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**TRAFFIC INSTABILITY THRESHOLDS AT FREEWAY OFF-RAMPS
UNDER MIXED AUTONOMOUS-HUMAN VEHICLE FLOWS:
ROLE OF AV BEHAVIORAL PROFILES**

Summary. Autonomous vehicles hold significant promise for improving urban traffic efficiency and reducing emissions; however, their impact on traffic stability at freeway off-ramps under mixed traffic conditions remains insufficiently understood. While existing studies have examined autonomous vehicle penetration rates in isolation, the interacting influence of autonomous vehicle behavioral profiles and traffic demand levels on instability at diverge zones has received limited attention. This study investigates traffic instability thresholds at the Eskisehir Road Golbasi Peripheral Road freeway off-ramp in Ankara, Türkiye, using Eclipse Simulation of Urban Mobility enhanced with the Traffic Control Interface application programming interface, which enables real-time per-vehicle behavioral parameter assignment, dynamic instability event detection, and high-resolution data collection at 0.5-second intervals. A full factorial experiment comprising 195 simulation scenarios examined five autonomous vehicle penetration rates (0% to 100%), three behavioral profiles (conservative, moderate, and aggressive), and three demand levels (600, 1000, and 1400 veh/h). One-way analysis of variance confirmed that autonomous vehicle behavioral profile

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($F=35.84$, $p<0.001$) and demand level ($F=53.93$, $p<0.001$) are the dominant determinants of traffic instability, while penetration rate alone produced no statistically significant effect ($F=0.15$, $p=0.93$). Aggressive autonomous vehicle profiles reduced instability by up to 62.7% and carbon monoxide emissions by up to 35.4% at high demand, whereas conservative profiles paradoxically increased instability by up to 110.7% and carbon monoxide emissions by up to 14.0% under the same conditions. These findings demonstrate that autonomous vehicle behavioral calibration represents a more decisive policy lever than fleet penetration rate alone, with direct implications for autonomous vehicle deployment strategies at freeway diverge zones.

Keywords: autonomous vehicles, traffic instability, freeway off-ramp, behavioral profiles, IDM car-following model, TraCI

1. INTRODUCTION

The rapid advancement of Autonomous Vehicle (AV) technology has positioned it as one of the most transformative developments in modern transportation systems. AVs promise to fundamentally reshape urban mobility by eliminating human error, optimizing vehicle spacing, and enabling coordinated traffic flow through advanced sensing and communication technologies [1, 2]. However, the transition toward full autonomy will not occur instantaneously. For the foreseeable future, road networks will operate under mixed traffic conditions in which AVs and human-driven vehicles share the same infrastructure at varying proportions, creating complex interaction dynamics that are not yet fully understood [3, 4].

Freeway off-ramps represent one of the most operationally challenging locations in urban road networks. At diverge zones, vehicles must simultaneously decelerate, execute lateral lane changes, and separate from the through traffic stream, generating significant traffic turbulence under high-demand conditions [5]. These dynamics are further complicated in mixed autonomous-human traffic environments, where the behavioral differences between AVs and human drivers can either stabilize or destabilize flow depending on the proportion and behavioral characteristics of the autonomous fleet [6]. As cities worldwide pursue smart mobility targets and sustainability goals, understanding how AV integration affects traffic stability and emissions at critical network locations has become an increasingly urgent research priority [7].

Despite growing interest in AV simulation research, most existing studies focus on basic freeway segments or signalized intersections and treat AV penetration rate as the primary variable of interest while giving limited attention to the role of AV behavioral calibration in shaping traffic outcomes. The extent to which AV behavioral profiles interact with traffic demand levels to determine instability at freeway diverging zones remains an open and practically important question with direct implications for AV deployment policy and traffic management.

1.1. Research problem

While AVs are designed to maintain optimal speeds, reduce reaction times, and eliminate driver imperfection, their interaction with human-driven vehicles in mixed traffic environments introduces new sources of instability that are not present in fully human-driven or fully autonomous networks [8]. This challenge is particularly acute at freeway off-ramps, where

the geometric complexity of the diverge zone amplifies the consequences of behavioral mismatches between AVs and human drivers.

Despite growing research interest, critical gaps remain. Most studies treat AV penetration rate as the sole independent variable, overlooking the role of behavioral calibration in determining traffic outcomes. The freeway off-ramp diverge zone has received limited attention relative to basic freeway segments and signalized intersections. The interactive effect of AV behavioral profiles and traffic demand levels on traffic instability, defined here as hard braking events, speed variance spikes, and near-collision conditions, has not been systematically investigated. Furthermore, the use of Traffic Control Interface (TraCI) for real-time per-vehicle behavioral control and dynamic instability detection remains underutilized in existing literature.

These gaps motivate the present study, which addresses whether AV penetration rate or behavioral profile is the more decisive determinant of traffic instability at freeway off-ramps, and how demand level moderates this relationship.

1.2. Research objectives

This study pursues the following objectives:

1. To develop a TraCI-enhanced microscopic simulation framework enabling real-time per-vehicle behavioral control and dynamic instability detection at a real freeway off-ramp network.
2. To quantify the individual and combined effects of AV penetration rate, behavioral profile, and traffic demand level on traffic instability, travel time, mean speed, and vehicle emissions.
3. To identify the conditions under which AV deployment improves or worsens traffic stability relative to the human-driven baseline, with particular attention to the effect of conservative AV profiles under high demand.
4. To provide statistically rigorous evidence through one-way Analysis of Variance (ANOVA), effect size analysis, and pairwise comparisons to support the interpretation of simulation results.

1.3. Research contributions

This study makes the following contributions to the existing body of knowledge:

First, it demonstrates that AV behavioral profile is a statistically more significant determinant of traffic instability than penetration rate alone ($F=35.84$, $p<0.001$ versus $F=0.15$, $p=0.93$), challenging the prevailing assumption that higher AV penetration rates uniformly improve traffic performance.

Second, it identifies a paradoxical instability effect of conservative AV profiles, in which increasing penetration beyond 25% worsens traffic instability relative to the human-driven baseline by up to 110.7% under high-demand conditions, a finding not previously reported in the context of freeway off-ramp diverge zones.

Third, it demonstrates that traffic demand level acts as an amplifying factor on the behavioral profile effect, with divergence between aggressive and conservative AV outcomes widening systematically as the network approaches capacity across all measured metrics.

Fourth, it introduces a TraCI-based simulation architecture enabling real-time per-vehicle Intelligent Driver Model (IDM) parameter assignment, high-resolution data collection at 0.5-second intervals, and dynamic detection of three instability indicators within a single integrated framework, advancing the methodological capabilities available for AV simulation research.

2. LITERATURE REVIEW

The growing body of research on AV has examined their potential impacts on traffic flow, emissions, and safety from multiple perspectives. Early studies focused predominantly on the theoretical benefits of full AV adoption, while more recent work has shifted toward the practical challenges of mixed traffic environments where AVs and human-driven vehicles coexist at varying penetration rates [9, 10]. Microscopic simulation has emerged as the primary methodological tool for investigating these dynamics, given the current absence of real-world AV fleets at scale [11]. This section reviews the existing literature across four thematic areas relevant to the present study: AV impacts on traffic performance, AV impacts on emissions, AV behavioral profiles in mixed traffic, and simulation approaches for AV research, culminating in the identification of the specific gaps that this study addresses.

2.1. AV penetration and traffic performance

The impact of AV penetration on traffic performance has been investigated across a range of network types and demand conditions using microscopic simulation tools. ElSahly and Abdelfatah [12] examined AV impacts on freeway traffic under undersaturated conditions, reporting average speed increases of approximately 15% and travel time reductions of around 12%, with delay reductions of 97% and 94% at demand-to-capacity ratios of 0.6 and 0.8 respectively, demonstrating that AVs can operate at significantly higher speeds than conventional vehicles under uncongested conditions. Alozi and Hamad [13] quantified the impacts of Connected and Autonomous Vehicles (CAV) on traffic operations in Dubai, finding that CAVs reduced average delay by up to 86% and increased average speed by 42% at bottleneck locations, highlighting the particular benefit of AV deployment at capacity-constrained points in the network. Abdeen et al. [14] developed a microsimulation framework for a real urban freeway network in Saudi Arabia, investigating five penetration rates from 0% to 100% and reporting progressive delay reductions of 26%, 34.4%, 63.7%, and 74.2% at 25%, 50%, 75%, and 100% AV penetration respectively, confirming a monotonically increasing performance benefit with penetration rate under the tested conditions. Rosca et al. [15] evaluated AV penetration impacts at a complex signalized intersection using Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (AIMSUN), finding that penetration rates exceeding 50% contributed significantly to improving traffic stability and efficiency, suggesting a nonlinear threshold effect in the relationship between penetration and performance. Shin et al. [16] examined traffic flow safety at varying AV penetration rates on a freeway section using VISSIM, reporting that conflict frequency increased up to 30% penetration before declining at rates of 40% and above, revealing the non-monotonic and transitional nature of AV safety impacts during mixed traffic conditions. Kuang and Zhang [17] investigated mixed traffic flow considering both AVs and heavy trucks, demonstrating that at lower penetration rates increased traffic density intensified speed fluctuations, while elevated penetration rates produced marked improvements in average speed and significant reductions in speed variance under high-density conditions.

Collectively, these studies indicate that AV penetration generally improves traffic performance, with benefits becoming more pronounced at higher penetration levels. However, the magnitude and direction of the effect depend on penetration level, network geometry, and demand conditions, and none of these studies examine the specific context of freeway off-ramp diverge zones or systematically vary AV behavioral profiles as an independent factor alongside penetration rate.

2.2. AV penetration and emissions

The environmental implications of AV integration have attracted considerable research attention, with studies generally reporting emission reductions under increasing AV penetration, though the magnitude and consistency of these benefits vary significantly across contexts and behavioral assumptions. Louati et al. [18] evaluated AV penetration scenarios of 0%, 10%, 30%, and 50% along an urban corridor in Riyadh using SUMO with Python-based Application Programming Interface (API), reporting travel time reductions of up to 25.5% and Carbon Dioxide (CO₂) emission reductions of 14.6% at 50% penetration, demonstrating that coordinated AV behavior produces measurable environmental benefits even at moderate penetration levels. Ercan et al. [19] adopted a broader system-level perspective, integrating fractional split multinomial logit and system dynamics models across 929 metropolitan areas in the United States, finding that autonomous electric vehicles could reduce greenhouse gas emissions by up to 34% of total transportation emissions by 2050, highlighting the long-term environmental potential of full AV adoption. Hua et al. [20] examined CAV impacts on urban highway sustainability using calibrated car-following models, reporting CO₂ reductions of up to 8.2% for human-driven vehicles and 13.8% for CAVs in mixed traffic, alongside average travel time improvements of 9.9% and speed gains of 11%, with sensitivity analysis revealing that the effect of market penetration rate on emissions varies by pollutant type and operating speed.

However, not all studies report uniformly positive emission outcomes. Alhariqi et al. [21] utilized the Waymo Open Dataset to investigate the effect of vehicle arrangement in mixed autonomy platoons on emissions, finding that AVs driving conservatively with larger time gaps and stronger deceleration when following human-driven vehicles in congested conditions produced higher CO₂ emissions than human-following-human arrangements, with cautious AV behavior resulting in lower average velocity of 2.16 m/s and higher CO₂ rates of 993 g/mile compared to 805 g/mile when a human vehicle followed an AV. This finding directly challenges the assumption that AV deployment uniformly reduces emissions and highlights the critical role of behavioral profile in determining environmental outcomes. Ali [22] investigated AV environmental impacts using real-world Waymo dataset data and microscopic emission models, reporting that AVs consumed approximately 8% less fuel and emitted around 66% lower pollutants compared to human-driven vehicles, providing rare empirical evidence to complement the simulation-based literature.

While much of the existing AV emission literature focuses on CO₂ as a primary greenhouse gas indicator, the present study reports carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NO_x). Although the Handbook Emission Factors for Road Transport version 3 (HBEFA3) model provides CO₂ output, CO, HC, and NO_x were selected as the primary emission metrics due to their direct relevance to near-road air quality and human health impacts at congested freeway off-ramp locations. CO and HC are sensitive indicators of driving aggressiveness and stop-and-go behavior, making them more appropriate for evaluating traffic-level emission effects of AV behavioral profiles than CO₂, which is primarily influenced by fuel type and engine efficiency rather than driving dynamics.

2.3. AV behavioral profiles in mixed traffic

The behavioral profile of AV has emerged as a critical but underexplored dimension of AV impact research, with growing evidence that the driving style of AVs – rather than their mere presence – determines the nature and magnitude of traffic outcomes in mixed environments.

Ahnan and Yun [23] compared cautious and aggressive AV behaviors across varying market penetration rates, finding that aggressive AVs consistently achieved higher levels of service, lower emissions, and reduced fuel consumption compared to cautious AVs, with cautious profiles producing poor service ratings at low penetration rates and only marginal improvements at higher rates. This finding directly supports the premise of the present study that behavioral calibration is a decisive factor in AV performance outcomes.

The interaction between human driver behavior and AV driving style introduces additional complexity. Ma and Zhang [24] investigated driver responses to AV interactions in mixed traffic through a supervised experiment with 36 participants classified as aggressive, moderate, and defensive drivers, finding that aggressive and moderate human drivers felt significantly more anxious and were more likely to behave aggressively when interacting with AVs compared to human-human interactions, with aggressive human drivers also more likely to exploit gaps created by AVs. This behavioral adaptation of human drivers to AV presence is a mechanistic explanation for the instability findings reported in the present study, particularly the paradoxical worsening of traffic conditions under conservative AV profiles. Saljoqi et al. [25] corroborated these findings in a driving simulator experiment with 160 participants, reporting that interactions with cautious AVs led to reductions in human driver time headway of 9.9%, 16.6%, and 17.3% at penetration rates of 25%, 50%, and 75% respectively, indicating that cautious AV profiles induce more aggressive following behavior in human drivers, amplifying rather than reducing traffic turbulence.

IDM has been widely adopted as the car-following framework for representing both human and AV behavior in simulation. Vasconcelos and Bandeira [26] presented a calibration technique for IDM parameters using instrumented vehicle trajectory data, demonstrating that physically interpretable parameter calibration enables precise replication of actual driving trajectories across diverse scenarios. Alhariqi et al. [27] extended this work by calibrating an adaptive IDM variant for mixed autonomy traffic using real-world experimental trajectory data, introducing real-time parameter adaptation based on prevailing traffic conditions and demonstrating that inclusion of speed standard deviation in the calibration objective function enables reproduction of stop-and-go traffic oscillations observed empirically. Yu et al. [28] examined traffic stability in heterogeneous platoon-based systems with CAVs and human-driven vehicles, demonstrating through frequency-based stability analysis that multi-anticipation topologies of CAVs significantly outperform single-anticipation configurations in ensuring head-to-tail string stability, with quantitative stability metrics confirming the superiority of coordinated CAV behavior in heterogeneous traffic.

2.4. Simulation approaches for AV research

Microscopic traffic simulation has become the primary methodological tool for investigating AV impacts, given the current absence of real-world AV fleets at scale and the need for controlled experimental conditions. Wegener et al. [29] introduced TraCI as a framework for interlinking road traffic and network simulators, enabling real-time control of vehicle behavior during simulation runtime rather than relying on pre-generated static mobility traces. This foundational contribution established the principle of online coupling between simulation engines and external controllers, which the present study extends to enable per-vehicle IDM parameter assignment and dynamic instability detection. Olaverri-Monreal et al. [30] demonstrated an application of TraCI through the TraCI as a Service (TraaS) library to couple SUMO with a 3D game engine for evaluating Vehicle-to-Everything (V2X) communication-

based systems, confirming the versatility of the TraCI interface for complex real-time simulation tasks beyond basic traffic modeling.

Anyin et al. [31] proposed a quantitative methodology for comparing microscopic traffic simulators, evaluating VISSIM, SUMO, and Multi-Agent Transport Simulation (MATSim) across runtime, memory usage, travel time accuracy, and scalability metrics. Their results indicated that SUMO demonstrates strong performance in runtime and memory efficiency and proves suitable for high-demand simulations, supporting the selection of SUMO as the simulation engine in the present study. Xie et al. [32] reviewed scenario-based test and evaluation methods for AV, categorizing data-driven, mechanism-based, and knowledge-based approaches and highlighting that scenario-based methods provide more comprehensive and accurate evaluations of AV behavior than traditional mileage-based approaches. This review provides methodological justification for the scenario-based factorial design adopted in the present study, in which demand levels, penetration rates, and behavioral profiles are systematically varied to evaluate AV impacts across controlled operational conditions.

2.5. Research gap and positioning of the present study

Despite the growing body of AV simulation research, several critical gaps remain. Studies on AV penetration and traffic performance predominantly examine basic freeway segments, signalized intersections, and urban corridors, while the freeway off-ramp diverge zone, one of the most geometrically complex locations in urban road networks, has received limited systematic attention. Furthermore, most existing studies treat penetration rate as the sole independent variable, overlooking the interactive role of AV behavioral profiles and traffic demand levels in shaping traffic outcomes. While recent evidence suggests that conservative AV profiles may paradoxically worsen traffic conditions by creating exploitable gaps that human drivers fill aggressively, this effect has not been systematically quantified at freeway diverge zones under varying demand conditions. Finally, although TraCI provides a powerful interface for real-time simulation control, its application for dynamic per-vehicle behavioral parameter assignment and real-time instability detection within a single integrated framework remains underutilized, with existing SUMO-based studies relying predominantly on static vehicle type definitions that limit penetration rate control precision and sub-second data resolution.

The present study addresses these gaps through a TraCI-enhanced microscopic simulation of a real freeway off-ramp in Ankara, Türkiye, employing a full factorial design of 195 scenarios across five penetration rates, three behavioral profiles, and three demand levels, with real-time instability detection and statistically rigorous analysis.

3. METHODOLOGY

3.1. Study area

The study focuses on the Eskisehir Road Golbasi Peripheral Road freeway off-ramp junction located in the Orhun neighborhood, Etimesgut district, Ankara, Türkiye (39.859727° N, 32.620511° E). This location was selected due to its operational complexity as a high-volume diverge point along the Eskisehir Road corridor, which serves as a primary arterial connection between central Ankara and the southwestern districts of Golbasi and Yasakent. The geometric configuration of this off-ramp, characterized by a multi-lane freeway approach, a clearly

defined gore area, and a curved deceleration section, is representative of the diverge zone typology commonly encountered in urban freeway networks and extensively studied in the AV simulation literature.

As illustrated in Fig. 1, the study area comprises a four-lane freeway approach section upstream of the diverge gore point. At the gore, the rightmost lanes transition into a dedicated off-ramp section that curves southward toward the Golbasi Peripheral Road, while the remaining lanes continue straight toward the Life Center intersection and the Yasakent district. Fig. 2 presents an aerial view of the complete off-ramp geometry, where the through lane configuration is highlighted in red and the off-ramp lane is highlighted in yellow, clearly delineating the physical separation between the two traffic streams.



Fig. 1. Street-level view of the Eskisehir Road freeway approach section upstream of the diverge gore point, Etimesgut, Ankara, Türkiye



Fig. 2. Aerial view of the Eskisehir Road Golbasi Peripheral Road freeway off-ramp, Ankara, Türkiye

The network modeled in this study encompasses three distinct segments, the geometric properties of which are summarized in Tab. 1. The total modeled network length is approximately 477 meters, comprising the upstream four-lane freeway approach section (E2: 257.63 m), the downstream three-lane through section (E3: 145.14 m), and the two-lane off-ramp deceleration section (E4: 74.41 m). All lanes maintain a standard width of 3.5 meters consistent with Turkish highway design standards. This segmentation corresponds directly to

the SUMO network edge definitions used in the simulation, ensuring full consistency between the physical geometry and the computational model.

Tab. 1

Network segment geometric properties

Edge ID	Segment Description	Length (m)	No. of Lanes	Function
E2	Freeway approach	257.63	4	Through + diverging traffic
E3	Through section	145.14	3	Straight traffic toward Yasakent
E4	Off-ramp deceleration	74.41	2	Diverging traffic toward Golbasi

3.2. Simulation framework

This study employs Eclipse SUMO, version 1.21.0, as the microscopic traffic simulation engine. SUMO is an open-source, space-continuous simulation platform that models individual vehicle movements at sub-second resolution, making it well-suited for evaluating traffic performance and emissions under heterogeneous vehicle compositions. The platform has been widely adopted in AV simulation research due to its flexibility in defining vehicle behavioral parameters, its integrated emission modeling capabilities, and its support for external programmatic control.

The simulation framework uses a two-layer architecture. The left layer features the Eclipse SUMO engine, managing core microscopic processes such as the IDM car-following model, HBEFA3 emission model, stochastic lane-changing, and a 0.5-second time step. The right layer consists of a dynamic TraCI Python controller with four modules: BehaviorSwitcher for real-time IDM parameter assignment, DataCollector for speed and emission retrieval, InstabilityDetector for identifying safety-critical events, and RunExperiment to orchestrate 195 scenarios across various penetration rates, behavioral profiles, and demand levels.

Communication between the two layers is established through the TraCI API via a TCP socket connection, through which SUMO transmits vehicle states, positions, and emission values to the Python controller, while the controller returns IDM parameter assignments and vehicle control commands at each simulation step. All simulation outputs, including per-step vehicle data, instability event logs, aggregated run-level metrics, and statistical analysis results, are recorded systematically for subsequent analysis. Each simulation scenario runs for a total duration of 130 minutes, comprising a 5-minute warm-up period during which vehicles fill the network without data collection, followed by a 60-minute data collection window. Five independent replications were conducted per scenario using different random seeds to account for stochastic variability in vehicle arrivals and lane-changing behavior.

3.3. Network modeling

The road network was constructed using the SUMO network editor (netedit) and the netconvert utility, based on the geometric characteristics of the Eskisehir Road Golbasi Peripheral Road off-ramp described in Section 3.1. The network geometry was digitized from satellite imagery of the study area and translated into SUMO XML format through three definition files: a node file (nodes.nod.xml) specifying the coordinates and types of all network junctions, an edge file (edges.edg.xml) defining the road segments and their lane

configurations, and a connection file (connections.con.xml) specifying the lane-to-lane assignments at the diverge node.

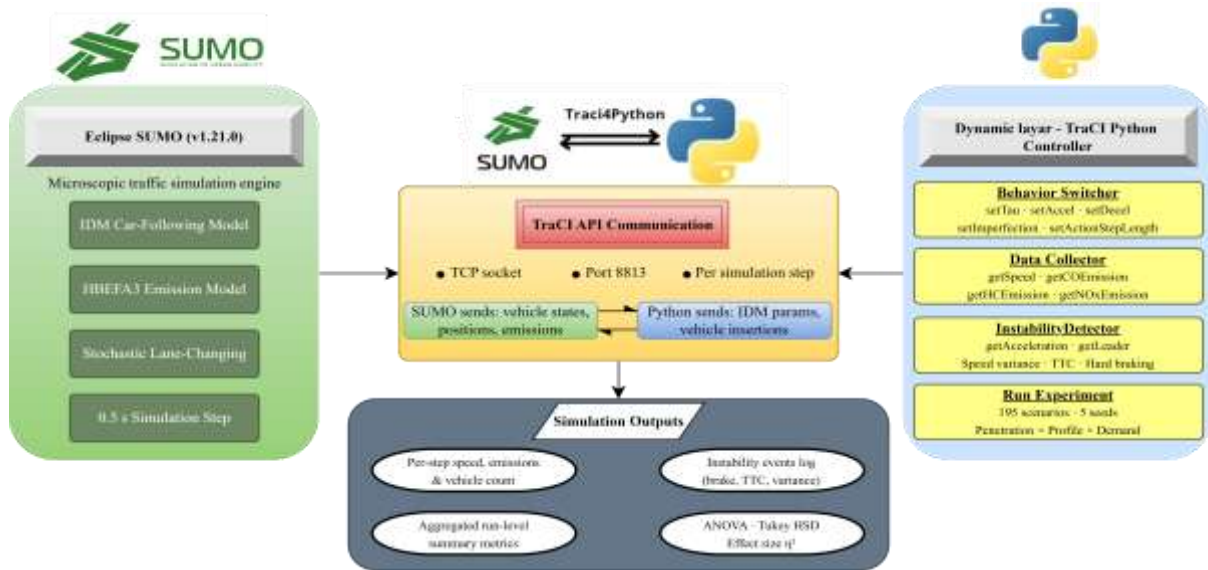


Fig. 3. Simulation framework architecture illustrating the two-layer design: Eclipse SUMO engine (static layer) and TraCI Python controller (dynamic layer) connected via Transmission Control Protocol (TCP) socket communication

The resulting network comprises three edges and four nodes, as illustrated in Fig. 4. Edge E2 represents the four-lane freeway approach section with a length of 257.63 m and serves as the entry point for all simulated vehicles at node J5. At the diverge node J6, lane assignments are defined such that the two rightmost lanes of E2 connect to the off-ramp edge E4, while the remaining three lanes connect to the through edge E3, replicating the physical lane configuration observed at the study site. The deceleration influence zone upstream of J6 marks the region where vehicles begin transitioning toward the off-ramp lane, while the diverging area at J6 represents the physical gore point where the two traffic streams separate. Edge E3 represents the three-lane through section with a length of 145.14 m, terminating at exit node J7 toward the Yasakent direction. Edge E4 represents the two-lane off-ramp deceleration section with a length of 74.41 m, following a curved geometric alignment consistent with the actual off-ramp trajectory, and terminating at exit node J8 toward the Golbasi Peripheral Road. All edges were assigned a standard lane width of 3.5 m.

The complete network was verified by loading it in the SUMO graphical interface, as shown in Fig. 5, where vehicle movements across all three edges and the diverge junction were visually confirmed to be consistent with the physical study area geometry. The simulation screenshot confirms that vehicles correctly distribute between the through and off-ramp sections at node J6 under mixed traffic conditions.

3.4. Vehicle type definitions and IDM parameterization

Vehicle behavior in this study is modeled using the Intelligent Driver Model (IDM), which describes longitudinal vehicle dynamics as a function of spacing, relative speed, and desired velocity. The model is widely adopted due to its continuous, collision-free formulation and its flexibility in independently parameterizing acceleration, deceleration, time headway, and

minimum gap (Treiber et al., [33]). It has also been extensively validated for both human-driven and autonomous vehicle simulations.

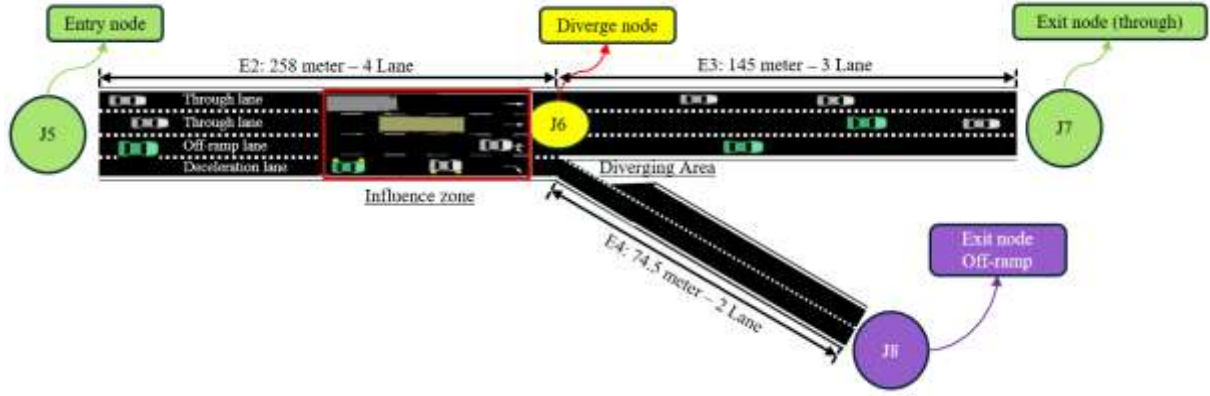


Fig. 4. Schematic diagram of the simulated network



Fig. 5. SUMO graphical interface

The IDM describes longitudinal acceleration as given in Equation (1):

$$\dot{v} = a \left[1 - \left(\frac{v}{v_0} \right)^\delta - \left(\frac{s^*(v, \Delta v)}{s} \right)^2 \right] \quad (1)$$

where v is the current speed, v_0 the desired speed, δ the acceleration exponent (typically $\delta = 4$), s the actual gap to the leading vehicle, and s^* the desired minimum gap defined in Equation (2):

$$s^*(v, \Delta v) = s_0 + \max \left(0, vT + \frac{v \cdot c}{2\sqrt{ab}} \right) \quad (2)$$

Where s_0 is the minimum gap at standstill, T is the desired time headway, Δv is the relative speed to the leader, a is the maximum acceleration, and b is the comfortable deceleration rate.

Four behavioral profiles were defined: one human-driven baseline and three autonomous vehicle profiles representing conservative, moderate, and aggressive driving strategies. The human-driven profile incorporates stochastic acceleration variability through a driver imperfection parameter $\sigma = 0.5$ and a perception-reaction time of 0.9 s, reflecting empirical human driver characteristics. All AV profiles are assigned $\sigma = 0.0$, representing the deterministic execution capability of autonomous systems, and a reaction time of 0.1 s,

reflecting electronic perception-actuation latency. The profiles are differentiated through their time headway parameter T , minimum gap s_0 , and acceleration bounds: the conservative profile adopts $T = 1.8$ s and $s_0 = 3.0$ m, prioritizing safety through larger following distances; the moderate profile adopts $T = 1.2$ s and $s_0 = 2.0$ m, representing a balanced efficiency-safety configuration; and the aggressive profile adopts $T = 0.8$ s and $s_0 = 1.0$ m, reflecting a high-throughput platoon-like driving strategy. The complete parameter set for all profiles is presented in Tab. 2.

Parameter values were adopted from established simulation studies [34, 35]. For each profile, three vehicle classes were defined – passenger car, bus, and truck – with class-specific geometric and speed characteristics. All vehicles were assigned the HBEFA3/PC_G_EU4 emission class as a consistent approximation, with CO, HC, and NO_x emissions computed at each 0.5-second simulation step using HBEFA3 emission factors.

Tab. 2

IDM car-following parameters for human-driven and AV behavioral profiles

Parameter	Human	Conservative AV	Moderate AV	Aggressive AV
Desired time headway τ (s)	1.5	1.8	1.2	0.8
Minimum gap (m)	2.5	3	2	1
Max acceleration (m/s ²)	2.6	1.5	2	2.5
Max deceleration (m/s ²)	4.5	3	3.5	4
Driver imperfection σ	1.5	1.8	1.2	0.8
Reaction time (s)	0.9	0.1	0.1	0.1

3.5. Experimental design

A full factorial experimental design was adopted to systematically investigate the combined effects of AV penetration rate, AV behavioral profile, and traffic demand level on traffic instability and emissions at the study off-ramp. This design ensures that all combinations of the three factors are tested, enabling the identification of main effects, interaction effects, and threshold conditions that would not be detectable through single-factor variation.

Three independent variables were defined. The first variable is AV penetration rate, representing the proportion of AV in the traffic stream, tested at five levels: 0%, 25%, 50%, 75%, and 100%. The 0% scenario serves as the human-driven baseline against which all AV scenarios are compared. The remaining four levels represent the gradual transition from predominantly human-driven traffic toward full autonomy, reflecting the expected real-world adoption trajectory of AV over the coming decades. The second variable is AV behavioral profile, tested at three levels: conservative, moderate, and aggressive, as defined in Section 3.4. At the 0% penetration baseline, behavioral profile is irrelevant since no AV are present; therefore, only the moderate profile was simulated at this level to avoid redundant runs, resulting in a consolidated baseline. The third variable is traffic demand level, tested at three levels corresponding to Highway Capacity Manual (HCM) 7th edition freeway off-ramp service level classifications: low demand at 600 veh/h representing Level of Service (LOS) C, medium

demand at 1000 veh/h representing LOS D, and high demand at 1400 veh/h representing LOS E.

To account for stochastic variability inherent in microscopic traffic simulation, five independent replications were conducted for each scenario combination using different random seeds. The use of multiple replications is a standard requirement in simulation-based transport research to ensure that reported metrics reflect stable mean behavior rather than individual random outcomes. The complete experimental design is summarized in Tab. 3, yielding a total of 195 simulation runs after consolidation of the 0% penetration baseline.

Tab. 3

Full factorial experimental design summary

Factor	Levels	Values
AV penetration rate	5	0%, 25%, 50%, 75%, 100%
AV behavioral profile	3	Conservative, Moderate, Aggressive
Traffic demand level	3	Low (600), Medium (1000), High (1400) veh/h
Random seeds	5	Seeds 1 to 5
Total scenarios	—	195 (after baseline consolidation)
Simulation duration	—	65 min (5 min warm-up + 60 min data collection)
Step length	—	0.5 seconds

3.6. Demand Modeling

Traffic demand was defined using three levels based on HCM 7th edition freeway off-ramp service levels: low (600 veh/h, LOS C), medium (1000 veh/h, LOS D), and high (1400 veh/h, LOS E), capturing the range from free-flow to near-saturated conditions. This scenario-based approach, consistent with simulation-based AV research, evaluates system behavior across controlled operational conditions rather than replicating a specific observed traffic state.

Demand was introduced through SUMO flow definitions in the route files and distributed between two routes: 75% of vehicles followed the through route via edges E2 and E3 toward Yasakent, and 25% followed the off-ramp route via edges E2 and E4 toward the Golbasi Peripheral Road, consistent with the lane configuration of the study network. The vehicle fleet comprised 82% passenger cars, 8% buses, and 10% trucks, with passenger car equivalent factors of 1.0, 2.25, and 1.75 respectively. The complete demand configuration is summarized in Tab. 4.

Tab. 4

Traffic demand configuration

Parameter	Value
Low demand	600 veh/h (HCM LOS C)
Medium demand	1000 veh/h (HCM LOS D)
High demand	1400 veh/h (HCM LOS E)
Through route split	75% (E2 → E3)
Off-ramp route split	25% (E2 → E4)

Passenger car proportion	0.82
Bus proportion	0.08
Truck proportion	0.1
PCE — passenger car	1
PCE — bus	2.25
PCE — truck	1.75

3.7. TraCI integration and real-time control

This study integrates TraCI API to establish a bidirectional TCP socket connection between the SUMO engine and an external Python controller at each 0.5-second simulation step. The complete control procedure is presented in Algorithm 1. The controller comprises four modules: the BehaviorSwitcher, which assigns IDM parameters to each vehicle upon network entry using `traci.vehicle.setTau()`, `setAccel()`, `setDecel()`, `setMinGap()`, `setImperfection()`, and `setActionStepLength()`, with AV designation determined deterministically via a hash-based function applied to the vehicle identifier; the DataCollector, which retrieves per-vehicle speed and emission values at each step using `traci.vehicle.getSpeed()`, `getCOEmission()`, `getHCEmission()`, and `getNOxEmission()`; the InstabilityDetector, described in Section 3.8; and the RunExperiment module, which orchestrates the full 195-scenario loop by launching a dedicated SUMO process per scenario, connecting TraCI on a unique port, and executing the warm-up and data collection phases sequentially.

This architecture provides three methodological advantages over static simulation approaches: precise penetration rate control at the individual vehicle level without requiring separate route files per scenario; high-resolution data collection at 0.5-second intervals capturing transient dynamics that aggregate outputs would mask; and real-time instability detection as events occur rather than through post-processing of trajectory data.

3.8. Instability metrics

Traffic instability is quantified through three real-time indicators computed at each 0.5-second simulation step via TraCI, moving beyond conventional aggregate metrics to directly measure flow turbulence at the microscopic level.

The first indicator is the network-level speed variance spikes, flagged when the standard deviation of instantaneous vehicle speeds exceeds 3.0 m/s, reflecting the onset of stop-and-go wave propagation. The second is the hard braking event, flagged when individual vehicle deceleration falls below -3.5 m/s^2 via `traci.vehicle.getAcceleration()`, indicating reactive car-following instability. The third is the near-collision event, flagged when the Time-To-Collision (TTC) between a following vehicle and its leader falls below 2.0 seconds, computed as the ratio of the intervehicle gap to relative speed via `traci.vehicle.getLeader()` and `traci.vehicle.getSpeed()`. A TTC below 2.0 seconds is widely recognized as a critical safety threshold requiring immediate evasive action. All three indicators are summarized in Tab. 5, and their counts per run serve as the primary instability metric in the statistical analysis.

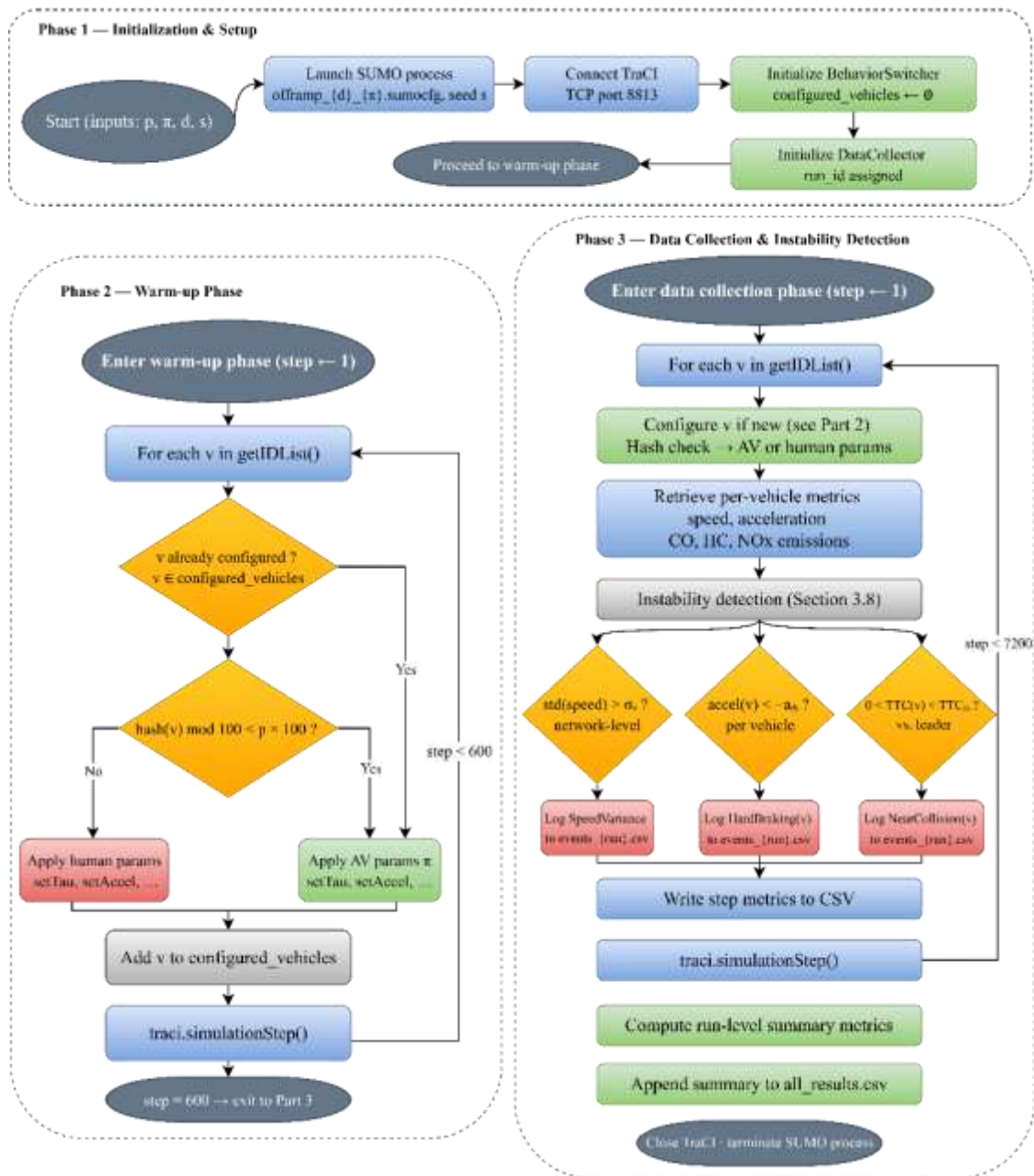


Fig. 6. TraCI real-time control loop flowchart

Tab. 5

Traffic instability detection thresholds

Indicator	Definition	Threshold	TraCI Method
Speed variance spike	Network-level speed std dev	$> 3.0 \text{ m/s}$	<code>getSpeed()</code>
Hard braking event	Individual deceleration	$< -3.5 \text{ m/s}^2$	<code>getAcceleration()</code>
Near-collision TTC	TTC to leader	$< 2.0 \text{ s}$	<code>getLeader()</code> , <code>getSpeed()</code>

3.9. Statistical analysis

The simulation outputs were analyzed using one-way and two-way ANOVA to assess the statistical significance of each experimental factor on the measured performance metrics. One-way ANOVA was applied separately for each metric, including mean travel time, mean speed, CO, HC, and NO_x emissions, and total instability events, with AV penetration rate, behavioral profile, and demand level each treated as independent grouping variables. Effect size was quantified using eta squared (η^2), where values above 0.06 and 0.14 indicate medium and large effects respectively. Two-way ANOVA was subsequently applied to examine the interaction effect between penetration rate and behavioral profile on traffic instability, as the one-way results indicated that penetration rate alone does not produce a statistically significant effect.

Pairwise comparisons between behavioral profiles were conducted using independent samples t-tests to identify which profile pairs differ significantly in their instability outcomes. All statistical tests were performed at a significance level of $\alpha = 0.05$. The stochastic variability of the simulation was addressed through five independent replications per scenario, providing sufficient degrees of freedom for parametric testing. All analysis was implemented in Python using the SciPy statistics library.

4. RESULTS

4.1. Effect of AV penetration rate on mean travel time

Fig. 7(a), 7(b), and 7(c) present mean travel time versus AV penetration rate under low, medium, and high-demand conditions, respectively. At 0% penetration, all scenarios share a common human-driven baseline of 29.654 s, 30.176 s, and 31.072 s under low, medium, and high demand respectively. With increasing AV penetration, the three behavioral profiles diverged progressively. The aggressive profile consistently reduced travel time, reaching 29.328 s, 29.554 s, and 29.934 s at 100% penetration under low, medium, and high demand respectively, representing reductions of 0.326 s, 0.622 s, and 1.138 s from the baseline. The moderate profile produced modest reductions across all conditions. The conservative profile exhibited the opposite trend, increasing travel time beyond the human-driven baseline at all demand levels, with the most pronounced deterioration under high demand where travel time rose to 31.824 s at full penetration, a worsening of 0.752 s. These findings demonstrate that the travel time effect of AV penetration is critically dependent on behavioral profile, with the magnitude of both improvement and deterioration amplified by increasing demand.

4.2. Effect of AV penetration rate on mean speed

Fig. 8(a), 8(b), and 8(c) present mean speed versus AV penetration rate under low, medium, and high-demand conditions, respectively, with error bars representing one standard deviation across five simulation replications. At 0% penetration, all scenarios share a common human-driven baseline of 13.462 m/s, 13.198 m/s, and 12.806 m/s under low, medium, and high-demand, respectively. With increasing AV penetration, the aggressive profile consistently increased mean speed, reaching 13.596 m/s, 13.474 m/s, and 13.288 m/s at 100% penetration under low, medium, and high demand respectively, representing gains of 0.134 m/s, 0.276 m/s, and 0.482 m/s from the baseline. The moderate profile produced modest increases across all conditions. The conservative profile reduced mean speed below the human-driven baseline at

all demand levels, with the most pronounced decline under high demand where speed dropped to 12.502 m/s at full penetration, a reduction of 0.304 m/s. These findings confirm that aggressive AVs improve network throughput through tighter headways and smoother acceleration, while conservative AVs reduce effective capacity, with both effects amplified under higher demand conditions.

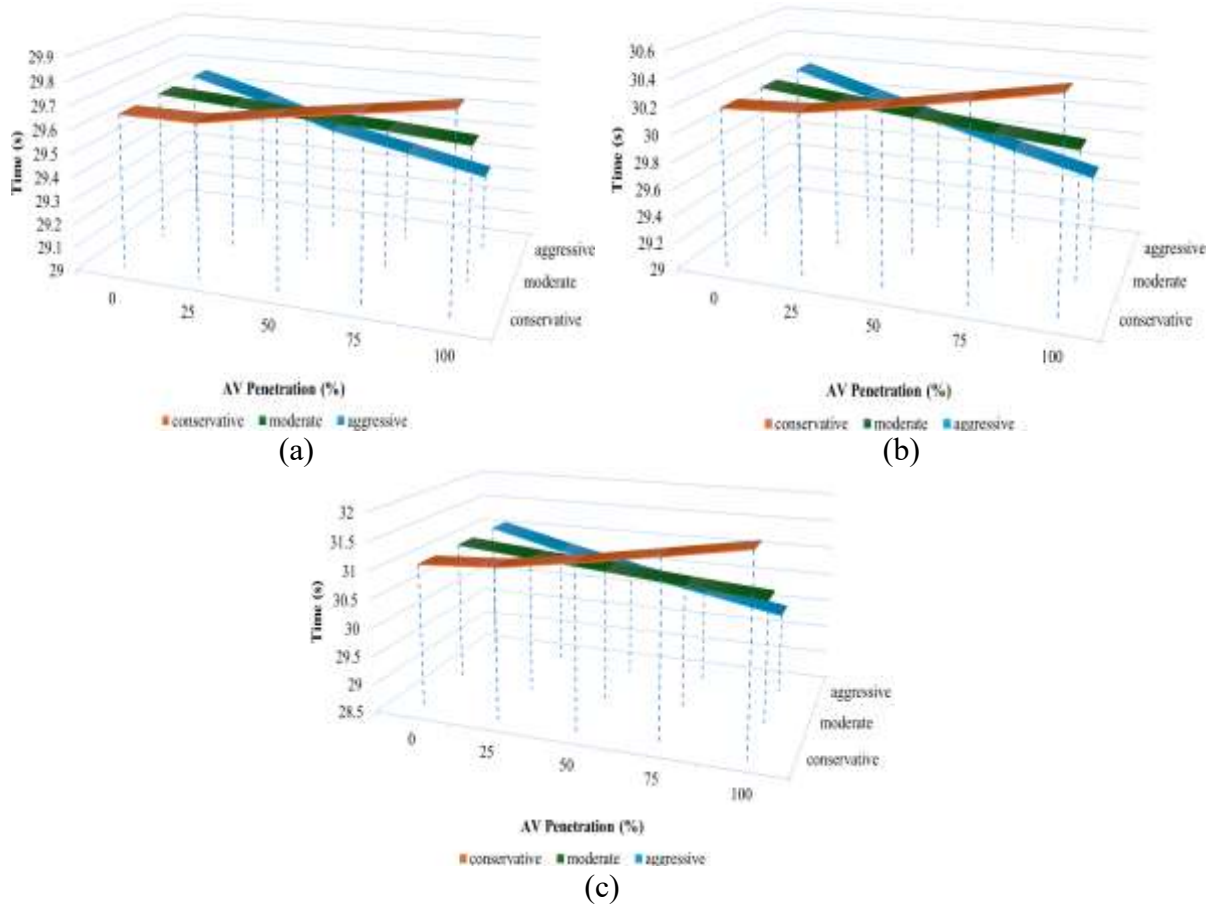


Fig. 7. Mean travel time versus AV penetration rate under (a) low demand (600 veh/h), (b) medium demand (1000 veh/h), and (c) high demand (1400 veh/h) conditions

4.3. Effect of AV penetration rate on traffic instability

Fig. 9(a), 9(b), and 9(c) present traffic instability events versus AV penetration rate under low, medium, and high-demand conditions, respectively. At 0% penetration, all scenarios share a common human-driven baseline of 317.2, 236.2, and 105.8 instability events under low, medium, and high demand respectively. With increasing AV penetration, the three profiles diverged in opposing directions across all demand levels. The conservative profile exhibited a paradoxical reduction followed by a continuous increase, rising from 163.2 at 25% to 221.0 events at 100% penetration under low demand, from 108.0 to 151.6 under medium demand, and from 56.0 to 118.0 under high demand, representing deteriorations of 35.4%, 40.4%, and 110.7% from the 25% penetration level. This behavior is attributed to the large time headways of conservative AVs creating exploitable gaps that human drivers fill aggressively, generating new instability in the mixed traffic stream. The moderate profile exhibited a slight increase across all demand levels. The aggressive profile produced the opposite trend, reducing

instability monotonically with increasing penetration, reaching 174.0, 132.2, and 93.6 events at 100% penetration under low, medium, and high demand respectively, with the most pronounced reduction of 62.7% observed under high demand between 25% and 100% penetration. These findings demonstrate that AV behavioral calibration is a more decisive determinant of traffic instability than penetration rate alone, with the magnitude of both improvement and deterioration amplified by increasing demand.

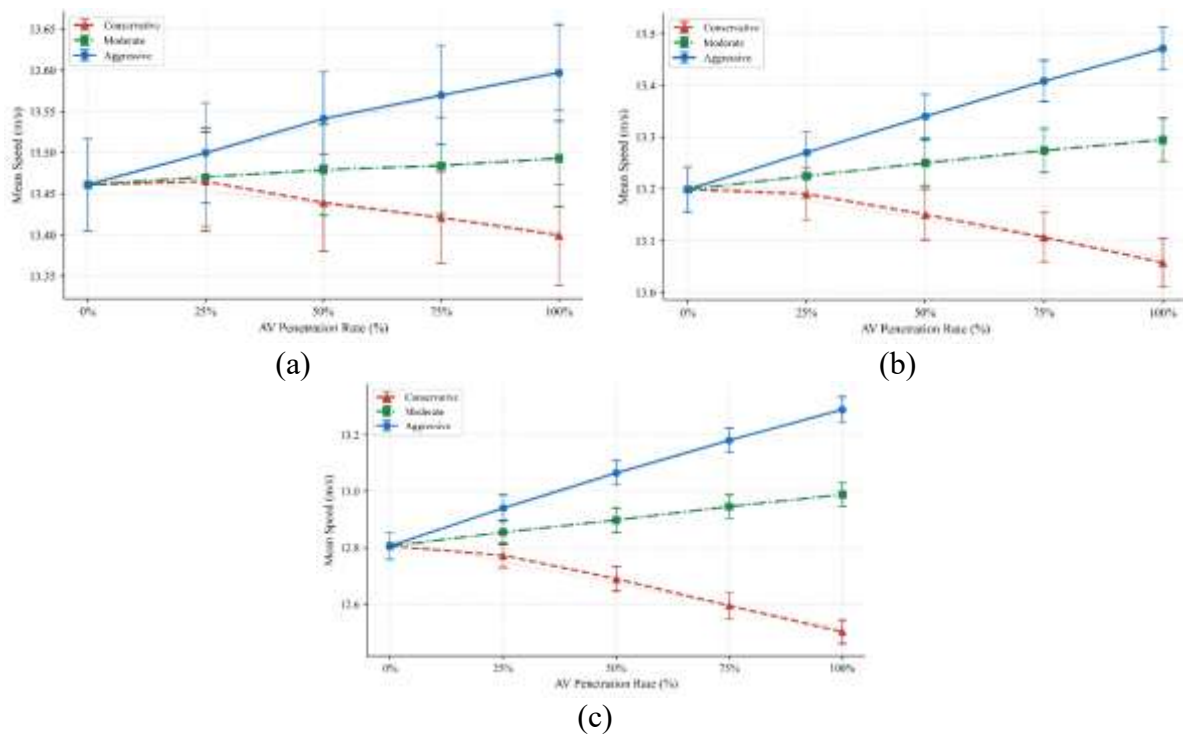


Fig. 8. Mean speed versus AV penetration rate under (a) low demand (600 veh/h), (b) medium demand (1000 veh/h), and (c) high demand (1400 veh/h) conditions

4.4. Effect of AV penetration rate on emissions

Fig. 10(a)-10(i) present CO, NO_x, and HC emissions across AV penetration rates and demand levels. The aggressive profile consistently reduced all emissions, while the conservative profile increased them, mirroring travel time and instability patterns.

For CO emissions (Fig. 10a-10c), the aggressive profile achieved reductions of 24.9%, 30.0%, and 35.4% under low, medium, and high demand, respectively (from baselines of 297,558 mg, 585,387 mg, and 1,195,309 mg to 223,341 mg, 409,792 mg, and 771,940 mg at 100% penetration). The conservative profile increased CO by 9.2%, 2.6%, and 14.0% under the same conditions.

For NO_x emissions (Fig. 10d-10f), reductions were modest: the aggressive profile achieved only 2.1-5.3% reductions, while the conservative profile produced negligible changes, indicating lower sensitivity to AV behavior.

For HC emissions, the aggressive profile reduced emissions by 14.1%, 19.9%, and 26.2% under low, medium, and high demand, respectively. Conversely, conservative driving worsened HC emissions, reaching up to 13,803 mg under high-demand. Higher demand amplified both effects.

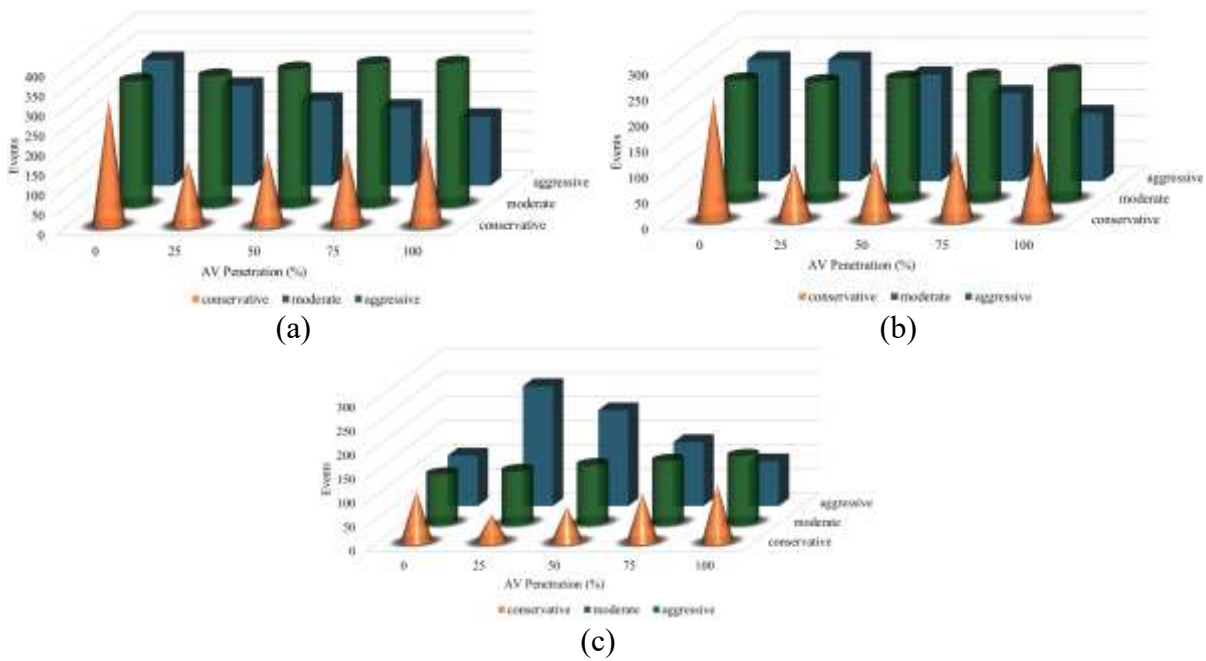


Fig. 9. Traffic instability events versus AV penetration rate under (a) low demand (600 veh/h), (b) medium demand (1000 veh/h), and (c) high demand (1400 veh/h) conditions

4.5. Interaction effects: penetration rate, behavioral profile, and demand level

The results presented in Sections 4.1 through 4.4 collectively reveal a consistent interaction pattern between AV penetration rate, behavioral profile, and traffic demand level across all measured metrics. This section synthesizes these findings to characterize the nature of the interaction and its implications for AV deployment.

Across all metrics, the effect of AV penetration rate was not independent of behavioral profile. Under the aggressive profile, increasing penetration consistently improved all performance metrics, reducing travel time, increasing mean speed, reducing instability events, and reducing CO and HC emissions, with the magnitude of improvement amplified by demand level. Under the conservative profile, the opposite trend was observed consistently across all metrics and demand levels, with performance deteriorating beyond the human-driven baseline as penetration increased, most severely under high-demand conditions. The moderate profile produced intermediate effects, with modest improvements in travel time and speed but slight increases in instability and marginal emission reductions.

The demand amplification effect represents a particularly important finding, as it reveals how network conditions determine the consequences of AV behavioral choices. The divergence between aggressive and conservative profiles widened systematically with increasing demand across every metric measured in this study. For instability events, the conservative profile worsened traffic stability by 35.4% under low demand but by a substantially larger 110.7% under high demand, both relative to the 25% penetration level. Similarly, for CO emissions, the aggressive profile achieved a reduction of 24.9% under low demand, yet this benefit grew to 35.4% under high demand. This consistent demand-dependent amplification indicates that the behavioral profile of AVs becomes increasingly consequential as the network approaches capacity. In practical terms, correct profile deployment offers greater benefits under congested conditions, while incorrect deployment causes disproportionately greater harm when the network is under stress. These findings underscore the importance of context-aware AV

calibration policies that prioritize well-designed behavioral profiles on high-demand corridors and during peak-hour operations.

These interaction effects collectively demonstrate that penetration rate alone is an insufficient descriptor of AV impact at freeway off-ramps. While higher AV penetration is often assumed to improve traffic, the behavioral profile of the deployed AV fleet determines not only the direction but also the magnitude of the effect on traffic performance, stability, and environmental impact. Demand level acts as a critical amplifying factor: the divergence between aggressive and conservative profiles widens systematically as traffic approaches capacity. These findings have direct implications for AV deployment policy, suggesting that regulatory frameworks should address AV behavioral calibration standards in addition to fleet penetration targets, particularly on high-demand corridors and at geometrically complex locations such as diverge zones.

4.6. Statistical analysis

Tab. 6 summarizes the one-way ANOVA results for all performance metrics across the three experimental factors. AV behavioral profile and demand level emerged as the dominant factors, with behavioral profile producing a statistically significant effect on traffic instability events ($F=35.84$, $p<0.001$), demand level producing significant effects on both travel time ($F=218.66$, $p<0.001$) and instability events ($F=53.93$, $p<0.001$). In contrast, penetration rate alone produced no statistically significant effect on any metric, with F -values ranging from 0.013 to 0.639 and p -values exceeding 0.63 across all metrics. Effect sizes confirmed these findings, with η^2 values for penetration rate ranging from 0.0003 to 0.0133, indicating negligible practical significance.

Tab. 6

One-way ANOVA results for all performance metrics

Metric	Factor	F	p-value	Significance	η^2
Travel time	Penetration rate	0.297	0.88	ns	0.006
Travel time	Demand level	218.657	<0.001	***	—
Mean speed	Penetration rate	0.28	0.891	ns	0.006
CO emissions	Penetration rate	0.191	0.943	ns	0.004
HC emissions	Penetration rate	0.128	0.972	ns	0.003
NO _x emissions	Penetration rate	0.013	0.999	ns	0.0003
Instability events	Penetration rate	0.639	0.635	ns	0.013
Instability events	AV profile	35.841	<0.001	***	—
Instability events	Demand level	53.926	<0.001	***	—

ns = not significant; *** $p < 0.001$

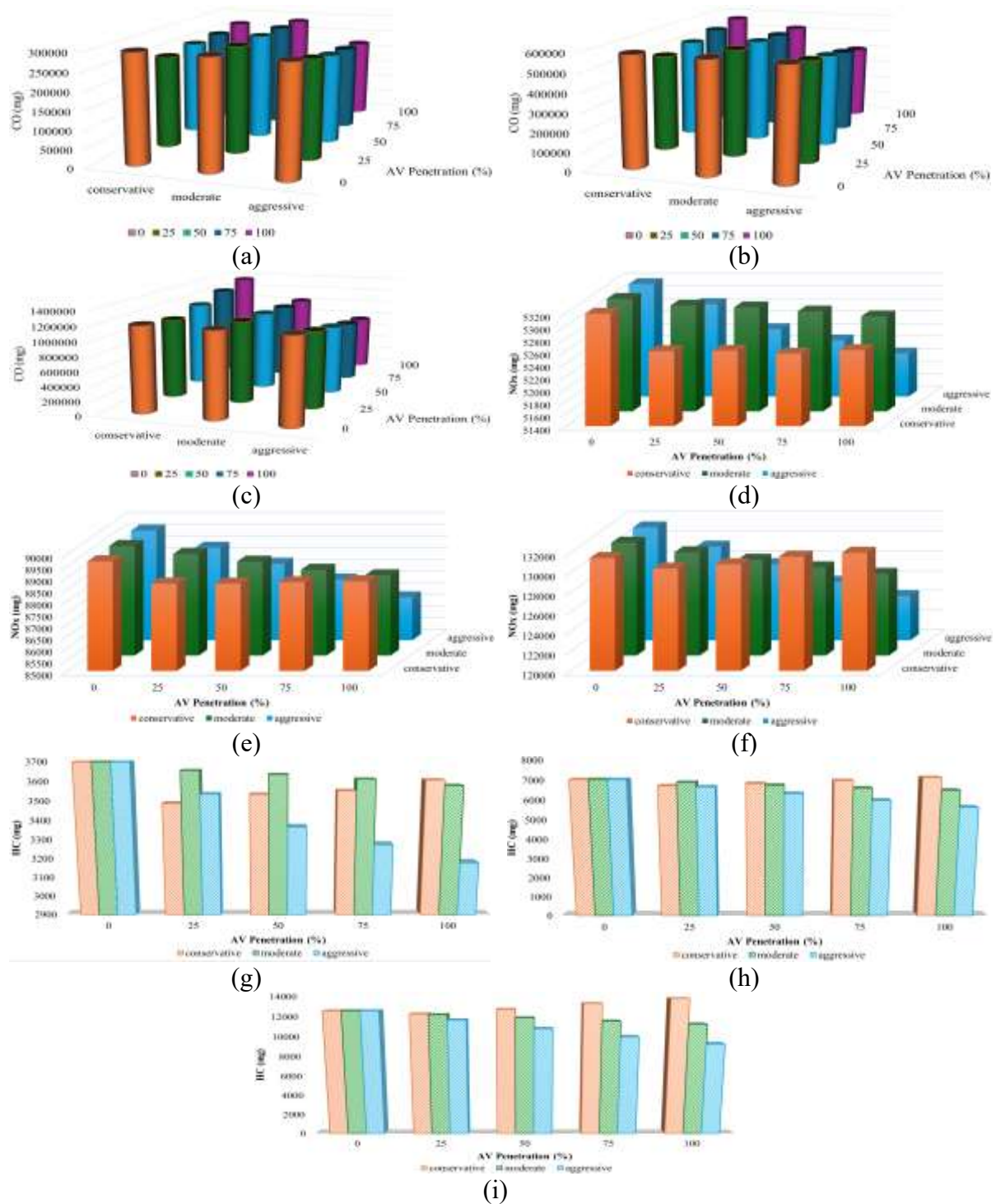


Fig. 10. Emission outputs versus AV penetration rate: CO emissions under (a) low, (b) medium, and (c) high demand; NO_x emissions under (d) low, (e) medium, and (f) high demand; HC emissions under (g) low, (h) medium, and (i) high-demand conditions

Pairwise t-tests confirmed that all three behavioral profile pairs differed significantly in their instability outcomes. Conservative versus moderate profiles produced $t=-7.671$ ($p<0.001$), conservative versus aggressive produced $t=-5.698$ ($p<0.001$), and moderate versus aggressive produced $t=3.773$ ($p<0.001$), indicating that each profile generates a statistically distinct

instability pattern. The interaction analysis revealed that the effect of penetration rate on instability was dependent on behavioral profile and demand level, with aggressive AVs reducing instability by up to 62.7% under high demand while conservative AVs increased instability by up to 110.7% under the same conditions, as detailed in Tab. 7.

Tab. 7

Instability event change by profile and demand level

AV Profile	Low Demand	Medium Demand	High Demand
Conservative	35.40%	40.40%	110.70%
Moderate	9.70%	8.40%	27.80%
Aggressive	-31.00%	-43.90%	-62.70%

5. DISCUSSION

The results presented in Chapter 4 reveal a complex and nuanced picture of AV impacts at freeway off-ramps that extend beyond the simplified narrative of higher penetration rates yielding uniformly better outcomes. This chapter interprets these findings in the context of the existing literature, provides mechanistic explanations for the observed behavioral phenomena, derives policy implications for AV deployment at freeway diverge zones, and acknowledges the limitations of the study. The discussion is structured to move from empirical comparison with prior work toward broader theoretical and practical implications, with the aim of situating the contributions of this study within the wider body of AV research.

5.1. Comparison with existing literature

The finding that AV penetration rate alone produced no statistically significant effect on any performance metric ($F=0.15$, $p=0.93$) contrasts with the prevailing findings in the literature, where studies such as Abdeen et al. [14] and ElSahly and Abdelfatah [12] reported progressive and monotonic improvements in traffic performance with increasing penetration. This divergence is attributable to the aggregation effect in those studies, where a single AV behavioral profile was tested at each penetration level, masking the opposing directional effects of conservative and aggressive profiles that cancel each other out when averaged across the full dataset. When profiles are analyzed separately in the present study, the direction and magnitude of penetration rate effects become clearly visible and consistent, confirming that penetration rate is a significant factor only when conditioned on behavioral profile.

The aggressive profile findings are broadly consistent with literature. The travel time reductions of 0.326 s, 0.622 s, and 1.138 s under low, medium, and high demand, respectively, and the CO emission reductions of up to 35.4% at high demand, align with the general direction of improvements reported by Alozi and Hamad [13], Louati et al. [18], and Hua et al. [20]. The demand-amplification pattern, where benefits grow with increasing congestion, is also consistent with the findings of Kuang and Zhang [17], who reported that elevated CAV penetration produced the most pronounced speed improvements under high-density conditions.

The conservative AV paradox identified in this study, where instability worsened by up to 110.7% under high demand at full penetration, finds mechanistic support in literature even though it has not been previously quantified in a simulation context. Alhariqi et al. [21] demonstrated using real-world Waymo data that conservative AV car-following behavior with

large time gaps produces higher emissions than human-following-human arrangements under congested conditions, consistent with the emission deterioration of up to 14.0% observed for conservative profiles in the present study. Saljoqi et al. [25] provided direct experimental evidence that cautious AV profiles induce larger reductions in human driver time headway than aggressive profiles, confirming the gap-exploitation mechanism that drives the instability increase observed here. The threshold-dependent improvement reported by Rosca et al. [15] and the non-monotonic conflict pattern observed by Shin et al. [16] further corroborate the finding that AV impacts are not linearly proportional to penetration rate and that critical thresholds exist beyond which behavioral profile determines the direction of the effect.

The emission findings are consistent with the broader literature in direction but more modest in magnitude. The CO reduction of 12.5% and HC reduction of 8.5% at full aggressive AV penetration fall within the range reported by Louati et al. [18] and Hua et al. [20], while the marginal NO_x reduction of 2.0% is consistent with the sensitivity analysis of Hua et al. [20], which identified varying emission response patterns across pollutant types. The real-world evidence of Ali [22], reporting approximately 66% lower pollutant emissions for AVs compared to human drivers, represents an upper bound that the present simulation results do not approach, likely reflecting the difference between real Waymo AV behavior and the IDM-based behavioral profiles used in this study.

5.2. Mechanistic explanation of the conservative AV paradox

The most counterintuitive finding of this study is the paradoxical worsening of traffic instability under conservative AV profiles, which increased instability by up to 110.7% relative to the 25% penetration level under high-demand conditions. This section provides a mechanistic explanation for this phenomenon by drawing on car-following theory, human behavioral adaptation research, and the specific operational characteristics of the freeway off-ramp diverge zone.

The conservative AV profile is characterized by a large desired time headway of 1.8 seconds and a minimum gap of 3.0 meters, values that are substantially larger than those of human drivers and aggressive AV profiles. Under low penetration conditions, these large gaps have a stabilizing effect because the few conservative AVs present act as buffers that absorb upstream disturbances and prevent shockwave propagation. This explains the initial reduction in instability observed at 25% penetration for the conservative profile across all demand levels. However, as penetration increases beyond this threshold, the network becomes populated with vehicles maintaining systematically larger gaps than human drivers expect or tolerate, creating a structural condition that triggers aggressive gap-filling behavior in the remaining human drivers.

This mechanism is directly supported by the experimental findings of Ma and Zhang [24], who demonstrated that aggressive and moderate human drivers were significantly more likely to behave aggressively when interacting with AVs than in human-human interactions, and that aggressive human drivers actively exploited gaps created by AVs on the road. Saljoqi et al. [25] quantified this effect precisely, reporting that cautious AV profiles induced reductions in human driver time headway of up to 17.3% at 75% penetration, meaning that human drivers following conservative AVs maintained significantly shorter gaps than they would in normal human-human traffic. In the context of the present study, this gap-exploitation behavior manifests as hard braking events, speed variance spikes, and near-collision conditions, all three of which are captured by the instability detection framework and contribute to the event count reported in Section 4.3.

The freeway off-ramp diverge zone amplifies this effect beyond what would be observed on a basic freeway segment. At the diverge gore point, vehicles must make time-critical lane-changing decisions under spatial and temporal constraints. When conservative AVs occupy the approach lanes with large headways, human drivers attempting to reach the off-ramp lane perceive these gaps as opportunities for aggressive lane changes, executing maneuvers at shorter TTC margins than would occur in normal traffic. This interaction between the geometric constraints of the diverge zone and the behavioral adaptation of human drivers to conservative AV gap sizes creates a compounding instability effect that intensifies with both penetration rate and demand level, producing the 110.7% deterioration observed under high-demand conditions.

5.3. Policy implications

The findings carry several direct implications for policymakers, traffic management authorities, and AV manufacturers involved in planning AV deployment at freeway diverge zones.

Most critically, AV penetration targets alone are insufficient as a regulatory framework. A fully conservative AV fleet at 100% penetration produces worse traffic instability than the human-driven baseline under high demand, while the same penetration level with aggressive AVs reduces instability by 62.7%. Regulatory frameworks should therefore extend beyond fleet penetration targets to include minimum behavioral calibration standards, particularly regarding time headway settings and gap acceptance behavior in mixed traffic environments.

The demand-dependent amplification of behavioral profile effects suggests that calibration standards should be prioritized for high-demand corridors and peak-hour conditions, where conservative AV behavior causes the greatest penalty and aggressive behavior yields the most pronounced benefit. Furthermore, the observed threshold effect for aggressive AVs between 25% and 75% penetration under high demand implies that targeted incentives to achieve a critical mass of well-calibrated AVs on specific corridors could deliver disproportionate stability benefits relative to the investment required.

For AV manufacturers, the results highlight the risk of defaulting to conservative behavioral calibration as a safety-first strategy without accounting for systemic network-level instability. The moderate profile, which produced consistently positive outcomes across all demand levels, may represent a more appropriate default calibration for mixed traffic environments than either extreme. Finally, the amplification of behavioral profile effects at the diverge zone suggests that infrastructure-specific calibration standards may be necessary to account for the distinct operational demands of different network locations.

5.4. Limitations

Several limitations of this study should be acknowledged when interpreting the findings and their generalizability.

First, the study adopts a scenario-based demand design in the absence of field-measured traffic counts at the study site. While demand levels were defined according to HCM 7th edition freeway off-ramp service level classifications to ensure practical relevance, the results cannot be directly validated against observed traffic conditions. Future studies incorporating real traffic count data and simulation calibration would strengthen the empirical grounding of the findings.

Second, the simulated network represents a simplified geometric abstraction of the study site, comprising three edges and four nodes. Real freeway off-ramp environments involve additional complexity including upstream and downstream signal control, weaving sections,

and variable geometry that may influence the magnitude of behavioral profile effects beyond what is captured in the present model.

Third, all vehicle types were assigned the HBEFA3/PC_G_EU4 emission class as a conservative approximation, without differentiation between vehicle classes. This simplification may affect the precision of absolute emission values, though the relative trends across scenarios and profiles are expected to remain consistent.

Fourth, the IDM parameters for the three AV profiles were taken from prior simulations, not real AV data. Thus, results indicate behavioral trends rather than predicting specific commercial AV performance.

Fifth, the study focuses on a single off-ramp location in Ankara, Türkiye. While the geometric and operational characteristics of this site are representative of urban freeway diverge zones, the generalizability of the specific threshold values and magnitudes reported here to other network configurations and geographic contexts requires further investigation.

6. CONCLUSION

This study investigated traffic instability thresholds at the Eskisehir Road Golbasi Peripheral Road freeway off-ramp in Ankara, Türkiye, under mixed autonomous-human vehicle flows using a TraCI-enhanced microscopic simulation framework. A full factorial experiment of 195 scenarios examined five AV penetration rates, three behavioral profiles, and three demand levels across traffic instability, travel time, mean speed, and vehicle emissions.

The results demonstrate that AV behavioral profile, rather than penetration rate, is the dominant determinant of traffic performance at freeway off-ramps. One-way ANOVA confirmed that behavioral profile produced a statistically significant effect on instability ($F=35.84$, $p<0.001$) while penetration rate alone yielded no significant effect across any metric, challenging the prevailing assumption that higher penetration rates uniformly improve traffic performance. Aggressive AV profiles consistently improved all metrics with increasing penetration, reducing instability by up to 62.7% and CO emissions by up to 35.4% under high demand. Conservative profiles paradoxically worsened all metrics beyond the human-driven baseline, increasing instability by up to 110.7% under the same conditions, a deterioration mechanistically attributed to gap-exploitation behavior of human drivers in response to large conservative AV headways at the diverge zone. Traffic demand level acted as an amplifying factor across all metrics, with behavioral profile divergence widening systematically as the network approached capacity.

These findings demonstrate that effective AV integration at freeway diverge zones requires regulatory frameworks addressing behavioral calibration standards in addition to penetration targets, and that infrastructure-specific deployment strategies must account for the amplifying role of diverge zone geometry on behavioral profile impacts.

Future research should pursue the following directions:

- Extending the simulation framework to multiple off-ramp geometries and geographic contexts to assess the generalizability of the instability threshold findings.
- Incorporating real traffic count data for simulation calibration to strengthen the empirical grounding of the results.
- Exploring dynamic AV behavioral adaptation strategies that adjust IDM parameters in real time in response to prevailing traffic conditions as a potential mitigation measure for the conservative AV paradox.

- Investigating the interaction between AV behavioral profiles and infrastructure modifications such as dedicated AV lanes, variable speed limit systems, and cooperative vehicle-infrastructure communication at freeway diverge zones.
- Extending the instability metric framework to include additional surrogate safety measures such as post-encroachment time and deceleration rate to avoid crashes, providing a more comprehensive characterization of traffic safety under mixed AV penetration scenarios.

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