
StyleDrive: Towards Driving-Style Aware Benchmarking of End-To-End Autonomous Driving

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<https://github.com/AIR-THU/StyleDrive>

Abstract

While personalization has been explored in traditional autonomous driving systems, it remains largely overlooked in end-to-end autonomous driving (E2EAD), despite its growing prominence. This gap is critical, as user-aligned behavior is essential for trust, comfort, and widespread adoption of autonomous vehicles. A core challenge is the lack of large-scale real-world datasets annotated with diverse and fine-grained driving preferences, hindering the development and evaluation of personalized E2EAD models. In this work, we present the first large-scale real-world dataset enriched with annotations capturing diverse driving preferences, establishing a foundation for personalization in E2EAD. We extract static environmental features from real-world road topology and infer dynamic contextual cues using a fine-tuned visual language model (VLM), enabling consistent and fine-grained scenario construction. Based on these scenarios, we derive objective preference annotations through behavioral distribution analysis and rule-based heuristics. To address the inherent subjectivity of driving style, we further employ the VLM to generate subjective annotations by jointly modeling scene semantics and driver behavior. Final high-quality labels are obtained through a human-in-the-loop verification process that fuses both perspectives. Building on this dataset, we propose the first benchmark for evaluating personalized E2EAD models. We assess several state-of-the-art models with and without preference conditioning, demonstrating that incorporating personalized preferences results in behavior more aligned with human driving. Our work lays the foundation for personalized E2EAD by providing a standardized platform to systematically integrate human preferences into data-driven E2EAD systems, catalyzing future research in human-centric autonomy.

1 Introduction

Personalization has long been recognized as a critical factor in enhancing user experience and building trust in autonomous driving systems Hasenjäger and Wersing [2017]. In conventional modular pipelines—comprising components such as motion planning, trajectory prediction, and decision-making—personalized strategies have been widely studied, enabling systems to adapt to individual driving preferences. However, these methods often rely on isolated, scenario-specific adaptations Tian et al. [2022], Liu et al. [2024] or unreal human-in-the-loop (HuIL) simulation Ke et al. [2024], resulting in limited generalization across diverse and dynamic real-world contexts. Moreover, the fragmented nature of modular systems Zhu et al. [2018], Cui et al. [2024a], Kou et al. [2025] hinders scalability, as preference modeling is tightly coupled to specific modules and does not transfer easily to integrated learning systems. Due to these limitations, personalization remains largely underexplored in end-to-end autonomous driving (E2EAD), where perception, planning, and

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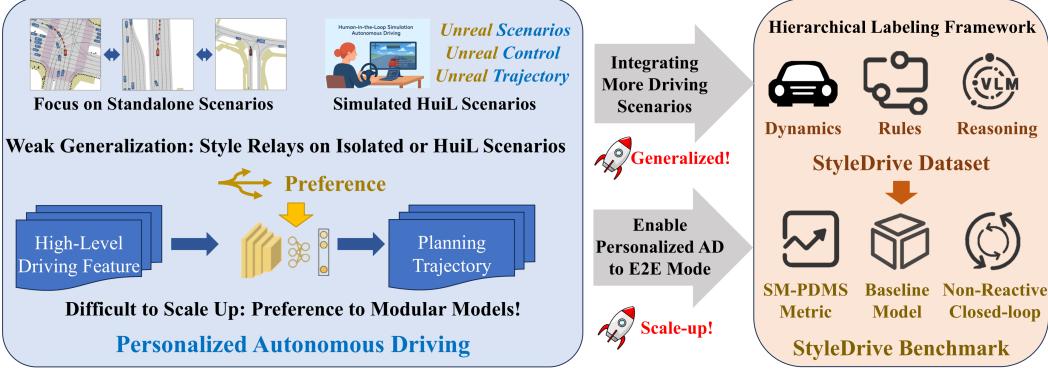


Figure 1: Motivation and Overview of StyleDrive.

control are jointly optimized in a single architecture Chib and Singh [2023]. This gap presents a significant barrier to realizing truly human-centric and adaptive autonomous driving at scale.

This gap is particularly pressing. As E2EAD systems become increasingly capable and are deployed across diverse, open-world driving environments, aligning vehicle behavior with user preferences becomes essential for enhancing comfort, perceived safety, and long-term user acceptance Speidel et al. [2019], Aledhari et al. [2023]. Yet integrating personalization into the end-to-end paradigm introduces unique challenges. Unlike modular systems operating within narrowly defined scenarios, E2EAD requires preference generalization across a broad spectrum of complex, real-world scenarios. Meeting this demand necessitates large-scale datasets that not only cover diverse traffic conditions but also provide fine-grained driving style annotations. Without such data, it is difficult to train or benchmark models that can scale with data and generalize across both users and environments. Consequently, data-driven personalization in E2EAD remains a critical and unresolved challenge.

To address this challenge, we introduce the **first large-scale real-world dataset explicitly designed for personalized E2EAD**. Our dataset captures both objective behavioral patterns and subjective driving preferences across a wide range of driving scenarios. Static environmental features are extracted from real-world road topologies, while dynamic context cues are inferred using a fine-tuned visual language model (VLM), enabling rich semantic scene understanding. Based on these scenarios, we generate objective annotations through behavior distribution analysis and rule-based heuristics. To incorporate subjectivity, we further employ the VLM to synthesize preference labels that integrate scene semantics and inferred driver intent, followed by human-in-the-loop verification to ensure quality and consistency. Building upon this dataset, we establish **the first benchmark for evaluating personalized E2EAD models**. We conduct extensive experiments on multiple state-of-the-art architectures, with and without preference conditioning, and show that incorporating personalization significantly improves alignment with human-like driving behavior.

Our work aims to bridge the gap between the growing momentum in E2EAD and the longstanding need for human-centric design in autonomous driving systems. By introducing both a large-scale data foundation and a standardized evaluation benchmark, we seek to facilitate future research on personalized, adaptive, and trustworthy autonomous driving. In summary, our key contributions are:

- **A novel large-scale real-world dataset** for personalized end-to-end autonomous driving, annotated with both objective behaviors and subjective driving style preferences across a wide range of traffic scenarios.
- **A multi-stage annotation pipeline** that integrates behavior analysis, rule-based heuristics, visual language models (VLMs), and human-in-the-loop verification to generate consistent and high-quality preference labels.
- **The first benchmark for personalized E2EAD**, which enables standardized, quantitative comparison of preference-conditioned behavior across different model architectures.
- **Comprehensive empirical results** demonstrating that incorporating user driving preferences significantly improves alignment with human-like behavior, underscoring the value of personalization in E2EAD.

Table 1: Comparison of driving datasets by data source, scenario coverage, evaluation protocol, end-to-end (E2E) support, and driving style annotations. **StyleDrive** is the only dataset that combines real-world data, diverse scenarios, semi-closed-loop (Semi-CL) evaluation, E2E learning capability, and structured driving style labels for personalized autonomous driving.

Abbreviations: OL = Open-Loop, CL = Closed-Loop, Semi-CL = Semi-Closed-Loop, HuiL = Human-in-the-Loop, E2E = End-to-End driving model support, Style = With Style or Preference Annotation

Dataset	Reality	Scenarios	CL/OL	E2E	Style
nuScenes Caesar et al. [2020]	Real	City	OL	✓	✗
OpenScene Peng et al. [2023]	Real	City&Rural	OL	✓	✗
Longest6 Chitta et al. [2022]	Sim	City	CL	✓	✗
CARLA Contributors [2024]	Sim	City	CL	✓	✗
MetaDrive Li et al. [2022]	Sim	City	CL	✓	✗
Bench2Drive Jia et al. [2024]	Sim	City	CL	✓	✗
NAVSIM Dauner et al. [2024]	Real	City&Rural	Semi-CL	✓	✗
HuiL-RM Li et al. [2023]	HuiL	Ramp-Merge	OL	✗	✓
HuiL-CF Zhao et al. [2022]	HuiL	Car-Following	OL	✗	✓
HuiL-LC Liao et al. [2023]	HuiL	Lane-Change	OL	✗	✓
HuiL-Mul Ke et al. [2024]	HuiL	City	OL	✗	✓
UAH Romera et al. [2016]	Real	City&highway	OL	✗	✓
Brain4Cars Jain et al. [2016]	Real	Lane-Change&Merge	OL	✗	✓
PDB Wei et al. [2025]	Real	City	OL	✗	✓
StyleDrive (Ours)	Real	City&Rural	Semi-CL	✓	✓

2 Related Work

Personalized Autonomous Driving Personalization has long been recognized as a key factor in enhancing user comfort, trust, and long-term acceptance of autonomous vehicles Liao et al. [2024]. In conventional modular pipelines—comprising separate stages for perception, prediction, and planning—personalized strategies have been extensively explored. These methods allow the system to adapt to user-specific preferences in specific driving scenarios, such as desired following distance, acceleration aggressiveness, and lane-change behavior Müller et al. [2018], Huang et al. [2021], Tian et al. [2022], Rosero et al. [2024], Liu et al. [2024].

Recently, the emergence of large language models (LLMs) has opened new possibilities for personalization in autonomous driving. Several studies have explored leveraging LLMs to encode user intent, interpret high-level preferences, and influence downstream decision-making Cui et al. [2024a], Xu et al. [2024], Cui et al. [2024b], Kou et al. [2025], Lin et al. [2024]. However, these approaches typically operate within modular or semi-modular frameworks and often rely on handcrafted integration points or high-level perception outputs. MAVERIC Schrum et al. [2024] represents a notable early attempt to enable end-to-end personalized driving via a unified latent representation of user style. Nevertheless, it is developed in a semi-simulated environment with limited sensory inputs—excluding modalities like LiDAR—and lacks a standardized benchmark for comparing methods, which constrains its scalability and broader applicability in real-world settings.

Despite these advancements, personalized E2EAD remains largely underexplored. Existing research seldom addresses how user preferences can be directly embedded into unified end-to-end frameworks. A key bottleneck in this direction is the lack of large-scale, real-world datasets with fine-grained annotations of personalized driving styles.

End-to-End Autonomous Driving End-to-end autonomous driving (E2EAD) has emerged as a promising paradigm that maps raw sensor inputs directly to driving actions or planned trajectories using deep neural networks Chen et al. [2024a]. Early work Codevilla et al. [2018], Kendall et al. [2019], Chen et al. [2020a] demonstrated the feasibility of E2E systems through imitation and reinforcement learning in both real-world and simulated settings. Over the past decade, research has advanced toward more sophisticated architectures incorporating temporal reasoning, multimodal fusion, and Transformer-based backbones Prakash et al. [2021], Jia et al. [2023], Shao et al. [2023]. Recent efforts have also focused on data-efficient training and task-conditioned control across diverse scenarios Kong et al. [2025].

Despite this progress, most E2EAD models are optimized for average-case behavior, lacking mechanisms to account for driver-specific preferences or personalized objectives. While recent architectures improve generalization and interpretability Chen et al. [2020b], Li et al. [2024], Zheng et al. [2024], Chen et al. [2024b], Jia et al. [2025], they remain limited in capturing nuanced, individualized driving styles. Moreover, the absence of dedicated datasets and standardized benchmarks for evaluating personalization continues to hinder systematic advancement in this area.

To address these limitations, we build on recent advances in model capacity and controllability to develop and evaluate E2EAD systems that explicitly incorporate user driving preferences. Our work represents the first systematic attempt to align end-to-end driving behavior with real-world personalized objectives, paving the way for more adaptive and user-aligned autonomous vehicles.

Benchmarking Autonomous Driving Benchmarking is essential for evaluating autonomous driving models. Early E2EAD benchmarks such as nuScenes Caesar et al. [2020] and OpenScene Peng et al. [2023] adopt open-loop protocols using real-world data, but lack real-time interaction and fail to capture feedback effects or behavioral consequences. Recent works have introduced closed-loop benchmarks in simulation, including Longest6 Chitta et al. [2022], MetaDrive Li et al. [2022], CARLA Leaderboard V2 Contributors [2024], and Bench2Drive Jia et al. [2024]. These allow online policy evaluation but rely on synthetic sensor data and simplified environments. Semi-simulated platforms like NAVSIM Dauner et al. [2024] strike a balance by replaying real-world scenes in simulation. However, existing benchmarks remain focused on task performance and ignore user preferences, offering no means to evaluate personalized driving behavior.

Efforts to benchmark personalized autonomous driving have resulted in two main types of datasets: human-in-the-loop (HuiL) simulation environments and real-world driving records. HuiL-based datasets are typically collected through controlled interactions between human drivers and simulated agents in targeted scenarios such as ramp merging (HuiL-RM) Li et al. [2023], car following (HuiL-CF) Zhao et al. [2022], lane changing (HuiL-LC) Liao et al. [2023], and multiple scenarios (HuiL-Mul) Ke et al. [2024]. While these setups enable precise behavior capture and fine-grained preference modeling, they often rely on simplified simulation engines and handcrafted environments, resulting in a significant domain gap from real-world conditions. In contrast, real-world datasets such as UAH-DriveSet Romera et al. [2016], Brain4Cars Jain et al. [2016], and PDB Wei et al. [2025] provide behavioral annotations related to aggressiveness, drowsiness, or maneuver intent. These datasets have contributed substantially to understanding driver behavior and intent modeling. However, they are typically constrained to narrow driving contexts—such as highways or intersections—and lack the visual, semantic, and behavioral diversity needed for general-purpose deployment. More importantly, they are not structured for end-to-end learning: most only provide high-level behavior labels without continuous perception-to-control supervision, and none include standardized evaluation protocols for comparing personalized driving policies.

To bridge the gap between these two lines of work, we introduce the first benchmark tailored for personalized E2EAD. Built on real-world data, our benchmark supports both supervised learning and semi-closed-loop evaluation of preference-conditioned driving behavior. It provides structured annotations of user driving styles, integrates them into a unified end-to-end learning pipeline, and enables systematic, reproducible evaluation of personalized E2E policies across diverse scenarios.

3 StyleDrive Dataset

The StyleDrive dataset is constructed upon the large-scale real-world autonomous driving dataset OpenScene, and contains nearly 30,000 driving scenarios annotated with style preferences. In addition to the original OpenScene labels, we enrich the dataset with broader road topology annotations and propose a unified framework for modeling and labeling personalized driving preferences.

3.1 Framework for Modeling and Annotation of Driving Preference

To enable reliable and interpretable driving style analysis, we construct a hierarchical modeling and annotation framework, as shown in Figure 2. We extract static environmental features from real-world road topology and infer dynamic contextual cues using a fine-tuned visual language model (VLM), enabling consistent and fine-grained scenario construction. Based on these scenarios, we derive objective preference annotations through behavioral distribution analysis and rule-based heuristics. To

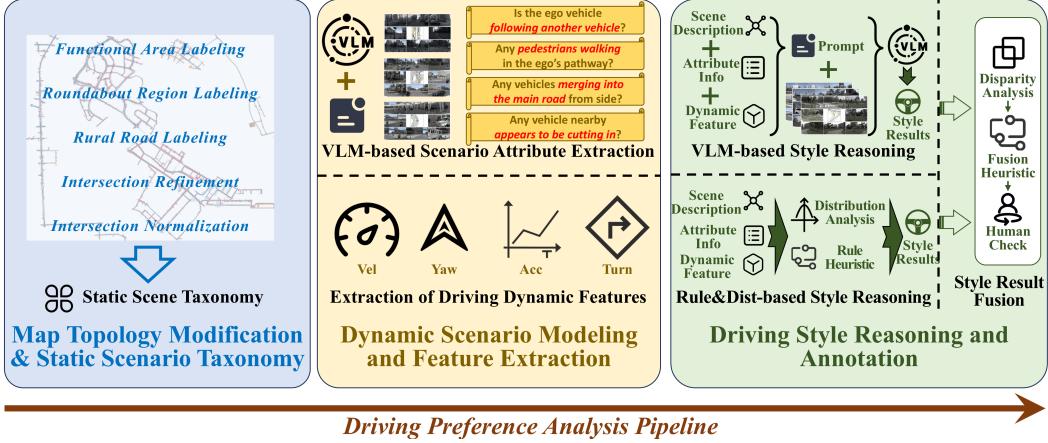


Figure 2: Framework for Modeling and Annotation of Driving Preference.

address the inherent subjectivity of driving style, we further employ the VLM to generate subjective annotations by jointly modeling scene semantics and driver behavior. Final high-quality labels are obtained through a human-in-the-loop verification process that fuses both perspectives.

Topology-Driven Static Scenario Taxonomy To facilitate structured analysis of driving behavior, we first categorize each driving clip into a coarse-grained traffic scenario type based on the topology of high-definition (HD) maps. This classification establishes a physically grounded and interpretable basis for subsequent semantic modeling. Specifically, we begin by enriching the topological structures based on the original nuPlan HD maps (details in Sect. VIII). We then align each clip data with detailed map elements—including lane geometries, stop lines, crosswalks, and intersection layouts—to assign each segment to one of 11 primary traffic scenario types. Each type captures the static constraints and navigational features of the road environment, providing a foundational layer of context for interpreting driving behavior. The complete type list is shown in the first column of Tab. 2.

Dynamic Semantic Refinement via Vision-Language Model To enrich the traffic scenario classification with dynamic, context-sensitive information, we apply a fine-tuned vision-language model (VLM) to extract high-level semantic cues from driving videos. While generic VLMs lack task-specific perception for autonomous driving, we adapt the Video-LLaMA3 model Zhang et al. [2025] via lightweight fine-tuning using the LingoQA dataset - a multimodal dataset for reasoning about road semantics (more details in Sect. X).

For each traffic scenario type, we craft targeted prompts related to key driving events. These include questions such as whether a lead car is present in the same lane, whether the ego is merging, or whether pedestrians are visible in crosswalk zones. The model’s responses are parsed into structured semantic attributes, such as presence of a lead vehicle, merge risk, pedestrian involvement, and turning direction. This dynamic semantic layer augments the static topology with interaction-aware cues, supporting downstream preference inference through both rule-based and VLM-driven reasoning.

Objective Preference Annotation via Rule-Based Heuristics Building on the enriched scene context, we generate objective driving style annotations using a set of interpretable heuristics informed by motion dynamics and semantic priors. We extract a set of behaviorally relevant physical features, including speed and acceleration trends, yaw rate variation, proximity to surrounding agents, and lane-relative positioning. Based on these features, we define scenario-specific rules calibrated from aggregated driving statistics (more details in Sect. IX). For example:

- Low speed and wide safety margins at intersections correspond to conservative tendencies;
- Sudden lane changes with low rear headway indicate aggressive behavior;
- Moderate-speed following and stable lane keeping fall into the normal category.

Table 2: Rule-based Heuristic Criteria for Driving Style Classification Across Scenarios

Traffic Scenario Type	Contextual Variants	Main Dynamic Features
Lane Following	Lead distance (Close/Far/None), Road shape (Straight/Curve)	Ego speed and acceleration trend, front vehicle proximity unsafe/safe frame ratio
Protected Intersections	Turn direction (Left/Right/Straight), pedestrian/lead presence	Ego speed, acceleration, front gap safety ratio turning intent and crossing semantics
Unprotected Intersections	Similar to protected, but without signal control	Speed and yaw change pattern, gap safety evaluation presence of pedestrian or lead car
Lane Change	Rear vehicle presence	Lateral dynamics (v_y , a_y , yaw diff, rear threat)
Special Interior Road	Lead/pedestrian presence, merging complexity	Unsafe duration, deceleration behavior merge risk indicator
Side to Main Ego	With/without merging risk	Ego speed trend, lateral velocity, merging maneuver assertiveness
Side Ego to Main	Main road vehicle/pedestrian presence	Ego speed and acceleration under incoming vehicle threat
Crosswalks	Pedestrian presence	Ego speed and acceleration trend near crosswalk behavioral intent (e.g., yield or accelerate)
Roundabout Entrance	With/without yield/merge risk	Ego speed and entry maneuver stability, yield behavior to surrounding traffic
Roundabout Interior	-	Circular stability, lateral acceleration and smoothness of ego motion
Countryside Road	Road shape (Straight/Curve)	Ego speed, curvature following longitudinal and lateral acceleration smoothness

These heuristics are derived from population-level patterns and refined through expert validation, offering a transparent, physically grounded basis for preference labeling—especially in scenes with occluded or ambiguous visuals.

Subjective Preference Annotation via VLM-Based Reasoning To complement rule-based methods, we leverage the contextual reasoning ability of our finetuned Video-LLama3 to generate subjective annotations that reflect human-like interpretations of driving style. Given the driving video, the structured scene description and corresponding extracted ego-vehicle motion features, the model is prompted to answer behavioral questions such as:

- “Does the driver appear cautious given the presence of pedestrians?”
- “Is the vehicle merging assertively or yielding?”

These responses capture high-level intent and interaction cues that go beyond what can be described by fixed rules. The VLM’s multimodal attention enables it to model nuanced behavioral patterns, especially in borderline or semantically rich situations.

Multi-Source Fusion and Human-in-the-Loop Verification Before finalizing the annotation protocol, we conduct a human-in-the-loop analysis to assess agreement and discrepancy between the rule-based and VLM-based labels. Manual inspection reveals the following patterns:

- Aggressive driving is often consistently identified by both sources. Even when disagreement occurs, each source frequently captures valid signals that the other misses. This complementary behavior suggests that aggressive tendencies are well suited to inclusive labeling.
- In contrast, conservative and normal styles are more easily conflated by VLM, particularly in low-speed or ambiguous interactions. This motivates a stricter condition for conservative assignments.

Based on these observations, we implement a risk-aware fusion strategy:

- If either the rule-based system or the VLM labels a clip as aggressive, we annotate it as aggressive;
- If both sources agree that the clip reflects conservative behavior, we label it as conservative;
- In all other cases, the driving style is marked as normal.

This strategy emphasizes safety by being inclusive for potential aggressive behavior while remaining strict about conservative assignments. It ensures that high-risk situations are not overlooked and that the final label set reflects both interpretability and robustness. Besides, final annotations are further verified in edge cases through targeted human review, ensuring label reliability.

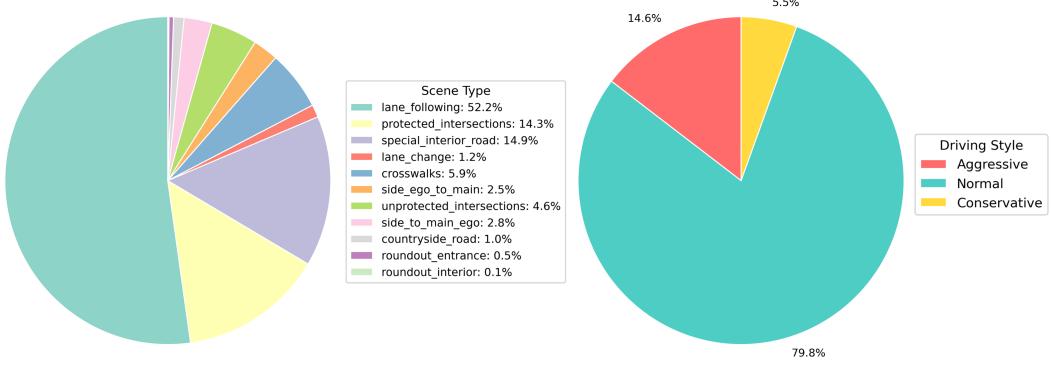


Figure 3: Dataset Statistics and Distribution Analysis.

3.2 Dataset Statistics and Distribution Analysis

To provide a global overview of the StyleDrive dataset, we present key statistics on both scenario composition and annotated driving preference. As shown in Figure 3, we visualize the distribution across static/dynamic scene types and behavioral styles using two complementary pie charts.

Scene Composition. The left chart shows the distribution of traffic scenario types along with their semantic refinements. Lane-following and intersection scenarios dominate the dataset, reflecting their real-world frequency. Contextually rich situations such as merging, lane changes, and pedestrian interactions provide diversity, enabling fine-grained behavior modeling across varied traffic settings.

Driving Style Distribution. The right chart illustrates the annotation outcomes for driving preferences. Normal behavior forms the majority, while aggressive and conservative styles are less common but adequately represented. This reflects natural driving patterns and supports balanced learning, especially for edge-case recognition. More dataset statistics are provided in Sect. VII.

4 StyleDrive Benchmark

To advance the study of interpretable and controllable driving behavior, we introduce the StyleDrive Benchmark—a non-reactive closed-loop evaluation framework for assessing driving preferences and performance in realistic scenarios. This benchmark evaluates whether autonomous agents can generate behavior that aligns with target driving styles while ensuring safety and social compliance. Built upon the rich scenario diversity and structured annotations of the StyleDrive dataset, the benchmark defines a standardized testbed consisting of four components: simulation environment, the proposed SM-PDMS metric, baseline models, and benchmark results with performance analysis.

Simulation Environment. Our benchmark is built on a lightweight, behavior-centric simulator NavSim framework Dauner et al. [2024]. NavSim emphasizes non-reactive closed-loop interaction, map-conditioned planning, and interpretable behavior decomposition. In our adaptation, scenarios extracted from StyleDrive are replayed using learned policies that receive local map context, scene semantics, and historical motion as input. The simulator allows preference-conditioned rollout, enabling quantitative evaluation of personalized E2EAD methods.

4.1 Evaluation Metric: Style-Modulated PDM Score (SM-PDMS)

To assess whether a model not only drives safely and feasibly but also aligns with the intended driving style, we propose the Style-Modulated PDM Score (SM-PDMS)—an extension of the Predictive Driver Model Score (PDMS) used in the NavSim framework Dauner et al. [2024]. PDMS is a composite metric inspired by the Predictive Driver Model (PDM) Dauner et al. [2023], designed to evaluate closed-loop driving behavior through interpretable sub-scores.

Our SM-PDMS builds upon this foundation by incorporating a behavior alignment module that captures the annotated driving style preferences—aggressive, normal, or conservative. Among the

sub-scores, those related to traffic safety and road adherence are preserved without modification, as they should remain invariant across driving styles. However, in practice, driving style is primarily reflected in the dynamics of the vehicle’s motion—such as following distance, speed, and angular velocity—which influence sub-metrics including comfort (Comf.), ego progress (EP), and Time-to-Collision (TTC).

Using the same metric configuration to evaluate both safety performance and stylistic alignment is suboptimal. To address this, we adjust the computation of style-sensitive sub-scores based on the specified driving style. Specifically, guided by the annotated driver preference, we:

- Assign different thresholds for comfort to reflect varying tolerance for acceleration and jerk;
- refine the expected ego progress target to match the intended level of assertiveness;
- Modify the acceptable TTC ranges to reflect differing levels of risk aversion.

More details on adjustments are provided in Sect. VI. They ensure that SM-PDMS not only evaluates safety and feasibility but also effectively reflects alignment with the intended driving style.

4.2 Baseline Methods

To establish a reference point for the community, we implement several baseline models that incorporate representative end-to-end autonomous driving (E2EAD) architectures augmented with driving style features. These baselines span different model complexities and design paradigms across various stages of E2EAD development. Specifically, we adapt three representative methods:

- **AD-MLP-Style:** Based on the AD-MLP baseline Zhai et al. [2023], this model uses a classic multi-layer perceptron for trajectory prediction. The input consists of standard ego-centric features concatenated with a one-hot encoded driving style vector. The combined features are fed into an MLP to produce style-aware trajectory predictions in a simple yet interpretable manner.
- **TransFuser-Style:** Built on the TransFuser architecture Chitta et al. [2022], which fuses image and LiDAR features for planning, we introduce driving style conditioning by concatenating a one-hot style vector with the trajectory query. The fused representation is processed by an MLP to restore the original query dimension before being passed to the trajectory head for style-aware generation.
- **DiffusionDrive-Style:** Based on the diffusion planning framework Liao et al. [2025], this variant conditions the trajectory generation head on a one-hot style vector. The style vector is concatenated with agent features and fused via a single-layer MLP, then passed to a regression MLP for trajectory prediction. Following DiffusionDrive, this block runs twice in a cascaded manner to refine outputs.
- **WoTE-Style:** Built on the BEV World model Li et al. [2025], which forecasts future BEV states for trajectory evaluation, this variant incorporates driving style by modifying the offset prediction head, following a similar strategy as in DiffusionDrive-Style.

4.3 Main Results Analysis

Table 3 presents the quantitative evaluation results of the proposed baseline models on the DriveStyle benchmark with proposed SM-PDMS metric.

Table 3: DriveStyle Benchmark Main Results. Style conditioning improves behavioral alignment, as reflected by higher SM-PDMS scores across most model families.

Models	NC ↑	DAC ↑	Style-Modulated Metric			SM-PDMS ↑
			TTC ↑	Comf. ↑	EP ↑	
AD-MLP Zhai et al. [2023]	92.63	77.68	83.83	99.75	78.01	63.72
TransFuser Chitta et al. [2022]	96.74	88.43	91.08	99.65	84.39	78.12
WoTE Li et al. [2025]	97.29	92.39	92.53	99.13	76.31	79.56
DiffusionDrive Liao et al. [2025]	96.66	91.45	90.63	99.73	80.39	79.33
AD-MLP-Style	92.38	73.23	83.14	99.90	78.55	60.02
TransFuser-Style	97.23	90.36	92.61	99.73	84.95	81.09
WoTE-Style	97.58	93.44	93.70	99.26	77.38	81.38
DiffusionDrive-Style	97.81	93.45	92.81	99.85	84.84	84.10

Style Conditioning Improves Behavioral Alignment. Among the three model families - TransFuser, WoTE, and DiffusionDrive - the style-conditioned variants achieve higher SM-PDMS scores than their vanilla counterparts, clearly demonstrating the benefit of style conditioning. In contrast, the AD-MLP-Style variant slightly underperforms its vanilla version on SM-PDMS. Overall, the improvements observed in TransFuser, WoTE, and DiffusionDrive - particularly on style-sensitive metrics like TTC, Comf., and EP - confirm the effectiveness of incorporating style information into planning. At an individual level, DiffusionDrive-Style delivers the strongest performance, achieving the highest scores across most key metrics. WoTE-Style and TransFuser-Style closely follow, and notably, both outperform the vanilla DiffusionDrive model in SM-PDMS, further highlighting the benefit of style conditioning.

The divergent trend observed in AD-MLP can be attributed to its input simplicity: lacking spatial perception of the surrounding environment, the model cannot effectively leverage style information. While EP shows a slight improvement - indicating marginally better intent preservation - the significant drop in DAC suggests ultimately leads to a lower overall SM-PDMS score.

Validation of Annotation Quality. The strong performance of style-conditioned models also provides compelling evidence for the validity of our driving style annotations in the DriveStyle dataset. Without consistent and behaviorally meaningful style labels, the observed improvements in SM-PDMS and style-modulated metrics (TTC, Comf., and EP) would not be possible. A direct indication of annotation effectiveness is that all style-conditioned variants outperform their vanilla counterparts in Comfort and EP, suggesting that well-defined style labels play a key role in enhancing comfort and aligning vehicle step distances with stylistic intent. These results confirm that our annotated driving preferences reflect real, consistent, and learnable variations in human driving styles.

Closeness to Human Demonstrations. To further assess the behavioral fidelity of style-conditioned models, we conduct an open-loop evaluation using L2 trajectory error against human driving demonstrations. As shown in Table 4, style-aware variants consistently exhibit lower prediction errors across all horizons (2s, 3s, 4s), with DiffusionDrive-Style achieving the best overall L2 average (1.001 m). These results highlight that style conditioning not only enhances stylistic expressiveness but also improves consistency with human driving behavior.

Table 4: L2 Open-loop Evaluation Results. Style-conditioned models exhibit lower L2 trajectory error compared to vanilla models, highlighting improved consistency with human driving behavior under preference-aware conditions.

Models	L2 (2s) ↓	L2 (3s) ↓	L2 (4s) ↓	L2 (Avg) ↓
WoTE Li et al. [2025]	0.733	1.434	2.349	1.506
AD-MLP Zhai et al. [2023]	0.503	1.262	2.383	1.382
TransFuser Chitta et al. [2022]	0.431	0.963	1.701	1.032
DiffusionDrive Liao et al. [2025]	0.471	1.086	1.945	1.167
WoTE-Style	0.673	1.340	2.223	1.412
AD-MLP-Style	0.510	1.230	2.321	1.354
TransFuser-Style	0.424	0.937	1.656	1.006
DiffusionDrive-Style	0.417	0.940	1.646	1.001

Qualitative Case Study of Style Effects. To further illustrate the behavioral influence of style conditioning, Figure 4 shows how our DiffusionDrive-Style model produces different trajectory predictions under aggressive (A), conservative (C), and normal (N) style inputs across identical scenarios. The left panels compare A vs. N, and the right compare C vs. N. Across scenarios, clear differences emerge in the model’s trajectory choices. These visualizations confirm that the same policy network, when conditioned on distinct style vectors, can produce behaviorally diverse outputs aligned with human-like style variations. This evidences the controllability and expressiveness afforded by the style-conditioning mechanism.

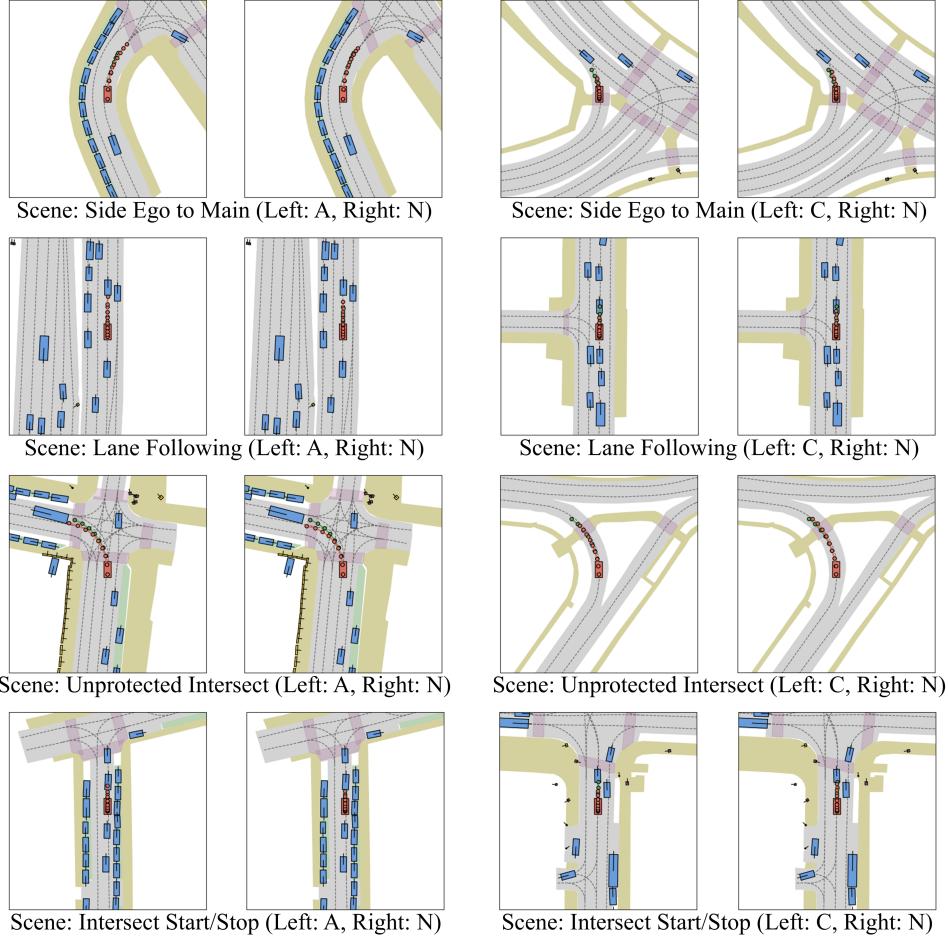


Figure 4: Qualitative illustration of DiffusionDrive-Style predictions under different style conditions across identical scenarios. Left: Aggressive vs. Normal; Right: Conservative vs. Normal. Red lines indicate the model’s predicted trajectory under the given style condition; green lines denote the ground-truth human trajectory. Clear behavioral differences emerge with style variation, reflecting the model’s ability to adapt its outputs to driving preferences.

5 Conclusion

This paper introduces StyleDrive, a novel large-scale dataset and benchmark tailored for advancing personalized end-to-end autonomous driving. By systematically integrating high-definition map topology, fine-grained semantic context from vision-language models, and a hybrid annotation pipeline combining rule-based heuristics with subjective reasoning, we establish a rich and interpretable foundation for driving style analysis at scale. The resulting dataset encapsulates a broad spectrum of real-world traffic scenarios annotated with carefully designed style preference labels.

To facilitate rigorous evaluation of preference-conditioned driving behavior, we further propose the StyleDrive Benchmark—a non-reactive closed-loop evaluation suite built upon the NavSim simulation framework. Central to this benchmark is the Style-Modulated PDMS (SM-PDMS) metric, which augments traditional safety and feasibility assessments with stylistic alignment measures calibrated to intended driver preferences. Extensive experiments across multiple architectural paradigms demonstrate the effectiveness of style conditioning in enhancing behavioral expressiveness while preserving core driving competence.

Outlook. While our benchmark offers four baseline models with style conditioning, further work is needed to jointly model scene context and driving style preferences. Additionally, effectively deriving driving styles from user profiles or history in real-world settings remains an open challenge.

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Supplementary Material Overview

This appendix provides additional experiments and detailed information related to the StyleDrive Dataset and Benchmark. Specifically:

- Section VI provides further details about the design of the style-aware evaluation metric.
- Section VII illustrates additional dataset statistics.
- Section VIII describes modifications to map topology aimed at supporting more diverse static driving scenarios.
- Section IX explains the preference annotation process using rule-based heuristics, along with related analysis.
- Section X discusses the details of VLM fine-tuning on driving scene understanding.

VI More Details about Style-aware Metric Design

This section provides a detailed explanation of how the Style-Modulated PDM Score (SM-PDMS) adjusts key sub-metrics: Comfort, Ego Progress, and Time-to-Collision on annotated driving styles: aggressive, normal, and conservative.

The adjustments ensure that the evaluation respects not only safety and feasibility, but also style-specific driving preferences. Below are the precise configurations used for each sub-score:

Comfort (Comf.). This sub-metric penalizes high acceleration and jerk. While the exact numeric thresholds vary with the simulation setup and motion scale, we define style-dependent tolerance margins for comfort-related dynamics:

- Conservative: Low tolerance for sudden acceleration or jerk. Thresholds are tightened by 20% relative to the baseline.
- Aggressive: High tolerance, allowing thresholds to expand by 20%.
- Normal: Uses the default Navsim thresholds.

These adjusted thresholds determine whether an action is penalized or considered smooth for the given style.

Ego Progress (EP). This sub-metric serves as a key indicator for evaluating driving style. Unlike the EP metric used in Navsim - which compares an evaluated agent against a PDM agent - we directly contrast the agent's trajectory progress with that of a human driver. This direct comparison more effectively captures stylistic driving preferences, such as a tendency toward aggressive acceleration or conservative behavior.

Specifically, we compute the cumulative distance between predicted discrete waypoints over a 4-second horizon, denoted as EP_{agent} . In parallel, we calculate the total distance traversed in the human driver's trajectory over the same time window, denoted as EP_{target} . The final EP score is then determined using the following formulation:

$$S_{EP} = 1 - \alpha \times \frac{(EP_{agent} - EP_{target})^2}{Ref^2} \quad (1)$$

Here, α is a sensitivity scaling factor, empirically set (e.g., $\alpha = 1.2$), and Ref is a reference tolerance parameter that modulates how much deviation is acceptable. We set different values of Ref based on the value of EP_{target} , as described below:

$$Ref = \begin{cases} 3, & \text{if } 3 < EP_{target} < 10 \\ 5, & \text{if } 10 \leq EP_{target} < 24 \\ 6, & \text{if } 24 < EP_{target} < 40 \\ 7, & \text{if } EP_{target} \geq 40 \end{cases} \quad (2)$$

This formulation penalizes both under- and over-progress based on how far the vehicle deviates from the intended style.

Time-to-Collision (TTC). This sub-score reflects perceived risk based on proximity to other agents. To model varying levels of risk aversion, we define a minimum acceptable TTC threshold for each style:

Conservative: $TTC_{min} = 1.2s$

Normal: $TTC_{min} = 1.0s$

Aggressive: $TTC_{min} = 0.8s$

The TTC score is computed by checking whether the predicted minimum TTC over a planning horizon drops below the style-specific threshold. Violations are penalized proportionally, promoting earlier braking and more cautious spacing for conservative styles.

VII More Illustration of Dataset Statistics

To provide a comprehensive overview of driving style annotations, we visualize the distribution of *Aggressive (A)*, *Normal (N)*, and *Conservative (C)* labels across key scenario types. Each pie chart summarizes the proportion of styles within a specific behavioral context. Figures 5a–5g present the distributions across 11 fine-grained scenario categories.

Lane-following scenes are primarily dominated by Normal behavior (85.1%), with Aggressive and Conservative styles accounting for 10.8% and 4.1%, respectively. Lane changes show a relatively higher proportion of Aggressive behavior (32.4%) and Conservative behavior (12.7%), suggesting diverse preferences in lateral maneuvers. In crosswalk scenarios, Normal behavior still dominates (80.3%), but with notable instances of Aggressive (14.7%) and Conservative (5.0%) driving.

In merging-related scenes, side-to-main (main road) shows 7.1% Aggressive and 5.1% Conservative behavior, while side-to-main (side road) records 13.8% Aggressive and 3.3% Conservative behavior, with 82.9% remaining Normal. Protected intersections contain 12.7% Aggressive behavior, slightly higher than the 12.2% observed in unprotected intersections, which also exhibit 2.0% Conservative driving.

At roundabouts, entrance segments exhibit 8.6% Aggressive behavior and 2.3% Conservative behavior, while interior segments are more stable, with 91.4% Normal and 8.6% Aggressive. Special interior roads show higher variability, including 37.3% Aggressive and 3.9% Conservative behavior. Countryside roads remain generally stable, with 90.9% Normal and only 6.2% Aggressive driving observed. In carpark areas, behavior is entirely Normal (100.0%).

VIII Map Topology Modifications towards More Diverse Scenarios

To enhance the accuracy of static scene classification, we manually refine the NuPlan HD map using QGIS. These adjustments target known limitations in the original topology and provide a more semantically meaningful foundation for behavior modeling.

Refined Intersection Semantics. The original intersection definitions are overly coarse. We introduce fine-grained polygonal annotations for:

- Merging Zones: areas where minor roads (e.g., side streets or on-ramps) merge into a major road. These regions often pose visibility challenges and merging-in risks.
- Main Road Merge Receptive Zones: areas along major roads where merging from adjacent lanes or secondary roads is expected. These zones carry merging-in conflicts and courtesy yield challenges.

Functional Area Roads. We add internal road polygons for areas such as casinos, hotels, hospitals, and airports. These environments feature irregular geometry, frequent stops, and dense interactions with non-standard road agents. They are often associated with low-speed navigation risks, occlusions, and high pedestrian density, making them crucial for evaluating slow-driving and cautionary styles.

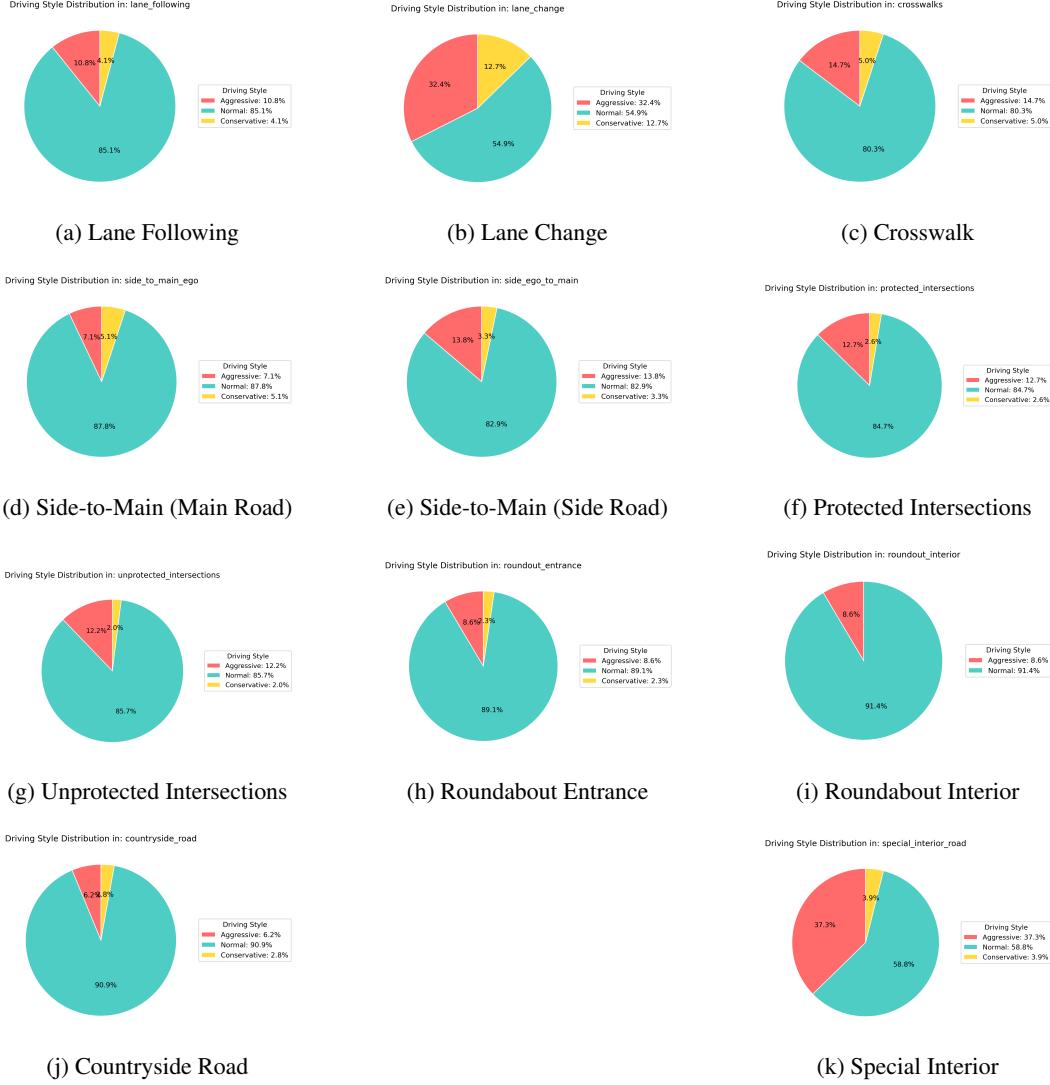


Figure 5: Per-scenario distribution of annotated driving styles (A: Aggressive, N: Normal, C: Conservative).

Roundabout-Specific Regions. We annotate both roundabout entries and interior roundabouts. These zones are associated with misjudgment of right-of-way, incorrect merging-in, and delayed exits, posing non-trivial planning challenges.

Rural Roads. Given the distinct structure of Pittsburgh’s rural roads - e.g., narrow lanes, limited markings, and relatively sharp curves - we isolate them to better capture related driving behaviors.

Intersection Normalization. We standardize NuPlan’s intersection types by aligning definitions and separating control logic (e.g., stop-sign vs. traffic-light), enabling consistent downstream scene labeling.

IX More Details about Preference Annotation via Rule-Based Heuristics

IX.1 Driving Style Classification in Lane-Following Scenarios

In lane-following scenarios, driving style is categorized as *Aggressive* (A), *Normal* (N), or *Conservative* (C) based on motion dynamics, road geometry, and interactions with leading vehicles.

Our classification framework is rule-based, utilizing both regression-derived velocity trends and context-aware features to determine driving style.

Velocity Trend Estimation. The ego vehicle’s speed profile $v(t)$ is analyzed using linear and quadratic regression fits to derive trends:

- *Accelerating or decelerating*: captured via linear fit with significant slope;
- *Accelerate-then-decelerate* or *decelerate-then-accelerate*: captured by non-monotonic quadratic fit;
- *Quasi-constant*: determined when $\text{std}(v(t))$ is low and no trend is dominant.

Contextual Modulation. Trend interpretation is modulated by road shape—*Straight* or *Curved*—and presence of a lead vehicle. For samples with a lead vehicle, we define an unsafe-following ratio to characterize risky proximity, as well as a safe-following ratio to detect cautious behavior. These thresholds are adaptively determined from empirical data statistics.

Rule-Based Classification. Final driving style is determined based on velocity trend, average speed, peak acceleration, acceleration variability, and safety proximity ratios:

- **Aggressive (A)**: Assigned when unsafe-following ratios are high, or motion signals such as velocity, acceleration, or variability significantly exceed normal ranges.
- **Conservative (C)**: Assigned when the ego vehicle maintains low speed, low acceleration variability, or consistently large gaps from lead vehicles.
- **Normal (N)**: Assigned to samples not satisfying either extreme condition.

The rule adapts across 6 sub-conditions: [Lead: Close / Far / None] \times [Road Shape: Straight / Curved]. For No Lead cases, classification relies purely on statistical motion descriptors without distance-based modulation.

IX.2 Driving Style Classification in Special Interior Road Scenarios

In *special interior road* scenarios—characterized by narrow lanes, merging zones, or pedestrian-prone areas—driving style is determined through a combination of ego-vehicle motion trends and local traffic semantics. The rule-based framework incorporates velocity and acceleration patterns modulated by contextual indicators, including merging interactions, lead vehicles, and pedestrian presence.

Velocity Trend Characterization. The ego vehicle’s longitudinal motion is analyzed by fitting the velocity sequence $v(t)$ using both linear and quadratic regression models. Based on model residuals and slope coefficients, the trend is categorized as *accelerating*, *decelerating*, *quasi-constant*, or *non-monotonic*, following the same trend extraction procedure.

Contextual Modulation. Two semantic cues modulate rule interpretation: (i) the presence of a lead vehicle; and (ii) pedestrian activity. These indicators adaptively influence thresholds derived from the statistical distribution of the dataset.

Rule-Based Classification. Style labels are determined by combining motion descriptors and context signals:

- **Merging-risk scenarios:** **Aggressive (A)** behavior is inferred when acceleration or velocity patterns are noticeably intense; **Conservative (C)** is assigned for slow and steady merging motion.
- **With lead vehicles or pedestrians:** **Conservative (C)** is assigned if the ego vehicle demonstrates cautious behavior under interaction constraints. Conversely, close following and high motion signals suggest **Aggressive (A)** behavior.
- **Isolated contexts (no leads or pedestrians):** Labels are purely determined by motion statistics, using thresholds extracted from the overall trajectory distribution in the dataset.

IX.3 Driving Style Classification in Intersection Scenarios

Intersection scenarios—comprising both *protected* (e.g., signalized or stop-controlled) and *unprotected* (e.g., unsignalized or yield-controlled) junctions—entail complex decision-making under spatial and social constraints. Driving style classification in these settings relies on vehicle maneuver intent, interaction risk with surrounding agents, and motion dynamics.

Maneuver Detection. The ego vehicle’s maneuver type is inferred from its yaw change over time. Turning maneuvers (left or right) are identified by sustained directional change, while low yaw variation indicates a straight traversal. This maneuver classification influences the interpretation of motion behavior and style thresholds.

Interaction Awareness. Interaction risk is determined through semantic cues such as the presence of lead vehicles and pedestrians. We define an *unsafe-following ratio* to measure whether the ego vehicle maintains insufficient headway relative to its speed. Conversely, we also define a *safe-following ratio* to capture especially cautious behavior. These quantities are computed over time and used to modulate style inference.

Rule-Based Classification. Driving style is assigned by integrating maneuver type, interaction context, and temporal motion features:

- **Aggressive (A):** Inferred when the ego vehicle exhibits insufficient headway to a lead agent, high average speed, or rapid acceleration profiles. This is particularly relevant during turns or when pedestrians are present, where aggressive dynamics raise potential safety concerns.
- **Conservative (C):** Assigned when the ego maintains large margins to other agents, exhibits smooth and slow motion, or maintains consistently safe gaps. Acceleration trends with minimal variability and substantial following distance also suggest conservative intent.
- **Normal (N):** Assigned in cases where the behavior does not strongly deviate toward either aggressiveness or caution, reflecting balanced dynamics.

Scene-Type Modulation. Though the classification rule is unified, its application is modulated by interaction context:

- **Turning Maneuvers (Left/Right):** Risk is elevated due to lateral trajectory change and frequent presence of conflicting traffic. Aggressive classification emerges when the vehicle shows assertive dynamics under close headway; conservative behavior arises from cautious yielding or wide gaps.
- **Straight Crossings:** Style differentiation is informed by motion trends—e.g., acceleration, deceleration, or constant speed—combined with lead proximity.
- **Control Influence:** Protected intersections (e.g., traffic lights) allow slightly more assertive behavior without penalty, while unprotected junctions impose stricter expectations for caution.

IX.4 Driving Style Classification in Crosswalk Scenarios

Crosswalk scenarios require heightened awareness due to potential pedestrian interaction, despite typically lacking complex traffic geometry or leading vehicles. The classification of driving style in this context relies solely on ego-vehicle motion characteristics and the presence of pedestrians.

Contextual Awareness. Each scene includes a binary indicator *pedestrians* specifying whether pedestrians are present near the crosswalk area. No lead vehicle information is considered, and the road is assumed to be straight by default.

Motion-Based Features. We extract key kinematic features:

- Average velocity v_{avg} ;
- Maximum acceleration a_{max} ;
- Acceleration standard deviation σ_a ;
- Motion trend (i.e., *accelerating*), detected using linear regression over the velocity sequence.

Rule-Based Classification. Style labels are assigned as follows:

- **Aggressive (A):** If any of the following holds:

- $v_{\text{avg}} > \theta_v$;
- $a_{\text{max}} > \theta_a$;
- $\sigma_a > \theta_\sigma$;
- motion trend indicates acceleration.

where θ_v , θ_a , and θ_σ are empirically chosen thresholds.

- **Conservative (C):** If v_{avg} is significantly low (e.g., < 2.0 m/s), regardless of other indicators.
- **Normal (N):** All other cases.

IX.5 Driving Style Classification in Side-to-Main (Ego on Main Road) Scenarios

In *side-to-main* scenarios—where the ego vehicle attempts to merge from a side road onto a main road—driving style is primarily influenced by gap acceptance behavior and merging aggressiveness. These scenarios demand real-time decision-making to balance caution and initiative, particularly under merging pressure.

Merging Context Identification. Scenes are annotated with a binary indicator `has_merging`, which denotes whether main-road vehicles are present at the time of ego's merging. This context shapes the interpretation of speed and acceleration—aggressive merging under pressure may reflect insufficient gap assessment.

Motion Features. We use the following kinematic attributes to infer driving style:

- Average speed v_{avg} ;
- Maximum total acceleration a_{max} ;
- Longitudinal velocity trend (*accelerating*), estimated via linear regression.

Rule-Based Classification. Classification follows this logic:

- **Aggressive (A):**
 - If `has_merging` is True and v_{avg} or a_{max} is high, or the velocity trend indicates acceleration;
 - If `has_merging` is False but v_{avg} or a_{max} is high, indicating assertive motion despite absence of merging pressure.
- **Conservative (C):** Assigned if v_{avg} is low, suggesting a yielding or slow merge, regardless of merging context.
- **Normal (N):** All remaining cases with moderate dynamics and no acceleration spikes.

IX.6 Driving Style Classification in Side-to-Main (Ego on Side Road) Scenarios

In *side-to-main* scenarios—where the ego vehicle is on the main road and may encounter merging traffic from a side road—driving style reflects how assertively or cautiously the ego navigates potential merging conflicts. This is especially relevant when assessing risk-aversion or dominance over right-of-way.

Interaction Context. The key semantic indicator `main_road_vehicles` signals whether merging traffic is present. Though pedestrian presence may also exist, classification primarily focuses on ego vehicle dynamics in response to merging activity.

Key Features. We use the following features to infer behavior:

- Average velocity v_{avg} ;
- Maximum acceleration a_{max} ;
- Acceleration standard deviation σ_a .

Rule-Based Classification.

- **Aggressive (A):** Assigned if both average speed and peak acceleration are high, i.e., the ego maintains assertive forward motion under merging conditions or in general. This includes patterns such as:

$$v_{\text{avg}} > \tau_v^A, \quad a_{\text{max}} > \tau_a^A$$

where τ_v^A and τ_a^A are empirically set thresholds.

- **Conservative (C):** Assigned if the ego vehicle exhibits consistently low average speed and stable acceleration, indicating cautious navigation:

$$v_{\text{avg}} < \tau_v^C, \quad \sigma_a < \tau_\sigma^C$$

- **Normal (N):** All cases in between, with moderate speed and neither aggressive nor cautious acceleration profiles.

IX.7 Driving Style Classification in Lane Change Scenarios

Lane change scenarios involve dynamic and potentially high-risk lateral maneuvers, requiring the ego vehicle to coordinate its motion with adjacent traffic. Driving style in this context is determined by the intended direction (left or right), spatial constraints (e.g., rear or front vehicle presence), and motion characteristics such as lateral velocity and acceleration variability.

Direction and Rear Vehicle Awareness. The intended lane change direction is inferred from yaw change $\Delta\psi$: left lane changes are detected when $\Delta\psi > 0.25$ radians, and right lane changes when $\Delta\psi < -0.25$. Rear vehicle presence in the target lane is denoted by scene indicators `has_left_rear` and `has_right_rear`. Additional indicators such as front vehicle proximity are used to determine urgency-driven maneuvers.

Motion Indicators. The following dynamic features are extracted to characterize maneuver intensity and stability:

- Maximum absolute lateral velocity: $v_y^{\text{max}} = \max |v_y|$;
- Average longitudinal velocity: v_{avg} ;
- Maximum acceleration: a_{max} ;
- Acceleration standard deviation: σ_a ;
- Yaw difference during maneuver: $\Delta\psi$.

Rule-Based Classification. Rules vary depending on lane-change direction and whether rear vehicles are present:

- **Aggressive (A):**
 - *Left change with rear vehicle:* If any of a_{max} , σ_a , or yaw change $\Delta\psi$ exceeds threshold—regardless of speed—indicating abrupt motion under risky context;
 - *Left change without rear vehicle:* Only if both v_{avg} is high and at least one of a_{max} , σ_a , or $\Delta\psi$ is large;
 - *Right change with rear vehicle:* Similar to left—if a_{max} , σ_a , or $\Delta\psi$ is high, label as aggressive;
 - *Right change without rear vehicle:* Must satisfy v_{avg} being high **and** any of a_{max} , σ_a , or $\Delta\psi$ being high.
- **Conservative (C):**
 - *Left change:* When $\Delta\psi$ and σ_a are both low, indicating smooth direction change;
 - *Right change:* When $\Delta\psi$ and v_{avg} are both low, reflecting gentle, controlled motion.
- **Normal (N):** Default for samples not matching extreme behaviors.

IX.8 Driving Style Classification in Countryside Road Scenarios

Countryside road scenarios are characterized by low traffic density and relaxed speed regulations, yet may involve substantial geometric variability—such as extended straightaways and sharp curves. These conditions afford greater behavioral latitude, necessitating classification rules that distinguish between permissible cruising and potentially hazardous or overly passive maneuvers.

Geometric Classification. Each scene is annotated as either *Straight* or *Curve*, based on map topology and trajectory shape. This binary classification contextualizes motion interpretation, as curved roads generally require tighter control and greater caution.

Motion Features. We extract the following indicators of ego dynamics to infer driving style:

- Average velocity v_{avg} ;
- Maximum acceleration a_{max} ;
- Acceleration standard deviation σ_a .

Rule-Based Classification. Rules are unified across straight and curved countryside settings, with style assigned as follows:

- **Aggressive (A):** Labeled if **any** of the motion indicators— v_{avg} , a_{max} , or σ_a —exceed predefined thresholds, indicating assertive or potentially unstable behavior regardless of road geometry.
- **Conservative (C):** Assigned if **both** v_{avg} and σ_a are low, reflecting slow and smooth progression consistent with cautious behavior.
- **Normal (N):** Default label for cases exhibiting moderate speed and variability, falling between the two extremes.

IX.9 Driving Style Classification in Roundabout Entrance Scenarios

Roundabout entrance scenarios involve complex maneuvering under potential merging pressure. Driving style is categorized into *Aggressive (A)*, *Normal (N)*, or *Conservative (C)* based on ego-vehicle velocity patterns, acceleration behavior, and contextual merging risk. A rule-based strategy is used to ensure interpretability and context sensitivity.

Contextual Modulation. Each scene is annotated with a binary indicator `merge_risk`, signaling whether surrounding vehicles are likely to merge into the roundabout concurrently. This flag modulates the aggressiveness threshold: in the presence of merging risk, even moderately assertive behaviors may be treated as aggressive, while cautious entries are emphasized as conservative.

Dynamic Features. The classification is based on a combination of behavioral indicators, including:

- Ego vehicle's average speed and longitudinal acceleration pattern;
- Variability in acceleration, as a proxy for control smoothness;
- Velocity trends derived from temporal fitting (e.g., accelerating, decelerating, quasi-constant).

Rule-Based Classification. The driving style is assigned through the joint evaluation of motion dynamics and contextual semantics:

• **With merge risk:**

- *Aggressive (A):* Identified when the ego vehicle exhibits assertive acceleration or non-monotonic trends associated with fast entry;
- *Conservative (C):* Assigned if the vehicle maintains slow, steady motion or shows clear deceleration before merging;
- Remaining behaviors are labeled as **Normal (N)**.

• **Without merge risk:**

- *Aggressive (A):* Assigned for high-speed or strong-acceleration entries, even in low-risk settings;

- *Conservative* (**C**): Assigned for low-speed and smooth trajectories;
- Intermediate behaviors default to **Normal** (**N**).

X VLM Fine-tuning towards Better Driving Scene Understanding

To enable accurate and context-sensitive semantic reasoning in driving scenes, we fine-tune the Video-LLaMA3 model using lightweight parameter-efficient tuning (LoRA). This process tailors the model to better understand autonomous driving scenarios, which are underrepresented in generic vision-language pretraining.

Training Data. We build upon the LingoQA dataset, a multimodal benchmark comprising video clips and scene-level question-answer pairs focused on road semantics, interactions, and intent recognition. The dataset includes approximately 267.8k video–prompt–response triplets, covering diverse topology and behavioral cases.

Model Setup. We adopt Video-LLaMA3 as the base model due to its strong multimodal reasoning capacity and open-source support. For fine-tuning:

- We freeze the vision encoder and most transformer layers.
- We insert LoRA adapters in the query and value projection matrices of selected attention layers.
- We train for 3 epochs on 6×A100 GPUs, a learning rate of 1e-4, and batch size of 96.
- The fine-tuning was completed in under 8 GPU-hours, making it suitable for scalable deployment.