as the arithmetic mean of performance indicators for each class. This metric is highly sensitive to the performance of minority classes. The calculation equation is presented below:

$$Macro_P = \frac{\sum_{k=1}^K P_k}{K} \quad (\text{Eq6.32})$$

$$Macro_R = \frac{\sum_{k=1}^K R_k}{K} \quad (\text{Eq6.33})$$

$$Macro_F1 = \frac{\sum_{k=1}^K F1_k}{K} \quad (\text{Eq6.34})$$

To simultaneously account for the prior information of the original distribution of the data, a weighted average metric is adopted for comprehensive evaluation. Specifically, the weighted average assigns a weight to each category based on the number of samples n_k in the test set:

$$Weighted_P = \frac{\sum_{k=1}^K (n_k \cdot P_k)}{\sum_{k=1}^K n_k} \quad (\text{Eq6.35})$$

$$Weighted_R = \frac{\sum_{k=1}^K (n_k \cdot R_k)}{\sum_{k=1}^K n_k} \quad (\text{Eq6.36})$$

$$Weighted_F1 = \frac{\sum_{k=1}^K (n_k \cdot F1_k)}{\sum_{k=1}^K n_k} \quad (\text{Eq6.37})$$

(3) Macro Area Under Curve ROC (*Macro_AUC*)

Compared with the F1 score, which relies on a predefined fixed threshold, the AUC can more comprehensively reflect the robustness of a model's output probability distribution. In this thesis, we adopt the macro-averaged multi-class AUC calculation method: specifically, the binary classification AUC_k is first calculated for each class k against all other classes, followed by taking the arithmetic mean of the obtained AUC_k values:

$$Macro_{AUC} = \frac{1}{K} \sum_{k=1}^K AUC_k \quad (\text{Eq6.38})$$

The $Macro_{AUC}$ metric ranges from 0.5 to 1.0. A $Macro_{AUC}$ value closer to 1 indicates that the model has stronger probability mapping capability across all risk levels, and produces clearer decision boundaries between distinct risk states.

6.4 Model results and analysis

To objectively evaluate the predictive performance of the proposed heterogeneous fusion framework and its benchmark models, this thesis conducted strict physical isolation via a three-way “train-validation-test” split on the collected dataset, which contains 2,061 lane-changing behaviours from expressway weaving sections, including 745 discretionary lane-changing events, 408 mandatory lane-changing events, 225 merging events, and 683 diverging events. Throughout the entire model evaluation workflow, the full dataset was first divided at an 8:2 ratio. Specifically, 20% of the data was completely retained as an unseen absolute blind test set, which was only used for final performance evaluation after the optimal model architecture, hyperparameters of individual models, and final fusion weights were all

determined, fundamentally eliminating the risk of data leakage. The remaining 80% of the data was designated as the development set, within which targeted training and validation strategies were designed to match the mathematical properties of different modules. When performing global Bayesian hyperparameter optimisation for machine learning models, 5-fold cross-validation was applied to ensure maximum robustness between recursive feature elimination and hyperparameter configuration. For the fitting of deep learning models and weight optimisation in the heterogeneous fusion framework, a dedicated validation subset was further strictly separated from the development set, which is specifically used to monitor the early stopping mechanism and conduct traversal search for fusion weights.

6.4.1 Hyperparameter tuning and feature selection

The hyperparameter configuration and feature dimensionality of the model exert a significant influence on the model's prediction performance. Following the TPE-based Bayesian global optimisation framework introduced in the preceding section, we determine the hyperparameters of the machine learning model. Table 6.3 summarises the optimal hyperparameter configuration of the model.

Table 6.3. Optimal hyperparameters of machine learning models.

Model	Hyperparameters	Hyperparameter values			
		$\Delta_t=0.5$ s	$\Delta_t=1.0$ s	$\Delta_t=1.5$ s	$\Delta_t=2.0$ s
SVM	Penalty coefficient	1.66	5.74	8.84	10.06
	Kernel parameters	0.01	0.01	0.01	0.01
	Number of decision trees	500	200	900	800
	Maximum depth per tree	20	50	14	15
RF	Minimum samples required for internal node repartitioning	5	5	2	2
	Minimum sample size for leaf nodes	1	1	1	1
	Number of base evaluators	600	1,000	800	800
	Maximum depth per tree	10	10	9	10
XGBoost	Learning rate	0.03	0.02	0.02	0.03
	Minimum weights required for child nodes	1	1	1	1
	The proportion of features randomly sampled for each tree	0.62	0.66	0.73	0.64
	The proportion of samples randomly sampled for each tree	0.84	0.70	0.63	0.72

Unlike machine learning models that rely on TPE-based Bayesian global optimisation, this study adopts a distinct approach for hyperparameter configuration of deep learning models. Given the prominent small-sample size and class-imbalance characteristics of lane-changing collision risk data, as well as the

inherently strong nonlinear topological fitting capability of the KAN at the frontend, excessively large search spaces and complex hyperparameter scheduling can easily trap the model in a local overparameterisation trap, leading to degraded generalisation performance on the out-of-sample blind test set. Accordingly, following the Occam’s Razor principle, this study employs structurally compact and physically interpretable robust empirical architectures for the three deep learning baseline models. The configuration of core hyperparameters for all deep learning models adopted in this thesis is presented in Table 6.4.

Table 6.4. Parameter configuration for deep learning models.

Model	Key Parameters	Set Values
Global training optimisation strategy	Optimisation algorithm	AdamW
	Initial learning rate	10^{-3}
	Weight attenuation coefficient	10^{-4}
	Batch size	64
	Early stop tolerance threshold	15
GRU	Hidden layer dimension	64
	Number of loops	1
	Dropout probability	0.3
	Number of residual blocks	3
	Convolution kernel size	3
TCN	Coefficient of expansion	1,2,4
	Number of hidden layer channels	64
	Dropout probability	0.3
	Number of encoder layers	2
	Head attention number of heads	4
Transformer	Feedforward network dimension	128
	Dropout Probability	0.3
	Spline mesh count	5
KAN	Spline order	3
	The classifier outputs dimensions	3

After determining the hyperparameter configuration of the machine learning model and obtaining the optimal feature count via recursive feature elimination, the overall objective is to identify the most representative feature subset and achieve

optimal model performance with the minimum number of features. In this study, the variation curves between the feature dimensionality and the key evaluation metric QWK is plotted to facilitate the selection of the optimal feature dimension, as shown in Figure 6.10. The curve trend of the RF model is highly similar to that of the XGBoost model, while the SVM model requires fewer input features. When the number of features is fewer than 50, QWK increases rapidly as the number of features increases. However, when the number of features exceeds 50, the growth rate of QWK gradually slows down. Considering model complexity, a smaller feature set that maintains strong predictive performance is prioritised. Finally, based on the results of recursive feature elimination, and considering both model simplicity and predictive performance, the number of features retained for each model is presented in Table 6.5.

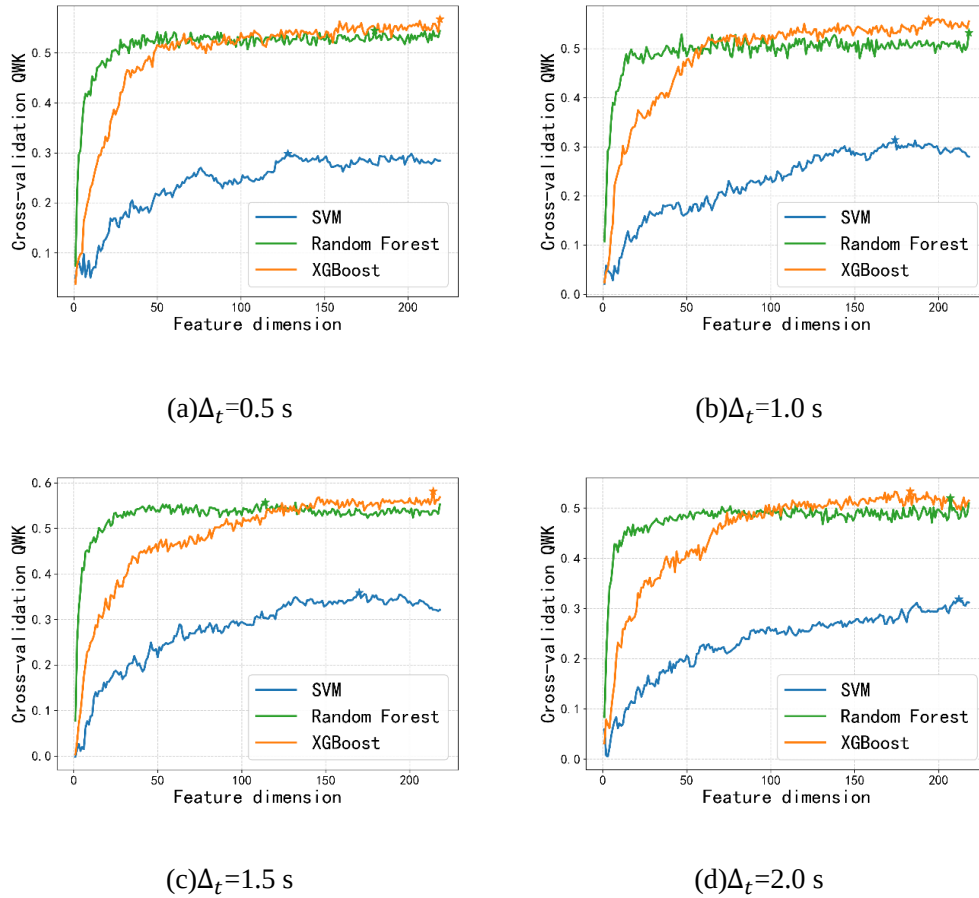


Figure 6.10 Graphs of the variation between the feature dimensions of each model and the important evaluation metric QWK of the model.

Table 6.5. Optimal number of features for machine learning models.

Model	$\Delta_t = 0.5$ s	$\Delta_t = 1.0$ s	$\Delta_t = 1.5$ s	$\Delta_t = 2.0$ s
SVM	76	76	77	78
RF	47	49	48	50
XGBoost	69	76	72	78

6.4.2 Model prediction performance

To objectively evaluate the predictive performance of the tested models, this study evaluated the performance of six single benchmark models (SVM, RF, XGBoost, GRU-KAN, TCN-KAN, and Transformer-KAN) and nine heterogeneous fusion models on a fully isolated blind test set. Multiple distinct early warning time windows were examined, including $\Delta_t = 0.5$ s, 1.0 s, 1.5 s, and 2.0 s. Model performance was quantified using nine evaluation metrics: QWK, *Accuracy*, *Macro_{AUC}*, *Macro_P*, *Macro_R*, *Macro_{F1}*, *Weighted_P*, *Weighted_R* and *Weighted_F1*. The performance evaluation results of all models are presented in Table 6.6.

Through horizontal comparison of results obtained from a unified evaluation baseline, the overall predictive performance of deep time series networks (e.g., GRU-KAN, TCN-KAN and Transformer-KAN) is significantly superior to that of traditional machine learning models (e.g., SVM, RF, XGBoost). Regarding the QWK evaluation metric, all tested deep time series networks achieved QWK values above 0.82, while traditional machine learning models only scored between 0.26 and 0.53. This empirical result strongly corroborates the core conclusion of the causal mechanism analysis in Chapter 5. The high-frequency dynamic interaction characteristics and relative motion states of microscopic vehicles have a decisive driving effect on the evolution of lane-changing collision risk, and their influence intensity is significantly higher than that of static spatial attribute parameters. However, although the global relative importance of fundamental lane-changing features and lane-changing decision features (e.g., vehicle type, initial lane-changing position, etc.) is secondary, these features still play an irreplaceable fundamental constraining role in defining the safe physical boundaries of lane-changing behaviour. Consistent with previous theoretical discussions, gradient optimisation-based deep learning networks are prone to falling into the feature flooding trap when processing discontinuous tabular static data, and thus fail to fully utilise static boundary information. In contrast, classical machine learning models based on spatial orthogonal segmentation can accurately parse such discrete and heterogeneous static attribute features.

Therefore, the performance gains of heterogeneous fusion models reported in Table 6.6 empirically validate the necessity of the spatiotemporal decoupling design. Across multiple prediction lead-time windows (0.5 s, 1.0 s, 1.5 s, 2.0 s), the QWK of all fusion combinations consistently remains in the range of 0.82 to 0.86, *Macro_{AUC}* generally falls between 0.85 and 0.89, and prediction Accuracy stays stable between 0.73 and 0.79. These results demonstrate that the proposed model has reliable probability calibration capability and clear class discrimination ability. The superior performance of the heterogeneous fusion architecture can be attributed to effective complementary modelling at the bottom level: the architecture combines the strength of machine learning models in extracting spatial representations from static tabular data, and the strength of deep learning models in mining transient dynamic patterns from high-frequency time series. This design effectively mitigates the inductive bias inherent to single-modality architectures,

enabling the predictive performance to break through the representation limitations of baseline models and achieve significant improvements across all evaluation metrics.

Based on the performance of all evaluation indicators presented in Table 6.6, this thesis ultimately selects XGBoost+GRU-KAN ($\Delta_t = 1.0s$), the model with optimal overall performance, as the final prediction model, which serves as the foundation for the subsequent analysis. Under this configuration, the model attains a maximum QWK of 0.86, an Accuracy of 0.79, and a *Weighted_F1* of 0.76. The confusion matrix and ROC curve of this optimal model are presented in Figures 6.11 and 6.12 respectively. In addition, 5-fold cross-validation results of the optimal model obtained in this study further verify its predictive robustness under imbalanced data distributions.

By comparing the model performance across different time windows, traditional machine learning models (including SVM, RF, and XGBoost) are observed to tend to reach peak performance with a 0.5-second time window, while fusion models exhibit higher sensitivity to variations in time window length. The optimal XGBoost+GRU-KAN model ultimately selected in this study achieved the highest Accuracy (0.79) and *Weighted_F1* (0.76) in the 1.0-second time window, with the QWK reaching 0.86, which is comparable to the result obtained with the 1.5-second time window. Additionally, the 0.5-second window yielded lower accuracy due to insufficient dynamic information, while although the 2.0-second window did not experience a significant performance degradation, it still underperformed compared with the 1.0-second window. Accordingly, 1.0 seconds was determined as the optimal early warning time window for the proposed model, as it achieves the best trade-off between information integrity and timeliness. The 1.0-second early warning window provides sufficient response time for ADAS while guaranteeing high accuracy to meet the requirements of deployment.

Although existing heterogeneous fusion models achieve competitive performance in synthesis tasks and weighted evaluation metrics, the macroscopic precision (*Macro_P*), recall (*Macro_R*), and F1 score (*Macro_F1*) still exhibit a non-negligible degree of asymmetry, with values ranging from 0.55 to 0.74. This phenomenon is primarily attributed to the inherent class imbalance of lane-changing conflict data, as well as the intrinsic difficulty of ordered multi-classification tasks with limited training samples. Further analysis of the independent predictive performance across each risk level reveals that the model achieves exceptionally high recognition accuracy for “extremely low lane-changing risk” and “high lane-changing risk” at the two ends of the risk spectrum, but delivers relatively weak prediction performance for “low lane-changing risk” and “moderate lane-changing risk” in the transition stage. The underlying reason may be that lane-changing behaviour is a highly complex continuous kinematic phase transition process, and the spatiotemporal interaction field encountered by the vehicle changes dynamically during manoeuvring. As a result, the decision boundaries between intermediate transition risk levels often exhibit a high degree of fuzziness and overlap. For example, the XGBoost+GRU-KAN model with $\Delta_t=1.0$ s achieves an exceptionally high recall for the “extremely low lane-changing risk” and “high lane-

changing risk” categories. This asymmetric predictive characteristic has considerable application value in engineering, as it aligns with the core requirement of ADAS: it maximises the guarantee of a low false negative rate for high-risk events, while minimising invalid interference alerts in extremely low-risk scenarios.

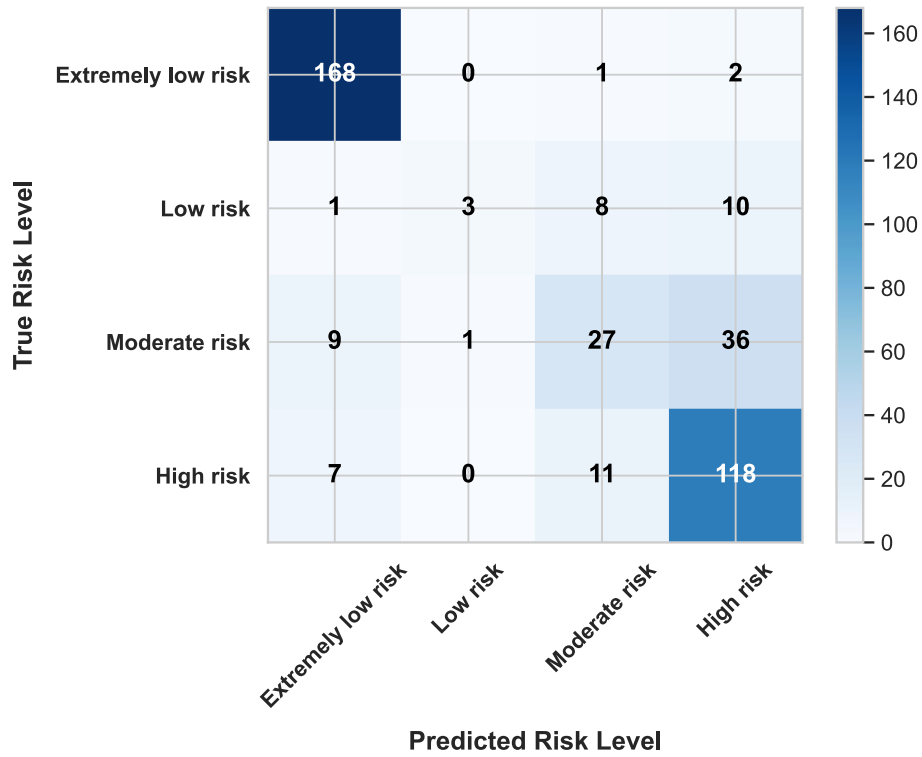


Figure 6.11 Confusion matrix of the XGBoost+GRU-KAN ($\Delta_t = 1.0s$) heterogeneous fusion framework (20% test set).

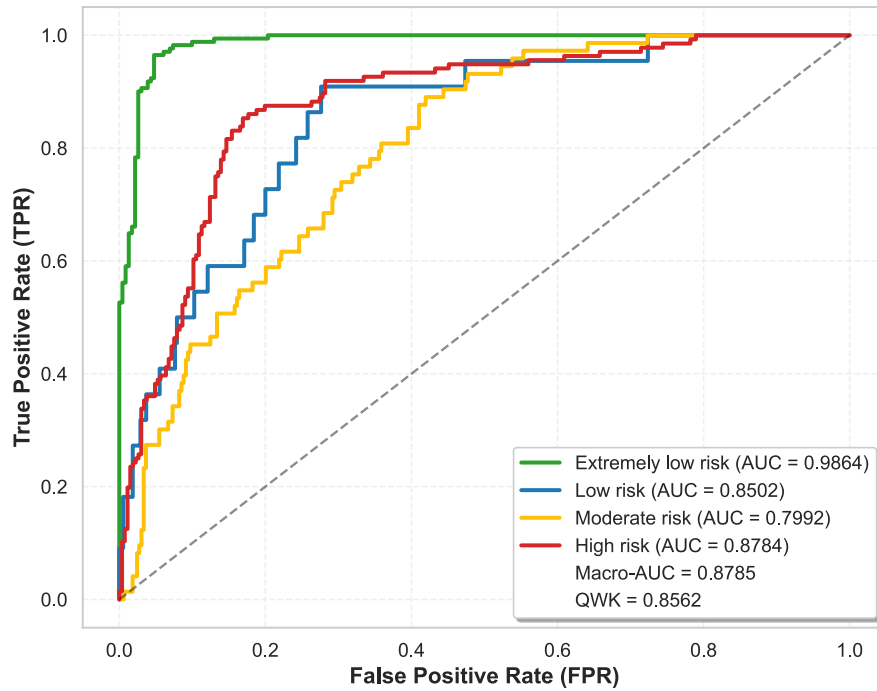


Figure 6.12 ROC curve of the XGBoost+GRU-KAN ($\Delta_t = 1.0s$) heterogeneous fusion framework (20% test set).

Table 6.6. Comparison of evaluation metrics across different models.

Model	Dataset	QWK	Accuracy	Macro_AUC	Macro_P	Macro_R	Macro_F1	Weighted_P	Weighted_R	Weighted_F1
SVM	$\Delta_t=0.5$ s	0.34	0.51	0.75	0.45	0.49	0.45	0.57	0.51	0.53
	$\Delta_t=1.0$ s	0.26	0.48	0.73	0.42	0.45	0.43	0.52	0.48	0.49
	$\Delta_t=1.5$ s	0.28	0.49	0.72	0.44	0.50	0.45	0.53	0.49	0.50
	$\Delta_t=2.0$ s	0.30	0.48	0.72	0.40	0.42	0.40	0.51	0.48	0.49
RF	$\Delta_t=0.5$ s	0.45	0.59	0.80	0.51	0.52	0.51	0.60	0.59	0.59
	$\Delta_t=1.0$ s	0.43	0.56	0.79	0.48	0.50	0.49	0.59	0.56	0.57
	$\Delta_t=1.5$ s	0.44	0.57	0.80	0.50	0.52	0.50	0.60	0.57	0.58
	$\Delta_t=2.0$ s	0.43	0.57	0.79	0.51	0.53	0.52	0.60	0.57	0.58
XGBoost	$\Delta_t=0.5$ s	0.53	0.62	0.81	0.52	0.51	0.51	0.62	0.62	0.62
	$\Delta_t=1.0$ s	0.46	0.60	0.81	0.52	0.52	0.52	0.60	0.60	0.60
	$\Delta_t=1.5$ s	0.45	0.59	0.81	0.51	0.51	0.51	0.59	0.59	0.59
	$\Delta_t=2.0$ s	0.46	0.59	0.80	0.49	0.49	0.49	0.59	0.59	0.59
GRU-KAN	$\Delta_t=0.5$ s	0.85	0.72	0.85	0.46	0.49	0.47	0.66	0.72	0.69
	$\Delta_t=1.0$ s	0.84	0.74	0.86	0.48	0.51	0.49	0.67	0.74	0.70
	$\Delta_t=1.5$ s	0.83	0.74	0.85	0.48	0.50	0.47	0.66	0.74	0.69
	$\Delta_t=2.0$ s	0.83	0.72	0.86	0.48	0.51	0.49	0.68	0.72	0.70
TCN-KAN	$\Delta_t=0.5$ s	0.82	0.73	0.85	0.55	0.50	0.48	0.67	0.73	0.68
	$\Delta_t=1.0$ s	0.83	0.73	0.85	0.46	0.49	0.47	0.66	0.73	0.68
	$\Delta_t=1.5$ s	0.84	0.74	0.85	0.48	0.51	0.49	0.68	0.74	0.71
	$\Delta_t=2.0$ s	0.84	0.75	0.84	0.57	0.52	0.50	0.70	0.75	0.70

Table 6.6. Comparison of evaluation metrics across different models (continued).

Model	Dataset	QWK	Accuracy	Macro_AUC	Macro_P	Macro_R	Macro_F1	Weighted_P	Weighted_R	Weighted_F1
Transformer-KAN	$\Delta_t=0.5$ s	0.83	0.72	0.85	0.48	0.50	0.48	0.67	0.72	0.69
	$\Delta_t=1.0$ s	0.82	0.73	0.86	0.46	0.49	0.46	0.65	0.73	0.67
	$\Delta_t=1.5$ s	0.83	0.74	0.84	0.49	0.51	0.48	0.67	0.74	0.70
	$\Delta_t=2.0$ s	0.83	0.74	0.84	0.50	0.49	0.46	0.68	0.73	0.68
SVM+GRU-KAN	$\Delta_t=0.5$ s	0.85	0.74	0.88	0.58	0.53	0.52	0.70	0.74	0.71
	$\Delta_t=1.0$ s	0.85	0.75	0.87	0.60	0.55	0.55	0.71	0.75	0.72
	$\Delta_t=1.5$ s	0.83	0.74	0.86	0.48	0.50	0.48	0.67	0.74	0.69
	$\Delta_t=2.0$ s	0.83	0.74	0.86	0.59	0.55	0.55	0.71	0.74	0.72
SVM+TCN-KAN	$\Delta_t=0.5$ s	0.82	0.75	0.88	0.59	0.54	0.53	0.71	0.75	0.71
	$\Delta_t=1.0$ s	0.86	0.76	0.87	0.62	0.57	0.58	0.72	0.76	0.73
	$\Delta_t=1.5$ s	0.84	0.75	0.87	0.65	0.56	0.57	0.72	0.75	0.72
	$\Delta_t=2.0$ s	0.84	0.76	0.85	0.62	0.53	0.53	0.72	0.76	0.71
SVM+Transformer-KAN	$\Delta_t=0.5$ s	0.83	0.75	0.88	0.63	0.57	0.58	0.72	0.75	0.72
	$\Delta_t=1.0$ s	0.84	0.75	0.87	0.62	0.52	0.50	0.71	0.75	0.70
	$\Delta_t=1.5$ s	0.84	0.76	0.86	0.51	0.52	0.50	0.69	0.76	0.71
	$\Delta_t=2.0$ s	0.82	0.75	0.86	0.51	0.50	0.47	0.69	0.74	0.69
RF+GRU-KAN	$\Delta_t=0.5$ s	0.86	0.75	0.89	0.62	0.53	0.53	0.72	0.75	0.72
	$\Delta_t=1.0$ s	0.85	0.77	0.88	0.69	0.60	0.61	0.75	0.77	0.75
	$\Delta_t=1.5$ s	0.85	0.78	0.89	0.65	0.58	0.59	0.75	0.78	0.75
	$\Delta_t=2.0$ s	0.84	0.76	0.88	0.68	0.56	0.56	0.74	0.76	0.73
RF+TCN-KAN	$\Delta_t=0.5$ s	0.83	0.75	0.89	0.55	0.52	0.51	0.70	0.75	0.71

Table 6.6. Comparison of evaluation metrics across different models (continued).

Model	Dataset	QWK	Accuracy	Macro_AUC	Macro_P	Macro_R	Macro_F1	Weighted_P	Weighted_R	Weighted_F1
RF+TCN-KAN	$\Delta_t=1.0s$	0.85	0.77	0.89	0.69	0.59	0.61	0.74	0.77	0.74
	$\Delta_t=1.5 s$	0.83	0.75	0.89	0.60	0.57	0.58	0.72	0.75	0.73
	$\Delta_t=2.0 s$	0.85	0.77	0.89	0.70	0.56	0.56	0.74	0.77	0.73
RF+Transformer-KAN	$\Delta_t=0.5 s$	0.85	0.77	0.89	0.66	0.56	0.56	0.74	0.77	0.74
	$\Delta_t=1.0 s$	0.85	0.76	0.88	0.61	0.55	0.55	0.72	0.76	0.72
	$\Delta_t=1.5 s$	0.85	0.77	0.88	0.67	0.57	0.57	0.74	0.77	0.74
	$\Delta_t=2.0 s$	0.83	0.76	0.88	0.72	0.55	0.54	0.75	0.76	0.71
	$\Delta_t=0.5 s$	0.85	0.73	0.87	0.47	0.50	0.48	0.66	0.73	0.69
XGBoost+GRU-KAN	$\Delta_t=1.0 s$	0.86	0.79	0.88	0.74	0.59	0.60	0.77	0.79	0.76
	$\Delta_t=1.5 s$	0.86	0.78	0.88	0.69	0.59	0.60	0.76	0.78	0.75
	$\Delta_t=2.0 s$	0.85	0.77	0.88	0.69	0.56	0.57	0.75	0.77	0.74
XGBoost+TCN-KAN	$\Delta_t=0.5 s$	0.83	0.76	0.88	0.65	0.55	0.54	0.73	0.76	0.72
	$\Delta_t=1.0 s$	0.84	0.76	0.88	0.63	0.56	0.57	0.72	0.76	0.73
	$\Delta_t=1.5 s$	0.85	0.77	0.88	0.66	0.58	0.59	0.74	0.77	0.75
	$\Delta_t=2.0 s$	0.85	0.77	0.86	0.66	0.55	0.55	0.74	0.77	0.73
	$\Delta_t=0.5s$	0.84	0.74	0.87	0.49	0.51	0.50	0.68	0.74	0.70
XGBoost+Transformer-KAN	$\Delta_t=1.0 s$	0.85	0.77	0.88	0.68	0.58	0.59	0.74	0.77	0.74
	$\Delta_t=1.5 s$	0.85	0.77	0.88	0.67	0.58	0.59	0.74	0.77	0.75
	$\Delta_t=2.0 s$	0.84	0.76	0.87	0.58	0.52	0.50	0.71	0.76	0.70

Note: The bolded numbers represent the best performance across all models.

6.4.3 Time complexity analysis of the models

To evaluate the practical engineering performance of the proposed models and verify whether it satisfies the requirements of real-time early warning, this thesis compares the total training time and average single-sample inference time of all compared models on a unified hardware platform. The experimental hardware environment consisted of a 64-bit Windows operating system, an Intel Core i7-12700KF@3.60GHz processor, and 32.0GB of RAM. To accurately simulate the common computationally constrained in-vehicle edge computing scenario, GPU acceleration was disabled throughout all tests, and all inference time measurements were obtained strictly using CPU-only computation. Specific results are presented in Table 6.7.

As shown in Table 6.7, the individual deep learning models (GRU-KAN, TCN-KAN, Transformer-KAN) achieved high inference efficiency, with single-sample inference time stabilising at 0.01 ms to 0.05 ms (microsecond level). This indicates that integrating deep networks based on causal convolution or self-attention mechanisms does not introduce additional computational burden to the system. In heterogeneous fusion frameworks, the overall single-sample inference delay is primarily determined by the computational overhead of the embedded machine learning sub-model. For the RF algorithm, the inference time of both standalone RF and its heterogeneous fusion framework increases to 30~112 ms. This is because RF requires sequential traversal of many decision tree nodes during single-sample prediction. In contrast, XGBoost benefits from its inherently highly optimised memory addressing logic, which significantly reduces the overhead of spatial feature extraction.

In practical in-vehicle collision warning applications, the processing frequency of streaming data typically needs to reach 30 Hz, corresponding to a maximum acceptable single inference delay of ≤ 33 ms. The proposed optimal model, XGBoost+GRU-KAN, achieves a stable single-sample end-to-end inference time of less than 8 ms, which is far below the 33 ms threshold. These results strongly confirm that the model proposed in this thesis simultaneously achieves effective high-dimensional feature space partitioning and nonlinear dynamic feature extraction, while maintaining low online computational overhead and high engineering feasibility for real-time deployment.

Table 6.7. Comparison of time complexity across different models.

Model	Dataset	Total training time (s)	Average inference time per single sample (ms)
SVM	$\Delta_t=0.5$ s	0.96	0.62
	$\Delta_t=1.0$ s	0.89	0.60
	$\Delta_t=1.5$ s	0.96	0.65
	$\Delta_t=2.0$ s	0.98	0.63
RF	$\Delta_t=0.5$ s	0.72	50.42

Table 6.7. Comparison of time complexity across different models (continued).

Model	Dataset	Total training time (s)	Average inference time per single sample (ms)
RF	$\Delta_t=1.0$ s	0.30	28.98
	$\Delta_t=1.5$ s	1.26	77.92
	$\Delta_t=2.0$ s	1.13	73.79
	$\Delta_t=0.5$ s	5.80	3.39
XGBoost	$\Delta_t=1.0$ s	10.66	5.01
	$\Delta_t=1.5$ s	6.84	3.61
	$\Delta_t=2.0$ s	6.68	3.78
	$\Delta_t=0.5$ s	5.21	0.01
GRU-KAN	$\Delta_t=1.0$ s	11.13	0.02
	$\Delta_t=1.5$ s	10.89	0.03
	$\Delta_t=2.0$ s	12.91	0.04
	$\Delta_t=0.5$ s	7.11	0.01
TCN-KAN	$\Delta_t=1.0$ s	7.70	0.02
	$\Delta_t=1.5$ s	9.08	0.02
	$\Delta_t=2.0$ s	9.69	0.02
	$\Delta_t=0.5$ s	8.76	0.01
Transformer-KAN	$\Delta_t=1.0$ s	26.94	0.01
	$\Delta_t=1.5$ s	27.78	0.03
	$\Delta_t=2.0$ s	30.24	0.05
	$\Delta_t=0.5$ s	20.06	1.67
SVM+GRU-KAN	$\Delta_t=1.0$ s	18.27	1.68
	$\Delta_t=1.5$ s	25.03	2.06
	$\Delta_t=2.0$ s	23.92	3.09
	$\Delta_t=0.5$ s	19.58	1.68
SVM+TCN-KAN	$\Delta_t=1.0$ s	15.22	1.98
	$\Delta_t=1.5$ s	20.24	1.77
	$\Delta_t=2.0$ s	21.65	2.14
	$\Delta_t=0.5$ s	23.91	2.10
SVM+Transformer-KAN	$\Delta_t=1.0$ s	36.75	2.08
	$\Delta_t=1.5$ s	44.78	2.24
	$\Delta_t=2.0$ s	43.58	2.00
	$\Delta_t=0.5$ s	13.32	60.43
RF+GRU-KAN	$\Delta_t=1.0$ s	16.93	30.41
	$\Delta_t=1.5$ s	20.93	95.38
	$\Delta_t=2.0$ s	22.48	110.64
RF+TCN-KAN	$\Delta_t=0.5$ s	14.90	71.17
	$\Delta_t=1.0$ s	14.35	42.62

Table 6.7. Comparison of time complexity across different models (continued).

Model	Dataset	Total training time (s)	Average single- sample inference time (ms)
RF+TCN-KAN	$\Delta_t=1.5$ s	16.96	112.49
	$\Delta_t=2.0$ s	22.10	112.62
	$\Delta_t=0.5$ s	15.16	70.07
RF+Transformer-KAN	$\Delta_t=1.0$ s	33.10	71.21
	$\Delta_t=1.5$ s	33.95	68.44
	$\Delta_t=2.0$ s	36.86	73.80
XGBoost+GRU-KAN	$\Delta_t=0.5$ s	13.99	6.19
	$\Delta_t=1.0$ s	24.47	7.74
	$\Delta_t=1.5$ s	20.64	7.56
XGBoost+TCN-KAN	$\Delta_t=2.0$ s	23.15	6.48
	$\Delta_t=0.5$ s	16.26	7.52
	$\Delta_t=1.0$ s	20.94	9.13
XGBoost+Transformer-KAN	$\Delta_t=1.5$ s	19.54	6.94
	$\Delta_t=2.0$ s	18.92	8.27
	$\Delta_t=0.5$ s	19.64	5.43
XGBoost+GRU-KAN	$\Delta_t=1.0$ s	38.77	6.36
	$\Delta_t=1.5$ s	37.80	5.47
	$\Delta_t=2.0$ s	39.90	5.58

6.4.4 Visualisation and analysis of model results

The preceding section compared the predictive performance of the candidate models across multiple evaluation metrics. This section further investigates the influencing factors of lane-changing collision risk warning. Specifically, we take the XGBoost+GRU-KAN ($\Delta_t=1.0$ s) heterogeneous fusion framework as a case study, and analyse the model outputs from two dimensions: the global sensitivity of the model to input features, and the temporal evolution of risk mutations.

(1) Analysis of global feature sensitivity

This thesis introduces the SHAP (SHapley Additive exPlanations) game-theoretic framework for global feature sensitivity analysis. First proposed by Lundberg & Lee (2017), the SHAP method is grounded in the Shapley value from cooperative game theory, and is designed to fairly quantify the contribution of each feature to the final prediction output of a model by computing the marginal contribution of each feature across all possible feature subsets. For any input sample x , the SHAP framework constructs an additive feature attribution model that linearly decomposes the complex nonlinear prediction $f(x)$ generated by the base model into the sum of the Shapley values of individual features:

$$g(z') = \phi_0 + \sum_{j=1}^M \phi_j z'_j \quad (\text{Eq6.39})$$

where, g denotes the interpretation model, $z' \in \{0,1\}^M$ represents the input for feature simplification, M indicates the total dimension of input features, ϕ_0 stands for the baseline prediction value of the model, and ϕ_j corresponds to the Shapley value of the j th feature. When $\phi_j > 0$, the j th feature exerts a positive effect on the predicted probability of the specific lane-changing collision risk level. Conversely, when $\phi_j < 0$, the feature has a negative impact.

The TreeExplainer algorithm, which is specifically optimised for tree-based models, was implemented to compute the global and local SHAP value matrices of test samples in the held-out blind test set. By constructing SHAP global importance stacked bar plots, feature contribution bee swarm plots, and nonlinear interaction dependence plots, this study provides a foundation for analysing the underlying mechanisms of lane-changing collision risks in weaving sections.

The stacked bar chart of the model's global feature importance is presented in Figure 6.13, where features are sorted in descending order according to the sum of the average $|SHAP|$ values of each feature across four risk levels. The top-ranked core features are dominated by microscopic relative kinematic features, which verifies the conclusion drawn in Chapter 5: the impact intensity of vehicle dynamic features and relative motion features on lane-changing risk is significantly greater than that of static attribute parameters. Among these features, the gap distance between the LCV and CLV at time T_s is the most critical feature influencing the global risk level. This feature characterises the longitudinal following gap of the LCV in the current lane, and to a certain extent reflects the real-time traffic conditions and the driver's driving style. Kinematic features with high global importance also include the maximum longitudinal distance between the LCV and CFV during the period $[T_s - \Delta_t, T_s]$, the speed difference between the LCV and TFV at time T_s , and the maximum longitudinal distance between the LCV and CLV during the period $[T_s - \Delta_t, T_s]$. These results confirm that within the 1.0-second warning time window, the collision risk level is not determined by the vehicle's absolute speed or absolute position, but by the instantaneous interaction state in terms of relative space and relative speed between the lane-changing vehicle and key lane-changing participants. The results in Figure 6.13 also indicate that the lane-changing behaviour decision variables AG_Lead and AG_Lag have a significant effect on the prediction of lane-changing collision risk level, which demonstrates the causal association between the behavioural decision outcome at the start of lane-changing and the occurrence of lane-changing collision risk. The static attributes of the vehicle and the lane-changing type also rank high in global feature importance, implying that the vehicle's geometric parameters and lane-changing motivation are also important preconditions that affect lane-changing collision risk.

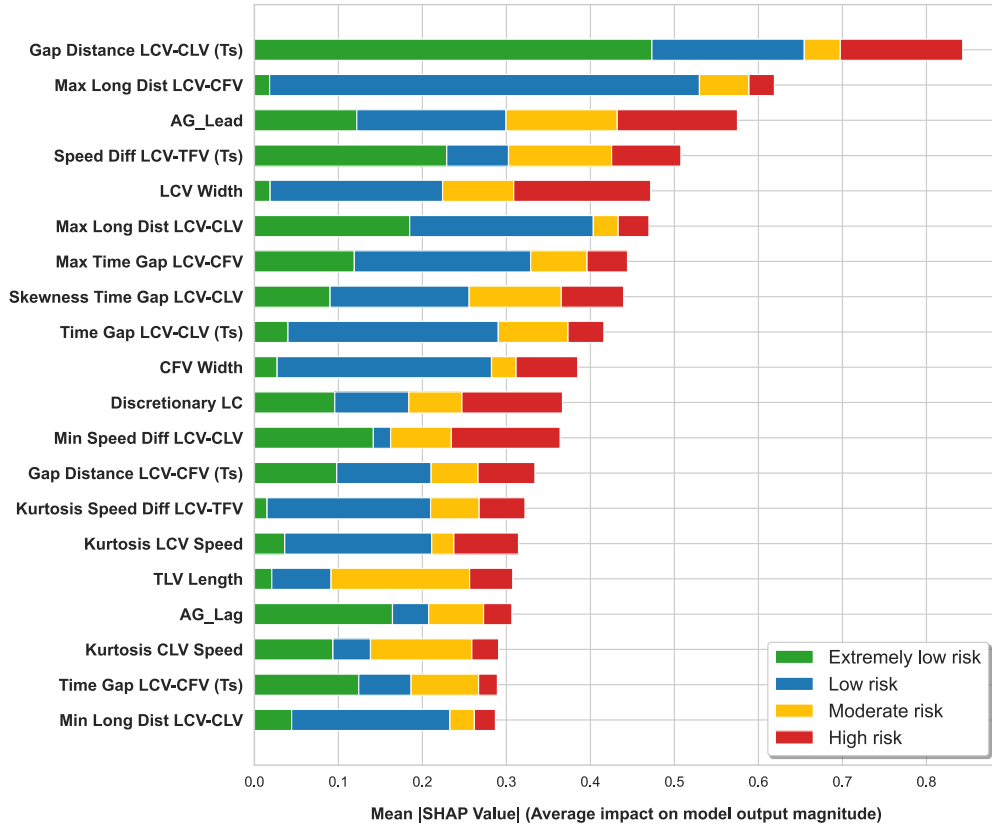


Figure 6.13 Global feature importance bar chart of XGBoost+GRU-KAN ($\Delta_t = 1.0s$) heterogeneous fusion framework.

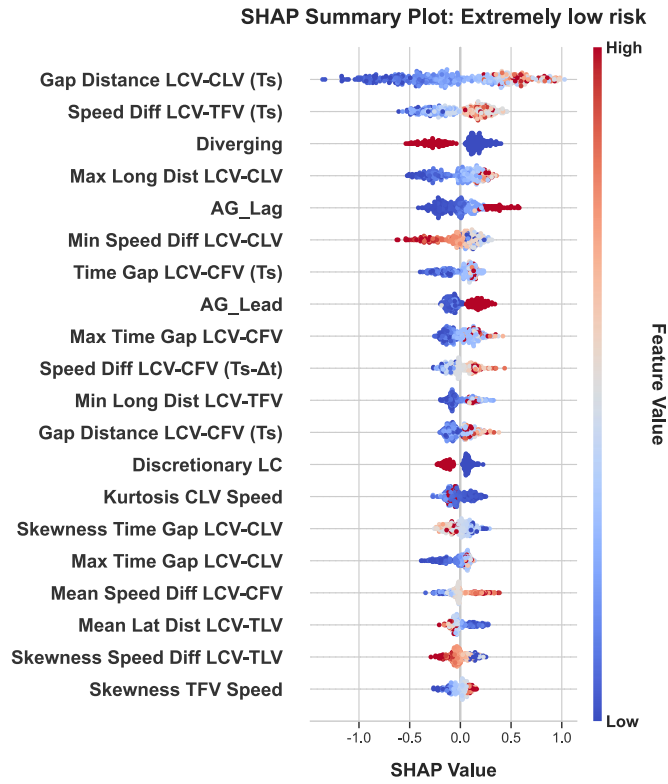
To further explore how each feature specifically influences the occurrence probability of different lane-changing collision risk levels, SHAP feature contribution honeycomb plots are constructed for the four risk levels, as presented in Figure 6.14. In each plot, the horizontal axis indicates the direction of the SHAP value's effect on the occurrence probability of the corresponding risk level: a positive SHAP value increases the occurrence probability, while a negative SHAP value reduces it. The colour of each hexagon denotes the magnitude of the feature's own value, with red and blue representing high and low feature values, respectively.

As shown in Figure 6.14(a), the classification of extremely low collision risk is highly dependent on sufficient lane-changing buffer space and moderate relative motion. When both the gap distance between the LCV and CLV at time T_s and AG_Lag take high values, the SHAP value is significantly positive. This increases the probability of classifying the lane-changing manoeuvre as safe, confirming that sufficient lane-changing buffer space is a prerequisite for safe lane-changing. Meanwhile, when the speed difference between the LCV and TFV at time T_s is large, it also provides a positive contribution to safety, which is consistent with the conclusion in Chapter 5 that actively creating a positive speed difference at the start of the lane-changing manoeuvre can expand the safety gap and reduce the lane-changing collision risk. When the lane-changing type is diverging, the SHAP value is significantly negative, indicating that diverging behaviour is more likely to induce lane-changing collision risk. This conclusion is consistent with the findings

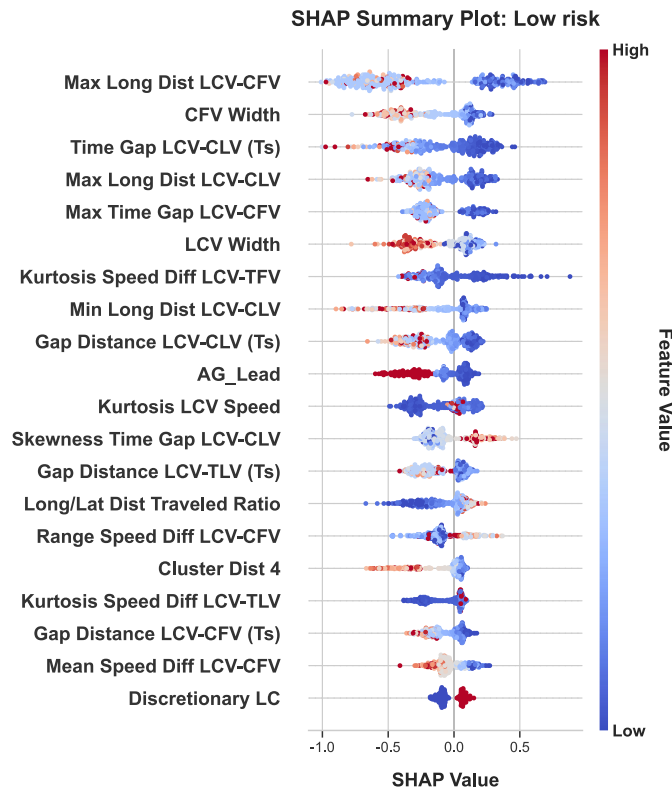
in Chapter 5, which may be attributed to the fact that diverging manoeuvre is often accompanied by mandatory adaptive deceleration and larger blind areas. In comparison, the scatter points of discretionary lane-changing are more concentrated near the zero axis, suggesting that lane-changing manoeuvres performed for improving driving comfort and efficiency are inherently less likely to cause collisions than diverging manoeuvres.

As illustrated in Figures 6.14(b) and (c), moderate and low risk levels exhibit a distinct transitional change mechanism. Compared with extremely low and high risk levels, the SHAP scatter distribution at the intermediate transition risk level demonstrates a more pronounced bilateral distribution characteristic. This observation corroborates the earlier conclusion that intermediate transition states exhibit a high degree of overlap at the risk dynamics boundary. Within these states, vehicle relative motion characteristics, vehicle size, lane-changing type, and lane-changing decision variables exhibit more complex coupling effects, indicating that risk assessment for intermediate transition states requires the incorporation of features from multiple dimensions.

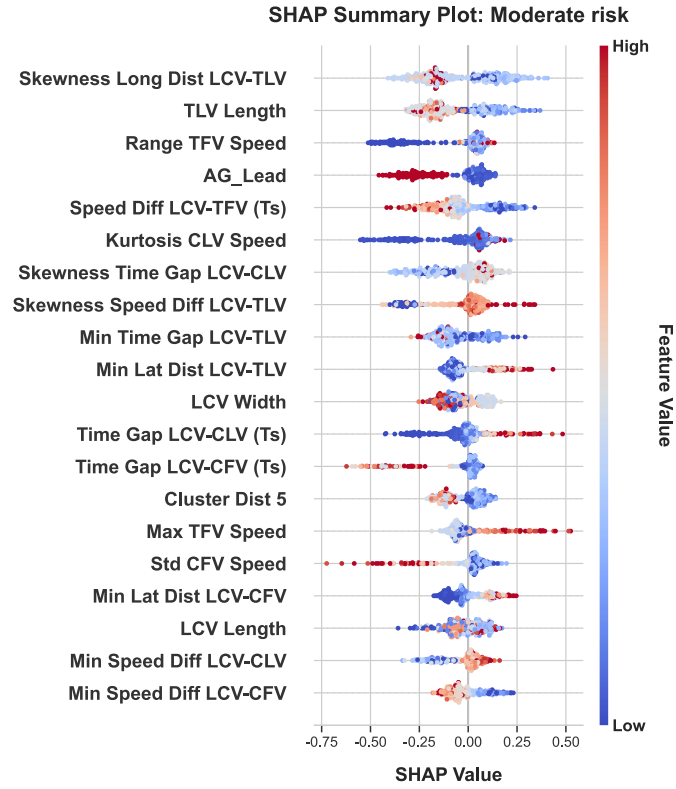
As illustrated in Figure 6.14(d), the results reveal a key contributor to the elevated collision risk during lane-changing. When the width of the LCV increases, collision risk rises significantly, as a wider vehicle reduces the lateral fault tolerance available to the driver. Wider vehicles not only exhibit poorer manoeuvrability but also are more susceptible to side collisions with vehicles leading and following the target lane. When the gap between the LCV and the CLV is small at time T_s , the SHAP value shows a strong positive contribution to high collision risk, indicating that a small forward gap in the lane (for example, when the leading vehicle suddenly executes emergency braking) often results in extremely high collision risk for an ongoing lane change. The high SHAP value of AG_Lead constitutes a forward hazard contribution, and this counterintuitive phenomenon may reflect a safety illusion: if the lane-changing vehicle detects a sufficiently large gap ahead of the target lane but fails to notice a fast-approaching vehicle from the rear, blind execution of an aggressive lane-changing manoeuvre easily leads to a collision with the TFV. The results also demonstrate that discretionary lane-changing have a mitigating effect on elevated collision risk, while non-discretionary lane-changing have an exacerbating effect. This finding confirms that stricter spatiotemporal constraints during lane-changing correspond to higher collision risk. When the minimum speed difference between the LCV and CLV over the interval $[T_s - \Delta_t, T_s]$ is large, this factor also positively correlates with higher collision risk. This suggests that maintaining an appropriate negative speed difference with the CLV prior to lane-changing can reduce the probability of rear-end collisions caused by insufficient safety buffers.



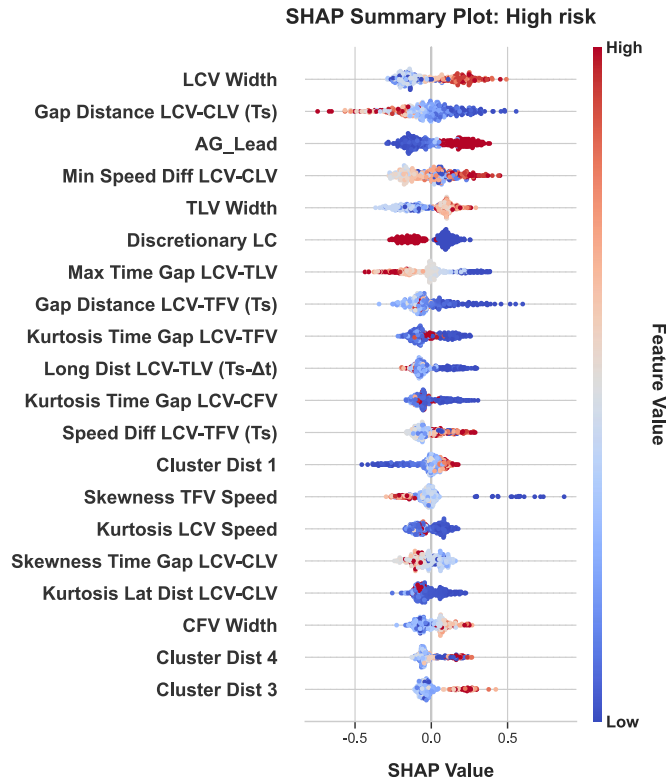
(a) Extremely low lane-changing risk



(b) Low lane-changing risk



(c) Moderate lane-changing risk



(d) High lane-changing risk

Figure 6.14 Honeycomb plot of feature contributions for the XGBoost+GRU-KAN ($\Delta_t=1.0s$) heterogeneous fusion framework.

After identifying the factors contributing to the elevated risk of lane-change collisions, further analysis using the SHAP-based interaction graph is conducted. This approach can not only precisely quantify the nonlinear step threshold at which an individual feature triggers higher risk, but also characterise the coupling complexity between features, thereby reconstructing the micro-triggering conditions of high-risk lane-changing collision scenarios.

As shown in Figure 6.15(a), the contribution of LCV width to elevated collision risk exhibits a typical nonlinear step pattern, and its SHAP value turns positive when the LCV width exceeds the zero critical point. This indicates that lane-changing vehicles with a wider width are associated with a higher collision risk. LCV width interacts with the spatially clustered feature 4, which encodes the macroscopic traffic scene. The red and blue scatter points in the figure do not show distinct stratified aggregation along the longitudinal SHAP value axis, which suggests that the main effect of vehicle over-width on collision risk has cross-scene penetration. In other words, regardless of the macroscopic traffic flow state of the weaving section, the risk of side collisions increases as long as the physical width of the vehicle exceeds the regulatory limit.

As shown in Figure 6.15(b), the gap distance between the LCV and the CLV at time T_s exhibits a significant downward trend. As the forward gap distance in the current lane is compressed, collision risk increases considerably. The most salient interaction feature is the standard deviation of the time gap between LCV and TLV over the interval $[T_s - \Delta_t, T_s]$, which captures the instability of traffic conditions in the target lane. When the forward gap distance of the current lane approaches the safety threshold, although the SHAP values of samples with large standard deviation all remain at high levels, the limited number of these extreme fluctuation samples leads to the main effect of forward longitudinal gap compression almost completely masking the interaction effect from the target lane. This phenomenon indicates that when LCV is forced to conduct an urgent lane change under the pressure from CLV, collision risk is already at a high level regardless of whether the time gap in the target lane is stable or not.

The AG_Lead curve in Figure 6.15(c) exhibits abrupt characteristics, with a positive jump in SHAP contribution when the normalised value of AG_Lead exceeds 1. In this scenario, the feature that interacts most strongly with AG_Lead is the cluster spatial distance feature 0. Dark blue scatters are clustered at high SHAP value intervals, while red scatters are distributed at relatively low SHAP value intervals. This interaction pattern reveals that a large time gap to the leading vehicle in the target lane often creates a safety illusion for drivers, inducing them to execute aggressive lane-changing manoeuvres. However, when such a large time gap occurs in a macroscopically unstable traffic flow, it may be a transient illusion caused by alternating acceleration and deceleration of the leading vehicle. Drivers' blind trust in this transient large gap makes them vulnerable to collision risks triggered by sudden braking of the leading vehicle or compression from surrounding vehicles, which ultimately amplifies collision risk.

In Figure 6.15(d), the minimum speed difference between the LCV and the CLV during the period $[T_s - \Delta_t, T_s]$ follows a V-shaped distribution, which

demonstrates the importance of speed coordination. When there is a considerable speed difference between the lane-changing vehicle and the current-lane leading vehicle, the collision risk increases sharply, regardless of whether the lane-changing vehicle approaches the leading vehicle with an excessively large speed difference or travels at a speed substantially lower than that of the leading vehicle and the surrounding traffic flow. The most salient interaction feature is the time gap range between the LCV and the TLV during the period $[T_s - \Delta_t, T_s]$. Although the SHAP values are high in the large gap range state, the main effect remains dominant due to the sparse distribution of samples with extremely large ranges. This indicates that uncoordinated speed differences within the original lane is itself a risk factor determining collision risk, while the fluctuation of the time gap in the target lane only plays a limited moderating role.

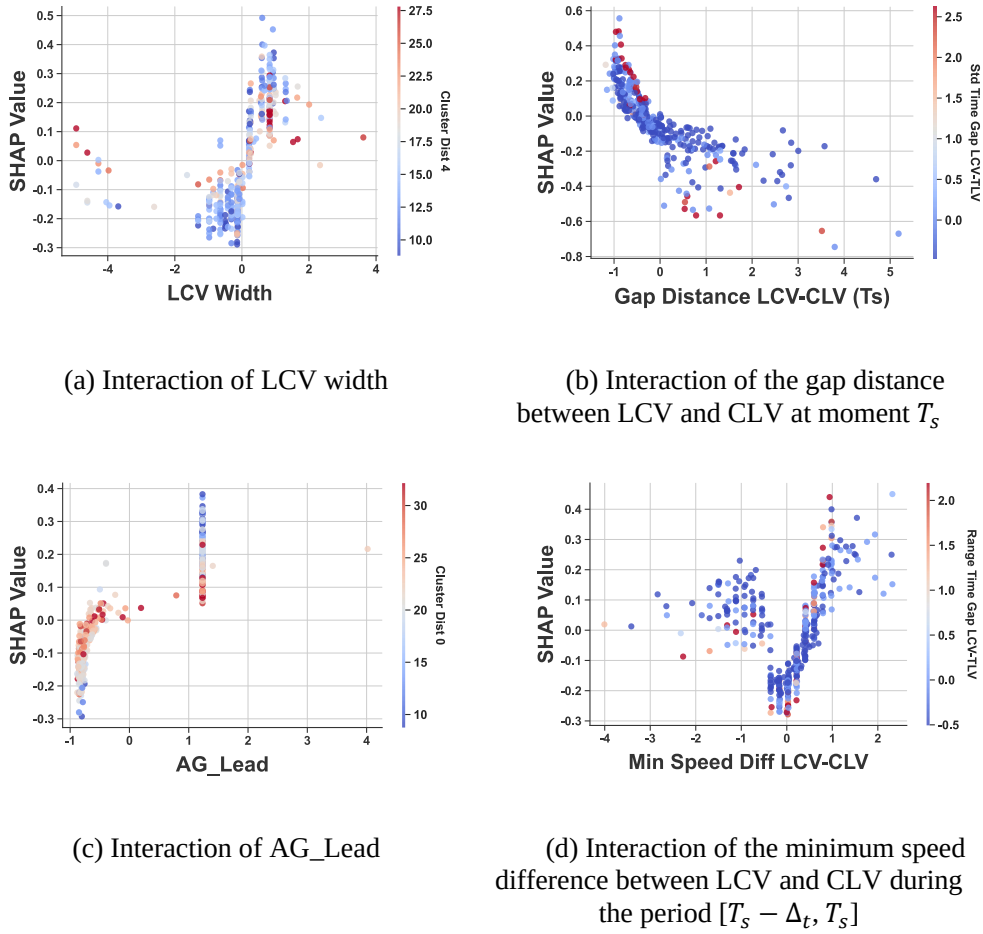


Figure 6.15 Schematic diagram of key feature interactions for the XGBoost+GRU-KAN ($\Delta_t=1.0$ s) heterogeneous fusion framework.

(2) Analysis of the temporal evolution mechanism of risk mutations

During the 1.0-second warning time window when the lane-changing collision risk reaches a high level, the kinematic state of the vehicle typically undergoes drastic changes. In this thesis, temporal inversion analysis is performed on true positive samples from the blind test set that were correctly identified by the model as having high lane-changing collision risk, and three most representative micro-dynamic evolution patterns of vehicles are extracted prior to the occurrence of high

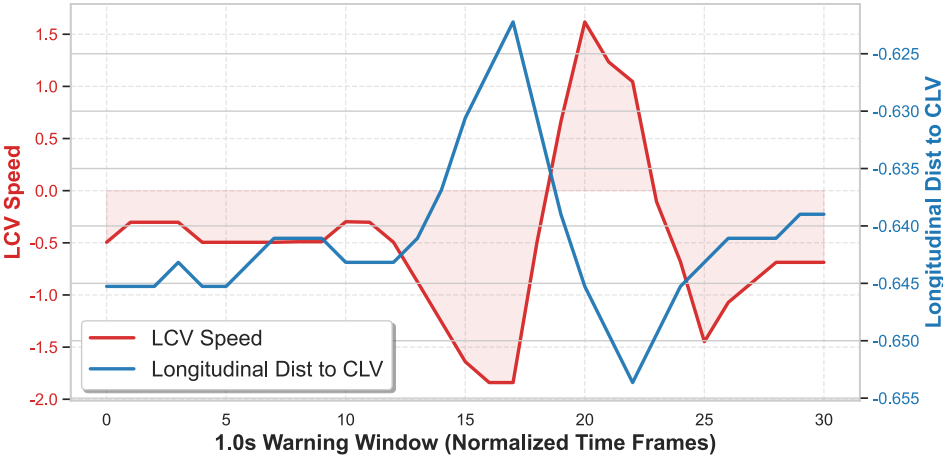
collision risk, as illustrated in Figure 6.16. The kinematic temporal characteristics of vehicles before lane-changing revealed in Figure 6.16 can provide an active real-time warning reference for lane-changing collision risk for ADAS, thereby effectively improving vehicle operation safety in weaving sections.

Figure 6.16(a) illustrates the alternating process of sudden acceleration and deceleration induced by the deep coupling between traffic flow instability and drivers' aggressive driving behaviours. Within the 1.0-second time window prior to the lane change, the speed of the LCV exhibited sharp fluctuations. After approximately frame 12, the vehicle's speed dropped abruptly, indicating that the driver performed emergency braking in response to unexpected road conditions. A subsequent abrupt speed increase occurred after frame 17, coinciding with the longitudinal distance between the LCV and the CLV approaching its minimum value. To avoid rear-end collision, the LCV conducted a second abrupt braking between frames 20 and 25, after which the longitudinal distance between the two vehicles increased slightly. Frequent interleaved lane changes in the weaving section reduce drivers' accuracy in perceiving the spatiotemporal margin for car-following. Such frequent acceleration and deceleration not only readily trigger chain-type fluctuations in traffic flow, but also push vehicles to the edge of dynamic instability, ultimately leading to substantially elevated lane change collision risk.

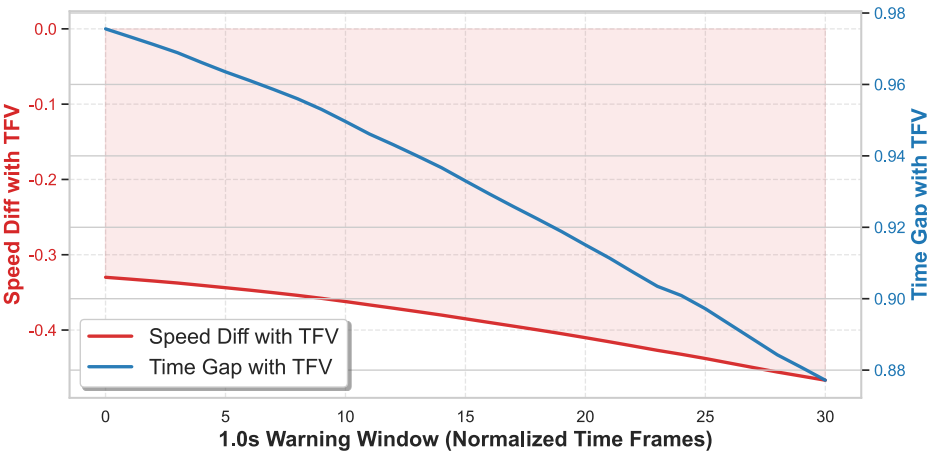
As shown in Figure 6.16(b), the speed difference between the LCV and the TFV remains consistently negative and continues to increase, indicating that TFV is approaching LCV at an increasingly higher relative speed, while the time gap between the two vehicles decreases sharply. This matches the characteristics of a typical forced lane-changing scenario. In this scenario, the LCV merges into the target lane without gaining a speed advantage under unfavourable lane-changing conditions, while the TFV does not adopt evasive or deceleration manoeuvres. This non-cooperative forced lane-changing behaviour continuously erodes the spatiotemporal safety buffer between the two vehicles, which can easily lead to severe side impacts or rear-end collisions without emergency intervention from active safety systems.

The high-risk evolution pattern of aggressive consecutive lane changes in the weaving section is presented in Figure 6.16(c). The blue curve in the figure shows a significant steady decline from frame 0 to frame 22, indicating that the vehicle is cutting diagonally across traffic with a large yaw angle. The red line exhibits a nearly vertical step change at frame 22, indicating that the LCV has finished crossing the lane marking and entered the adjacent lane at this moment. Within a very short time window after crossing the line, the red line stabilises, indicating that the vehicle has completed a brief attitude adjustment in the adjacent lane. The start point of the subsequent lane change T_s identified by wavelet transform is located at frame 30, which indicates that the driver forms the intention to change to the target lane again within a very short interval after completing the first aggressive lane change. When the vehicle completes the first lane crossing at frame 22, it has accumulated considerable lateral kinetic energy and roll angle due to the large steering angle and high driving speed. In an unstable state where lateral fluctuations have not completely dissipated, the driver immediately initiates the intention for a

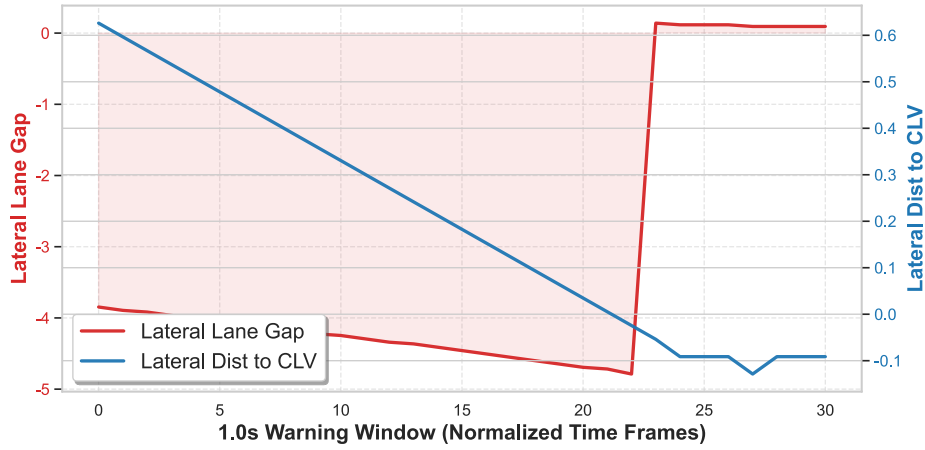
second lane change. This extremely high-frequency lateral manoeuvre causes the lateral adhesion limit of the vehicle’s tires to be reached repeatedly, which can easily trigger severe lateral displacement instability. In addition, this continuous lane-crossing behaviour within a short period significantly reduces the reaction time available to the TFV and introduces unpredictable vehicle conflicts, thereby substantially increasing the risk of side scrapes and multi-vehicle chain collisions.



(a) Sudden acceleration and deceleration alternation



(b) Forced lane changes



(c) Consecutive lane changes

Figure 6.16 Example of temporal evolution with high collision risk mutation for the XGBoost+GRU-KAN ($\Delta_t = 1.0s$) heterogeneous fusion framework.

6.5 Conclusions

This chapter constructs and thoroughly evaluates a spatiotemporal representation decoupling information fusion framework for lane-changing collision risk prediction in the weaving section. This work completes a rigorous theoretical loop ranging from data reconstruction and underlying algorithm decoupling to physical mechanism analysis, and its prediction results strongly support the theoretical deduction of lane-changing risk causation analysis in Chapter 5 from an empirical perspective. For the lane-changing collision risk prediction task, this thesis first decouples and constructs static topology and dynamic time series candidate feature sets under four distinct warning time windows. To address the inherent class imbalance issue in risk-level data, this chapter extracts spatial distance features via the K-means algorithm to enhance global topological awareness, and further adopts the SMOTE-Tomek hybrid resampling technique to clean multi-dimensional decision boundaries, without introducing high-frequency false noise. This process provides a class-balanced, clearly bounded foundation of high-quality data for the subsequent heterogeneous fusion framework. To tackle the problem that single models are prone to feature flooding when processing heterogeneous traffic data, this chapter proposes an information fusion mechanism based on spatiotemporal representation decoupling that takes QWK maximisation as the objective function. This mechanism leverages the spatial parsing advantage of classical machine learning models for discrete static tabular data, and complements the transient capture capability of advanced deep time series networks for underlying high-frequency dynamic data. Meanwhile, the edge spline function of KAN is introduced at the output of the deep network for nonlinear probability mapping, which is supplemented by an ordinal regression structure with progressive risk constraints and an early stopping breaker mechanism.

The model test results indicate that the heterogeneous fusion framework integrating XGBoost and GRU-KAN achieves optimal generalisation performance when the warning time window $\Delta_t=1.0$ s. The model obtains strong performance across three evaluation metrics: QWK (up to 0.86), Accuracy (up to 0.79), and *Weighted_F1* (up to 0.76). It can accurately identify lane-changing risks while effectively suppressing severe misclassifications across all risk levels. To investigate the time complexity of the proposed model, this thesis compares the total training time and average single-sample inference time of all compared models on a unified hardware platform. The experimental results demonstrate that the proposed model can process high-frequency streaming data in microscopic traffic scenarios, and exhibits high engineering feasibility for real-time deployment. To demystify the black box nature of the heterogeneous fusion framework and validate its microscopic working mechanism, this thesis adopts the SHAP attribution method to analyse the optimal prediction model. The analysis confirms that high collision risk during lane-changing is not only driven by extreme spatiotemporal compression in microscopic vehicle dynamics (e.g., extremely small inter-vehicle gap distance and insufficient time gap), but also affected by non-linear step penalties from fundamental lane-changing features and lane-changing decision features (e.g., vehicle size, accepted target lane gap, etc.). Further feature interaction analysis reveals the infiltration induction mechanism of macroscopic traffic scene features derived from K-means clustering on microscopic traffic conflicts, and explains the safety illusion phenomenon of aggressive lane-changing behaviour labelled AG_Lead under specific macroscopic congestion conditions. Finally, leveraging the temporal traceability capability of the GRU-KAN module, this chapter successfully extracts three of the most representative micro dynamic evolution paths of high lane-changing risk within the 1.0-second warning window: sudden acceleration and deceleration alternation, forced lane changes, and consecutive lane changes. This finding not only characterises the dynamic phase transition process of transient lane-changing collision risks explicitly, but also provides robust fundamental algorithmic support for ADAS to develop differentiated intelligent active safety intervention strategies.

Chapter 7

7. Conclusions and future prospects

7.1 Main research conclusions

This thesis investigates the mechanism of lane-changing behaviour and associated collision risks in the weaving section. By integrating trajectory data collected from field observations via drones and driving simulation experiments, this study conducts an in-depth exploration along four core dimensions: lane-changing behavioural characteristic analysis, decision-making mechanism modelling, collision risk causation analysis, and accurate quantitative risk prediction. The main research findings are presented as follows:

(1) Analysis of lane-changing behaviour in the weaving section by comparing field observation data with driving simulation data

Based on the video trajectory data of the weaving section collected via field observations using drones, this thesis constructs a high-fidelity driving simulation experimental environment, designs the experimental protocol through the response surface central composite design method, and recruits Italian and Chinese drivers to perform comparative experiments. A two-sample K-S test is adopted to conduct a comprehensive comparative analysis of lane-changing behaviour characteristics between the driving simulation data and field observation data. The results indicate that for variables characterizing macroscopic traffic efficiency, the simulation data and field data satisfy both absolute and relative validation criteria. For parameters characterizing the microscopic lane-changing process, the fundamental requirements for relative validation are fulfilled. This study identifies systematic differences between the simulation data and field data, which reveals that the lane-changing behaviour in the weaving section is jointly affected by multiple factors including data collection methods, lane-changing types, and demographic characteristics such as driver nationality and age.

(2) Heterogeneous modelling of lane-changing behaviour decisions in the weaving section using a hierarchical Bayesian framework

This thesis develops a hierarchical Bayesian model and two hierarchical Bayesian double-hurdle models to investigate driver lane-changing decision-

making mechanism. Random effects incorporated in these models are applied to quantify the decision heterogeneity across different data types, lane-changing types and lane-changing events. The estimation results of the lane-changing start position decision model indicate that, compared with right lane-changing manoeuvres, left lane-changing in the weaving section requires longer weaving length. Additionally, the physical dimensions and types of surrounding vehicles significantly influence drivers' choices of lane-changing start positions. An increase in the speed of the following vehicle in the current lane raises drivers' perceived time pressure, which prompts drivers to select a more downstream start position for lane-changing, and this speed pressure effect exhibits substantial heterogeneity across individuals. The results of the hierarchical Bayesian double-hurdle model verify the two-stage independence of drivers' decisions regarding accepted target lane gaps: namely, the binary decision of "whether to choose a positive accepted target lane lead/lag gap" and the continuous decision of "how much the value of accepted target lane lead/lag gap" are dominated by distinct influencing factors. Dynamic variables including gap distance in the target lane and relative speed difference significantly affect drivers' binary decision on accepting a positive time gap, while the determination of the time gap magnitude is further jointly influenced by multiple factors, including the size characteristics of the lane-changing vehicle and surrounding vehicles, as well as traffic speed conditions.

(3) Etiological analysis of lane-changing collision risk in the weaving section considering unobserved heterogeneity

This thesis develops a comprehensive Lane Change Risk Assessment Index (LCRAI) based on two dimensions: the duration of risk exposure (ERI) and the expected collision severity (SRI), which enables comprehensive and accurate quantification of lane-changing collision risk levels. An enhanced K-means clustering algorithm is applied to categorise lane-changing events into risk levels with significant discrimination according to their risk characteristics. On this basis, a random-parameter ordered Probit model considering both heterogeneity of mean and variance is established to effectively identify the key determinants of lane-changing risk and uncover unobserved heterogeneity across different influencing factors. The results indicate that vehicle physical attributes (type, size parameters), motion state characteristics (average speed, speed fluctuation, relative speed), relative motion characteristics (gap distances, time gaps), and lane-changing scenario elements (lane-changing type, spatial position) together form the key variable set that influences lane-changing risk. Notably, the findings reveal that the impact of dynamic vehicle motion parameters on lane-changing risk is substantially greater than that of static attribute parameters, which provides an important reference for lane-changing risk intervention in weaving sections.

(4) Prediction of lane change collision risk in the weaving section based on spatiotemporal representation decoupling

In this thesis, static and dynamic candidate feature sets were constructed separately, and spatial distance features were extracted using the K-means algorithm. Boundary cleaning was then implemented via the SMOTE-Tomek hybrid sampling method, which provided a high-quality data foundation with

balanced class distribution and clear decision boundaries for subsequent model training. Based on the information fusion mechanism of spatiotemporal representation decoupling, a heterogeneous fusion framework was developed with the maximisation of QWK as the objective function, integrating both machine learning and deep learning models. Comprehensive evaluation results show that the heterogeneous fusion framework combining XGBoost and GRU-KAN achieves the optimal generalisation performance when the warning time window Δ_t is set to 1.0 second. The SHAP method was adopted to interpret the model, and the results reveal that vehicle kinematic characteristics are the core dominant features for driving risk assessment. A clear causal association is verified between lane-changing decision outcomes and lane-changing collision risk, while vehicle geometric dimensions and lane-changing motivation are confirmed as critical prerequisites influencing lane-changing collision risk. Within the 1.0-second warning window, three most representative micro dynamic evolution paths of lane-changing collision risk were extracted, namely sudden acceleration and deceleration alternation, forced lane changes, and consecutive lane changes, which explicitly characterise the occurrence and evolution process of high-risk collision events.

7.2 Major contributions

Compared with existing studies, this thesis makes the following contributions at the levels of theoretical framework, methodology, and engineering practice:

(1) Enriched the theoretical system for analysing the lane-changing behaviour mechanism in weaving sections

Given the complex road geometry of expressway weaving sections, this thesis presents a comparative validation study of microscopic lane-changing behaviour characteristics based on integrated data from driving simulation and field observation. Using the two-sample K-S test, this research performs comprehensive comparative validation across two dimensions: macroscopic traffic efficiency indicators and microscopic lane-changing behaviour characteristics. This analysis identifies systematic differences and complementary relationships between driving simulation data and field observation data. The findings not only provide new empirical evidence for validating the effectiveness of driving simulators in complex road scenarios, but also establish a methodological reference for subsequent lane-changing decision experiments conducted on driving simulation platforms.

(2) Extended the decision modelling method for lane-changing behaviour in weaving sections considering heterogeneity and hierarchical structure

This thesis integrates a three-level nested structure encompassing data types, lane-changing types, and lane-changing events into a unified hierarchical Bayesian modelling framework, and develops a lognormal double-hurdle model for forced lane-changing behaviour. This model reveals the independent characteristics of the two-stage decisions: “whether to choose a positive accepted target lane lead/lag gap” and “how much the value of accepted target lane lead/lag gap”. This contribution expands the theoretical scope of lane-changing behaviour decision

modelling at the methodological level, and provides a new analytical tool for investigating the decision-making mechanism of lane-changing behaviour in weaving sections.

(3) Established a framework for comprehensive quantification of lane-changing risk and the analysis of heterogeneous contributing factors

This thesis develops the Lane Change Risk Assessment Index (LCRAI) based on two dimensions: the duration of risk exposure and the expected collision severity. The study then realises the scientific classification of lane-changing risk levels via an enhanced K-means clustering algorithm. Furthermore, a random-parameter ordered Probit model considering heterogeneity of mean and variance is established to uncover the mechanisms through which vehicle physical attributes, motion state characteristics, spatial relationship indicators, and lane-changing scenario factors influence lane-changing collision risk. The results indicate that the magnitude of the effect of vehicle dynamic motion parameters exceeds that of static attribute parameters, and a quantitative linkage from lane-changing decision variables to safety outcomes is constructed. At the methodological level, this thesis improves the granularity of modelling the risk factors of lane-changing collisions in weaving sections, which provides a theoretical foundation for targeted traffic safety interventions.

(4) Proposed an accurate prediction model of lane-changing collision risk based on spatiotemporal representation decoupling

Given the heterogeneous representation mechanisms of different data types, a heterogeneous fusion framework that combines the complementary strengths of traditional machine learning and deep learning models is constructed. Then interpretable analysis methods are used to quantify the influence of key features on lane-changing collision risk, and further revealed the micro-dynamic evolution trajectory of high collision risk based on risk mutation time series inversion. This work constitutes a valuable exploratory contribution to the field of lane-changing collision risk prediction, and provides foundational algorithmic support for real-time risk warning and targeted intervention in ADAS.

7.3 Research prospects

Although this thesis has obtained research findings with both theoretical value and practical implications, limitations in data availability, technical resources, and research duration leave multiple research directions that can be further expanded and deepened in future work:

(1) Integrate a wider range of diverse weaving section scenarios and extreme environmental factors

This thesis only focuses on Type A1 weaving sections under off-peak traffic conditions. In future research, more data from diverse types of weaving sections across various traffic operational conditions should be collected to investigate the coupling mechanism between lane-changing behaviour, static road characteristics and dynamic traffic characteristics. Furthermore, all data collection and simulation scenarios in this thesis are conducted under good daytime weather conditions.

However, in weaving sections, when exposed to low-visibility weather conditions such as rain, snow, and fog, or low-light night conditions, drivers' perception of following gaps and lane-changing decision thresholds may change substantially. Thus, targeted research on extreme environmental factors is required in future studies. In addition, the weaving section analysed in this thesis is located on the Changsha Airport Expressway, which has a maximum speed limit of 100 km/h. Compared with conventional freeways, this site differs in traffic volume, operating speed, and truck proportion. Therefore, future research needs to further examine scenarios on conventional freeways with higher speed limits to verify the generalizability of the conclusions drawn in this thesis.

(2) Introduce causal inference methods to deepen the analysis of lane-changing risk mechanisms

This thesis primarily adopts machine learning models for risk prediction and improves the interpretability of the constructed models via the SHAP method. However, the causal linkage between the prediction outputs and the traffic behaviour mechanism remains to be further explored. Future research can introduce causal inference methods (e.g., double machine learning, counterfactual analysis, structural equation modelling) to conduct in-depth verification of the causal chain connecting lane-changing motivation, vehicle interaction, driving style and risk evolution. This will address the gap in causal interpretation of existing machine learning prediction models, and provide a more robust theoretical foundation for proactive traffic risk intervention strategies.

(3) Research on lane-changing cooperative decision-making and game-theoretic mechanisms for connected and automated driving

With the gradual increase in the penetration rate of CAVs, traffic flow at weaving sections will consist of a mixed fleet of human-driven vehicles and automated vehicles. In this mixed traffic environment, CAV lane-changing decisions require not only predictions of human driving behaviour, but also consideration of coordination games among multiple vehicles. Future research can extend the analytical framework established in this thesis to model the lane-changing game mechanism under mixed human-automated mixed driving traffic, develop cooperative lane-changing algorithms that adopt LCRAI as the reward function, and quantify the impacts of different CAV penetration rates on traffic safety, operational efficiency, and vehicle emissions at weaving sections via simulation evaluation.

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