Variations in Driver Behavior: An Analysis of Car-Following Behavior Heterogeneity as a Function of Road Type and Traffic Condition

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ABSTRACT

Microsimulation modeling is a tool used by practitioners and researchers to predict and evaluate the flow of traffic on real transportation networks. These models are used in practice to inform decisions and thus must reflect a high level of accuracy. Microsimulation models are comprised of sub-models, which control individual vehicle movements throughout the simulated network. These sub-models must be calibrated to accurately capture realistic driving behavior. This research utilizes data collected by the FHWA Living Laboratory instrumented research vehicle to produce evidence of global trends in car-following behavior. Unlike similar studies, this analysis focuses on the physical action taken by the driver—the acceleration—rather than the outcome of that action—speed selection or temporal/spatial gap. This approach enables better interpretation and comparison between car-following behavior in varying “driving environments”: that is, on different roadway functional classifications (freeway vs. interstate), operational conditions (work zone vs. non-work zone), and traffic conditions (congested vs. uncongested). This analysis produces conclusive evidence that intra-driver car-following behavior is heterogeneous and is a function of the driving environment. Trends in acceleration behavior are examined on an aggregated psychophysical plane, which accounts for inter-driver heterogeneity, and a statistical analysis identifies regions of significantly different acceleration behavior. Lastly, heterogeneity in car-following acceleration behavior in work zones and non-work zones was also verified.

Key Words: car-following, psychophysical, driver behavior, work zones, acceleration, intra-driver heterogeneity

1. INTRODUCTION

With the enactment of Moving Ahead for Progress in the 21st Century (MAP-21), there has been an increase in emphasis on performance-based planning and scenario development for federally funded transportation investments (*1*). Thus, the accuracy and robustness of modeling tools is of interest to transportation agencies, consultants, and researchers alike. Microsimulation software can be leveraged as a powerful tool in scenario analyses, as the outputs are an explicit representation of different characteristics of an individual driver. However, increased resolution of model output requires the modeler to ensure simulation accuracy in producing reasonable approximations of individual driver behavior. Outputs of these models are used to inform multimillion dollar investments in transportation, and thus the realism of the inputs and algorithms housed within a model are of upmost importance.

Several studies have shown that both intra-driver heterogeneity and inter-driver heterogeneity exist within microscopic data (*2*, *3*). Intra-driver heterogeneity describes the phenomenon where a driver exhibits inconsistent driving behavior when exposed to different driving environments. On the other hand, inter-driver heterogeneity describes the notion that different drivers exposed to the same driving environment may behave differently. Multiple studies have identified intra-driver heterogeneity when comparing driver behavior among different functional classifications (e.g., interstate v. freeway), operational conditions (e.g., work zone v. non-work zone segments), and traffic conditions (e.g., congested v. uncongested conditions); the combination of these conditions is defined as the *driving environment*.

Research into driver heterogeneity has focused on the consequence of a driver's action (e.g., headway or speed) instead of the action itself—the acceleration. Hence, many common methods used to evaluate driving behavior were not designed to highlight the nuances that exist in car-following behavior, which involves both human perception and relative behavior between a pair of vehicles. Therefore, this study utilizes the psychophysical car-following plane, which is the foundation of perception-reaction (action-point) car-following models, as a more appropriate method to analyze car-following behavior.

Using instrumented research vehicle (IRV) data from FHWA's Living Laboratory (*4*), this study provides qualitative and quantitative evidence that intra-driver differences in car-following acceleration behavior exists both (a) among distinctively different traffic conditions and (b) between different functional classifications and/or operational conditions holding traffic conditions constant. This evidence is illustrated and described using an innovative procedure for merging trajectories of multiple vehicles to identify global behavioral trends while accounting for inter-driver heterogeneity.

Due to the nature of the FHWA Living Laboratory IRV data, this study highlights key differences in driving behavior in work zone (WZ) and non-work zone (non-WZ) interstate segments. The insights of this research set the stage for building and calibrating new car-following models that will improve the accuracy and realism of the models, whose outputs inform important decisions and reporting metrics.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 details the data collection and post-processing methodologies. Section 4 highlights key results from the analysis. Section 5 summarizes conclusions and insights gleaned from the data.

2. LITERATURE REVIEW

There are three key areas of prior research that were used to build this analysis. Section 2.1 highlights the state of practice for intra-driver heterogeneity research. Future work will explore insights into inter-driver heterogeneity; however, for the purposes of this study, inter-driver heterogeneity is only accounted for in the aggregated psychophysical framework discussed in Section 3.3. Section 2.2 discusses the psychophysical car-following framework and the state phase (relative velocity (dV) – relative distance (dX)) plane of car-following behavior.

2.1 Intra-Driver Heterogeneity

It has long been established that roadway functional classification (e.g., interrupted flow vs. uninterrupted flow), operational conditions (including the presence of a work zone), and the onset of traffic congestion significantly impact operational performance (*5*, *6*). The last 20 years of research have been marked by efforts to better understand the presence and impacts of intra-driver differences attributable to varying conditions in the driving environment.

Al-Kaisey and Hall (*6*) examined loop detector data for six work zones (WZs), compiling over 72.5 hours of traffic data. They concluded that driver familiarity with a segment of roadway is correlated with following headway selection, and this strongly impacts the capacity and performance of the facility. Similar conclusions were made by Maze et al. (*7*) and Benekohal et al. (*8*).

In later research, Lochrane et al. quantified the differences in driving behavior between WZs/non-WZs and congested/uncongested conditions via microscopic IRV data (*9*). This study used mean time gap as the indirect measure of driver behavior. Results showed that 75% of participants increased their time gap while driving in WZs compared to non-WZs under congested conditions.

Distributions of headway have also been used to quantify the differences in driving behavior in WZs/non-WZs and congested/uncongested conditions. Dijker, Bovy, and Vermjis examined the differences in headway—segmented by vehicle type—on two Dutch freeways (*10*). Holding speed fixed, they found significant differences in headways between congested and uncongested conditions. The existence of different headways in congested and uncongested conditions is corroborated by Yin et al. (*11*). This research concluded that vehicle headways are best described by a lognormal distribution in uncongested conditions and a log-logistic distribution in congested conditions. This analysis was confirmed to be statistically significant using Kolmogorov-Smirnov tests. Brackstone et al. (*12*) found conflicting results; they concluded that the localized flow of traffic (congestion level) has negligible impact on headways.

Though analyses of indirect measures of driver behavior are heavily represented in literature, results are occasionally conflicting. Hence, analyzing driver behavior directly using acceleration—the driver's reaction—as presented in this paper, is hypothesized to be a more robust and reliable approach.

2.2 Psychophysical Car-Following Framework

Driving behavior has been analyzed using a variety of methods, including time-series trajectory analyses (e.g., vehicle speed, acceleration, steering angle) and behavioral profiles (e.g., probability distributions of vehicle speed, acceleration). While many of these mechanisms for evaluating driving behavior have been used to analyze car-following behavior, these studies measure the driver behavior differences using consequences of driver's action (headway or speed) instead of the direct behavior or action itself (acceleration or deceleration). Hence, they were not explicitly derived for capturing the nuances in car-following behavior.

In the early 1960s, Barbosa (*13*), Michaels (*14*), and Todosoiev (*15*) laid the foundation for the evaluation of relative driver behavior through the introduction of a psychophysical framework, which identifies driver actions and reactions relative to the perceived and detectable behavior of a lead vehicle. The psychophysical car-following framework seeks to explain the natural oscillations in car-following behavior attributed to the limits of human perception. The cornerstone of psychophysical models can be summarized in a car-following phase plane (in the $dV - dX$ plane). The segmentation of this plane into regimes of reaction and no reaction is a function of driver “action” points, defined as points where a driver makes a change in their behavior because of perceived changes in behavior of the leading vehicle. Drivers can react to changes in relative distance (the spatial gap) and relative velocity once perception thresholds are reached. Each of the regimes within a psychophysical framework are defined under different psychological driving assumptions and represent distinctly different driver behavior (e.g., approaching, separating, no reaction) (*16*). FIGURE 1 describes subconscious car-following behavior on a psychophysical plane with relative velocity on the x-axis and relative distance on the y-axis. Subconscious car-following behavior produces a spiral in this plane, where a driver continuously perceives their relative velocity and following distance with respect to the lead vehicle, and reacts accordingly by accelerating or decelerating (see FIGURE 1). Psychophysical representations of car-following trends enable the detailed analysis and evaluation of high resolution trajectory-level data, such as the FHWA Living Laboratory IRV data. According to (*17*), of all car-following paradigms, psychophysical models are “the most coherent and best able to describe most of the features that we see in everyday driving behavior” (pg. 191). For this reason, the psychophysical car-following framework was determined to be the most appropriate tool to explore the acceleration trends in the car-following data.

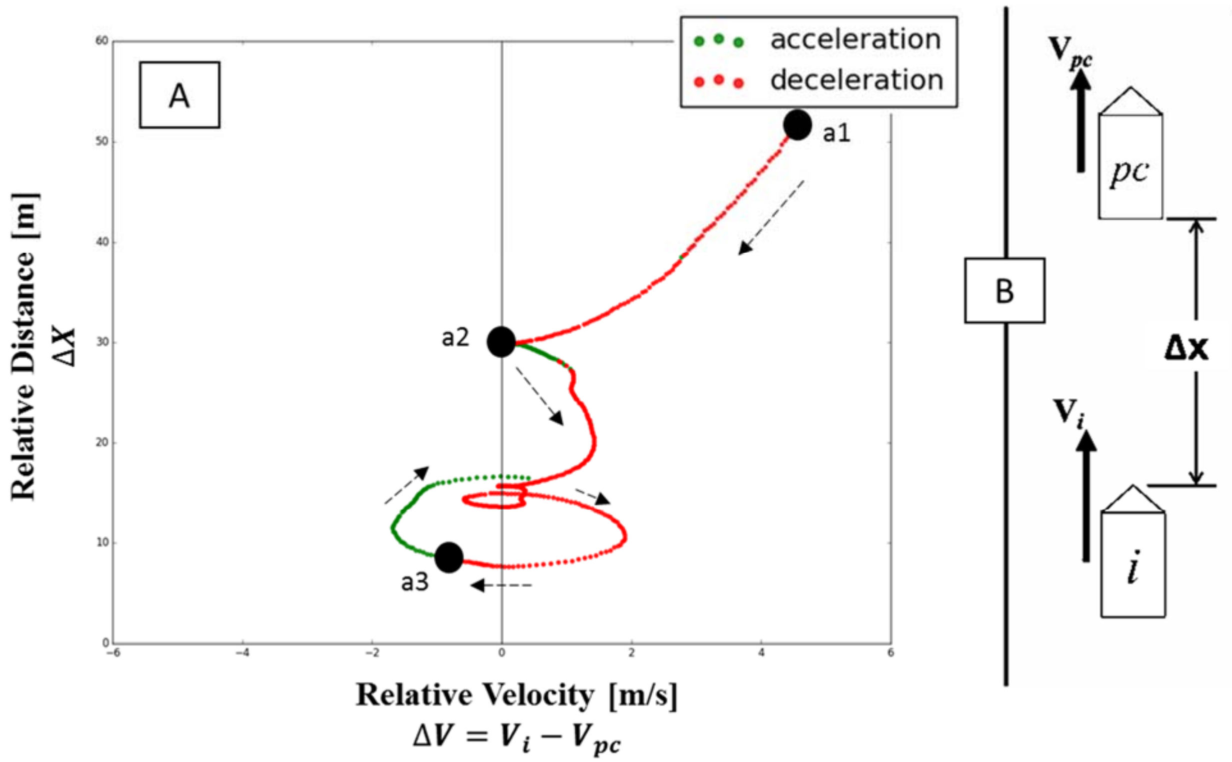

FIGURE 1 Spiral trend observed in a car-following event. (A) Plot A shows a car-following spiral and provides indication of vehicle acceleration (green) and deceleration (red). Starting from "a1", progressing through the event, the following vehicle is traveling faster than the lead vehicle; thus, deceleration behavior is observed until the driver begins traveling the same speed. At "a2" the following vehicle begins to accelerate—once again gaining on the lead vehicle—thus, quickly begins decelerating until reaching "a3" where the following vehicle is traveling slower than the lead vehicle and accelerates to catch up. (B) Plot B defines the physical relationship between the relative distance and relative velocity.

3. METHODOLOGY

This research was completed using the FHWA Living Laboratory IRV data, which provides a unique opportunity to explore driving behavior in various driving environments (*4*). This section briefly describes the data collection system, the data processing protocol, the procedure used to extract car-following events and match them with other car-following events occurring in similar driving environments, and the analytical approach used to evaluate groupings of heterogeneous driving behavior.

3.1 Data Collection: Living Laboratory

Many data collection strategies aiming to quantify intra-driver behavior heterogeneity relative to variations in the driving environment have been developed. Fitzpatrick (*18*) identified existing methods of data collection and detailed each of their strengths and weaknesses. Detailed data is typically collected using either traditional fixed sensors (e.g., pneumatic tubes with automated traffic recorders, RADAR/LiDAR speed guns, and inductive loops) or probe sensors via vehicle instrumentation. The latter are also referred to as IRVs.

This study makes use of the FHWA Living Laboratory IRV data. IRV studies enable the collection of microscopic, trajectory-level information that can better describe driver actions and reactions to their environment—as opposed to the consequence of their actions. IRV studies allow researchers to collect information pertaining to the driving environment (e.g., radar, video) as well as high resolution vehicle data (e.g., acceleration, speed, steering angle).

In 2013, a sport utility vehicle was equipped with the necessary on-board equipment for trajectory-level data collection: two universal medium range radars (UMRR) for the collection of relative velocity and position of adjacent vehicles at 40Hz, a GPS-based speed sensor to collect and record the IRV's speed at 10Hz, a 30 frames per second video recording system, and a computer for data acquisition. For details on equipment specs, please reference (*4*).

As part of this study, a total of 66 participants drove along a pre-defined route, approximately 50 miles in length, during peak hour and clear weather conditions on a weekday. Four interstate WZs were located along the route: two with a lane closure and two without. Of the 66 participants, trip files from 62 drivers were used in this analysis.

3.2 Data Processing

The 62 trip files were processed to extract car-following events and define the conditions under which each car-following event occurred. Car-following events were then sorted and aggregated by similarities in the driving environment to create frameworks.

Car-Following Events

Car-following events were manually identified, classified, and extracted using video and radar data from the 62 trip files. To ensure all extracted car-following events were long enough to illustrate continuity in car-following behavior, a minimum length of continuous car-following was defined to be 10 seconds. In addition, 80 meters was selected as the maximum relative distance between a lead and following vehicle to consider the actions relevant for car-following. After car-following event start and stop timestamps were recorded, the radar and GPS data were compiled and filtered to produce 62 processed driver books; the processed driver books summarize each car-following event experienced during a trip. Additional post-processing was required to remove inherent noise from the radar data.

Compiling Car-Following Events into Frameworks

In addition to identifying the start and stop timestamps for car-following events, video observers recorded details related to the driving environment for each car-following event: functional classification (freeway v. interstate), operational condition (WZ v. non-WZ), work zone type (lane closure v. shoulder closure), and traffic condition (uncongested v. congested conditions). Congested and uncongested conditions were defined as a speed reduction caused by surrounding vehicles: below 35mph in non-WZs or 25mph in WZs. The local congestion levels were verified in manual video observation of each trip. The driving conditions for each framework are shown in

TABLE 1.

TABLE 1: Driving Environment Defined for each Framework

Framework #	Functional Classification	Operational Condition	Traffic Condition
1	Freeway (2 lane divided)	Non-WZ	C
2	Freeway (2 lane divided)	Non-WZ	U
3	Interstate (IS)	Non-WZ	C
4	Interstate (IS)	Non-WZ	U
5	Interstate: Advanced Warning (AW)	WZ	C
6	Interstate: Advanced Warning (AW)	WZ	U
7	Interstate: Taper Zone (TZ)	WZ	C
8	Interstate: Taper Zone (TZ)	WZ	U
9	Interstate: Work Zone (WZ1) (with lane closure)	WZ	C
10	Interstate: Work Zone (WZ1) (with lane closure)	WZ	U
11	Interstate: Work Zone (WZ2) (with shoulder closure)	WZ	C
12	Interstate: Work Zone (WZ2) (with shoulder closure)	WZ	U

Aggregate Representation of Car-Following Behavior

The limitation of many studies investigating trajectory-level car-following behavior is that they often limit evaluation to an individual driver or a small population of drivers, which doesn't enable the identification of collective behavioral tendencies. Generally, car-following behavior on a psychophysical plane represents a single car-following event, as shown in FIGURE 2A; however, when considering hundreds of car-following events for a single framework, this representation becomes difficult to interpret, as shown in FIGURE 2B.

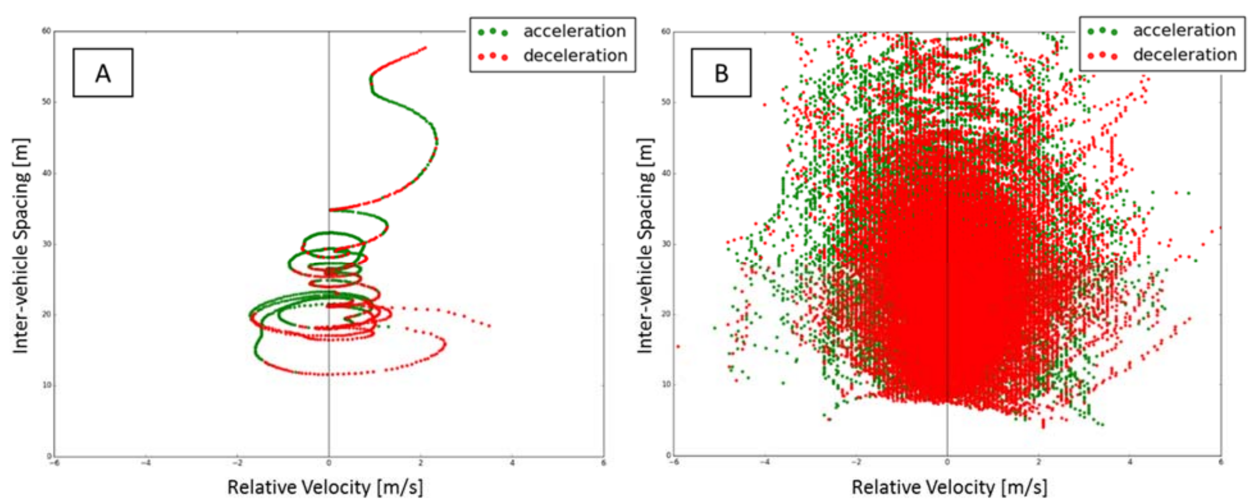

FIGURE 2 Car-following behavior on a psychophysical plane. (A) Plot A represents a single car-following event, where a distinct spiral of driver reaction can be identified. (B) Plot B represents the combination of all car-following events for framework 2, where trends cannot be identified.

3.3 Data Analysis

This study introduces an approach to account for inter-driver heterogeneity inherent in a large group of drivers, leveraging the psychophysical $dV - dX$ car-following plane. This study partitions the $dV - dX$ space into a grid, creating the individual bins shown in FIGURE 3A. Every car-following point that falls within the bounds of a bin is summarized as the "contents" of that bin; example summary statistics include the frequency of points and the standard deviation of point values. In this analysis, each bin represents the average acceleration of all points within the bin. To ensure regions of the $dV - dX$ plane with limited data or significant outliers do not skew results, minimum frequency requirements (i.e., a minimum number of data points required for each bin) and a maximum standard deviation of acceleration points within each bin were established. If a bin failed either criterion, the bin was removed from the analysis and null values were reported.

The data analysis for this study takes both qualitative and quantitative forms. Visual evidence of acceleration behavioral trends is illustrated via aggregated acceleration car-following plots, which are described in FIGURE 3A. While visual trends produced substantial evidence of acceleration behavioral differences, two-tailed paired T-tests were used to compare "regions" of acceleration behavior between framework pairs to determine if a statistically significant difference (at a 95% confidence level) exists. The regions were selected to represent conceivable areas of car-following behavior: segmented into regions of standard car lengths (6m) from the lead vehicle for the relative distance increments and 2m/s (4.5mph) relative velocity increments, as shown in FIGURE 3B.

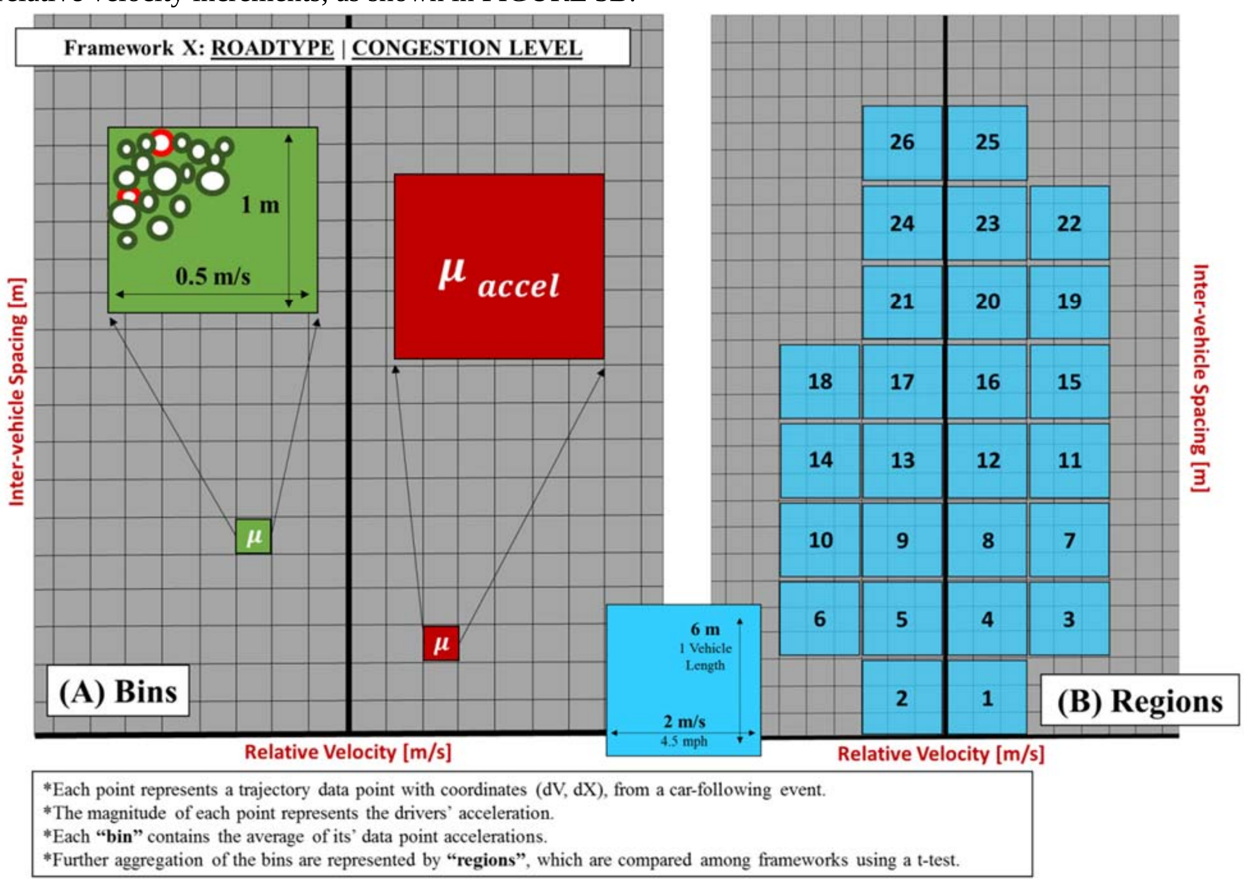

FIGURE 3 Description of "bins" and "regions" on the psychophysical plane used for data analysis. (A) Each square within the grid represents a bin and contains data points with characteristics (i.e., acceleration). The bins are summarized by taking the mean of the acceleration of all included points. Bins highlighted in red

indicate a negative average acceleration (deceleration), while bins highlighted in green indicate a positive average acceleration. (B) Regions represent groups of bins that are used in the statistical analysis to identify significant differences in driver behavior between frameworks.

4. RESULTS

An analysis of the observed acceleration behaviors was conducted on two levels: (i) holding level of congestion constant and (ii) holding functional classification/operational condition constant. First, driving behavior observed on each roadway functional classification (i.e., interstate, freeway) was compared in congested conditions. Then, driver behavior on interstates under different operational conditions was compared in congested conditions. Variation in operational conditions, that is presence of a work zone, was not observed for the freeway functional classification. Lastly, the observed driving behavior on a roadway with a specific functional classification and operational condition is compared under congested and uncongested conditions. The acceleration behavior is compared qualitatively—to visually identify and describe prevalent trends—and quantitatively via two-tailed paired t-tests—to identify regions where statistically significant differences in acceleration behavior exists.

4.1 Driver Behavior by Road Type

As described in the literature review, many studies have shown intra-driver heterogeneity among different functional classifications and operational conditions. FIGURE 4 represents the aggregated car-following acceleration behavior for all 62 drivers divided into "frameworks", which are combinations of the driving environment—as described in Table 1—in congested conditions. Positive acceleration trends are denoted on a green color scale and deceleration is represented on a red color scale. Bins with data points of no acceleration—that is, data points with acceleration equal to 0m/s—are shown in white. TABLE 2 provides the t-test results, as described in Section 3.3, to compare the different functional classifications and operational conditions in congested conditions.

TABLE 2 T-Test Comparison for Different Functional Classifications and Operational Conditions

Region Location and Number		FW1 v. FW3	FW3 v. FW5	FW3 v. FW7	FW3 v. FW9	FW3 v. FW11	FW5 v. FW7	FW5 v. FW9	FW5 v. FW11	FW7 v. FW9	FW7 v. FW11	FW9 v. FW11
7-8 Car-Lengths | 0-4.5mph Slower	26				0.935							
7-8 Car-Lengths | 0-4.5mph Faster	25	0.917			0.047							
6-7 Car-Lengths | 4.5-9mph Slower	24	0.003			0.015							
6-7 Car-Lengths | 0-4.5mph Slower	23	0.000	0.407	0.000	0.186	0.210	0.001	0.659	0.368	0.000	0.000	0.754
6-7 Car-Lengths | 0-4.5mph Faster	22	0.702	0.935		0.152	0.010		0.008	0.000			0.002
5-6 Car-Lengths | 4.5-9mph Slower	21	0.035		0.798	0.088					0.041		
5-6 Car-Lengths | 0-4.5mph Slower	20	0.001	0.241	0.722	0.003	0.266	0.320	0.009	0.771	0.039	0.319	0.004
5-6 Car-Lengths | 0-4.5mph Faster	19	0.975	0.388	0.003	0.064	0.016	0.025	0.075	0.189	0.094	0.016	0.027
4-5 Car-Lengths | 4.5-9mph Slower	18	0.023	0.003	0.097	0.010	0.229	0.225	0.095	0.111	0.562	0.000	0.245
4-5 Car-Lengths | 0-4.5mph Slower	17	0.369	0.066	0.051	0.138	0.001	0.007	0.018	0.000	0.892	0.170	0.220
4-5 Car-Lengths | 0-4.5mph Faster	16	0.100	0.821	0.011	0.054	0.353	0.350	0.117	0.365	0.916	0.431	0.055
4-5 Car-Lengths | 4.5-9mph Faster	15	0.027		0.068								
3-4 Car-Lengths | 4.5-9mph Slower	14	0.114	0.017	0.001	0.146	0.132	0.003	0.018	0.805	0.096	0.039	0.116
3-4 Car-Lengths | 0-4.5mph Slower	13	0.000	0.331	0.141	0.464	0.001	0.348	0.187	0.011	0.100	0.030	0.039
3-4 Car-Lengths | 0-4.5mph Faster	12	0.084	0.868	0.040	0.394	0.045	0.091	0.580	0.046	0.052	0.011	0.024
3-4 Car-Lengths | 4.5-9mph Faster	11	0.003	0.354									
2-3 Car-Lengths | 4.5-9mph Slower	10	0.004	0.243	0.754	0.136	0.329	0.309	0.004	0.719	0.567	0.432	0.066
2-3 Car-Lengths | 0-4.5mph Slower	9	0.036	0.129	0.000	0.008	0.004	0.006	0.233	0.048	0.044	0.410	0.245
2-3 Car-Lengths | 0-4.5mph Faster	8	0.000	0.685	0.000	0.494	0.351	0.000	0.710	0.275	0.005	0.000	0.269
2-3 Car-Lengths | 4.5-9mph Faster	7	0.313	0.554									
1-2 Car-Lengths | 4.5-9mph Slower	6	0.039	0.275	0.889	0.042	0.918	0.663	0.002		0.302		
1-2 Car-Lengths | 0-4.5mph Slower	5	0.307	0.249	0.712	0.729	0.009	0.880	0.518	0.473	0.856	0.705	0.757
1-2 Car-Lengths | 0-4.5mph Faster	4	0.016	0.225	0.558	0.005	0.023	0.629	0.000	0.001	0.003	0.006	0.928
1-2 Car-Lengths | 4.5-9mph Faster	3	0.113	0.033									
0-1 Car-Lengths | 0-4.5mph Slower	2	0.006	0.042									
0-1 Car-Lengths | 0-4.5mph Faster	1	0.052	0.481	0.213	0.774		0.056	0.341	0.001	0.400	0.630	0.082

* # Car Lengths (6m) from lead vehicle | # mph speed difference between the lead and following vehicle.

** Results of a Two-Tailed, Paired T-Test. Cells indicate P-Value. At Alpha = 0.05 (95% confidence level)

*** Highlighted cells indicate a significant difference exists between the mean accelerations in that region.

**** Blank cells & regions not included on the table indicate insufficient data to complete analysis

In each framework (FW), acceleration in the upper region of the $dV - dX$ plot—indicative of larger relative distances between vehicles—is of lighter color, which indicates a lower magnitude of acceleration or deceleration. This behavior is expected because as the separation distance between vehicles increases, the perceived necessity to react, due to the lead vehicle's presence, is smaller. The white, or the "no-reaction" zone, indicates locations on the $dV - dX$ plane where drivers are not reacting to the lead vehicle.

Each framework in FIGURE 4 shows a clear diagonal originating on the plane where relative distance is small and relative velocity is positive (which indicates that the following vehicle is traveling faster than the lead vehicle), and moves towards a larger relative distance and a more positive relative velocity. The most prominent trend is seen in the congested advanced warning framework (FIGURE 4C), which extends out to a relative velocity of 5.5m/s at a following distance of 14m (just over two standard car lengths). This diagonal deceleration trend illustrates the following drivers' recognition of their speed differential and their consequent deceleration action taken to avoid a collision.

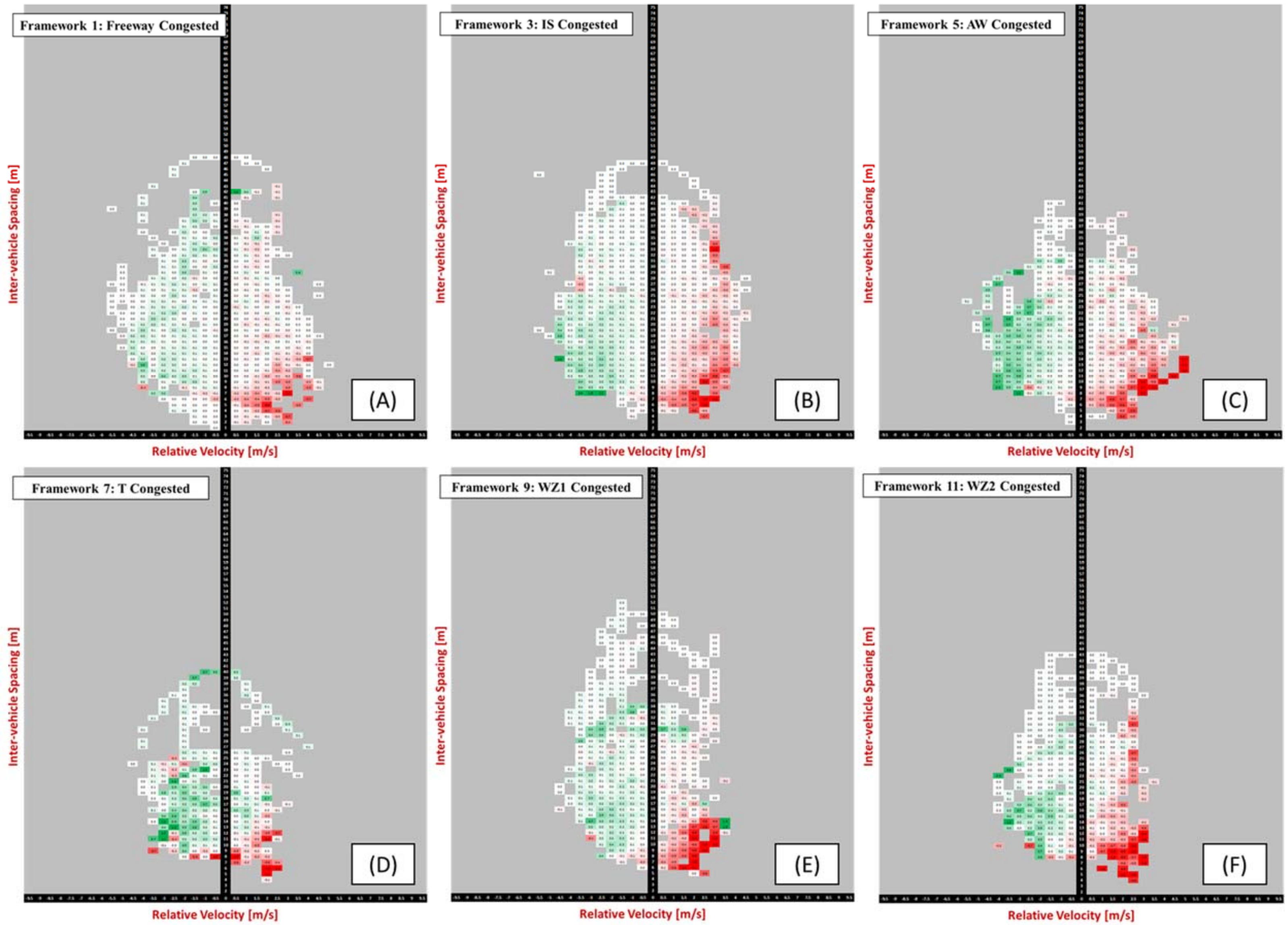

FIGURE 4 Aggregated car-following acceleration behavior on a psychophysical plane, representing each functional classification and operational condition in congested traffic conditions.

The "cleanest" spirals are detected in the interstate framework (FIGURE 4B), where areas of deceleration are seen sweeping from the top (larger values of dX) along the exterior of the observed data in the region of positive relative velocity. The spiral trend then continues from the bottom (smaller values of dX) with heavier acceleration propagating along the exterior of the observed data in the region of negative relative velocity (where lead vehicle is traveling faster than following vehicle). Equivalently clean spirals are not detected in freeway conditions. Statistical analysis between FW1 and FW2, as provided in TABLE 2, supports this observation showing 12 of the 21 regions had significant differences in acceleration behavior. The clearly defined spiral acceleration trend observed in interstate conditions is likely due to the nature of uninterrupted flow facilities.

Another interesting trend is observed in the congested advanced warning framework (FIGURE 4C) and the congested taper zone framework (FIGURE 4D). Strong acceleration patterns are prevalent at greater following distances, indicating drivers of the following vehicles began to accelerate (to close the gap between themselves and their lead vehicle) more often than in other congested interstate operational conditions. This is supported by TABLE 2 (FW3 v. FW5), which indicates a statistically significant difference in interstate and advanced warning acceleration behavior in regions 13, 14, 17, and 18. This phenomenon can be attributed to drivers' recognition of the WZ advanced warning and their desire to decrease following distance, likely in anticipation of reduced speeds and in expectation that other drivers may begin to change lanes due to an upstream lane or shoulder closure, or other characteristics of driving in a WZ.

The least populated frameworks are the interstate taper zones (FW7 and FW8). FIGURE 4D (FW7)—interstate taper zone in uncongested conditions—is shown to have a substantially larger acceleration trend, stretching into the space where relative velocity is positive at smaller following distances. A significantly smaller deceleration trend is also evident. This is supported by TABLE 2, where significantly different acceleration behavior is observed in regions 8, 12, and 16 of the $dV - dX$ plane when comparing the interstate taper zone and non-WZ interstate frameworks (FW3 and FW7). This behavior is likely due to previously reduced speeds resulting from advanced warning signage as drivers approach the taper zone; therefore, less deceleration is required and drivers begin to accelerate after passing through the merging/diverging taper zone.

Deceleration behavior within both WZ frameworks (FIGURE 4E&F) is noticeably stronger at smaller relative velocities, compared with behavior in the other frameworks. This is supported in TABLE 2, as both WZ frameworks (FW9 and FW11) have statistically significant differences in deceleration rates when compared against non-WZ interstate driving (FW3) in region 4 of the $dV - dX$ plane. This indicates that drivers react more quickly to perceived velocity "gains" on the lead vehicle while in the WZ.

When comparing WZ 1 (FIGURE 4D, i.e. WZ with a lane closure) and WZ 2 (FIGURE 4E, i.e. WZ with a shoulder closure), a difference in acceleration magnitude and location is observable. In WZ 2, acceleration behavior is stronger on the outer boundary of the acceleration bins, but propagates inward at lower following distances; comparatively, strong acceleration is less frequently detected in WZ 1. This reduction in strong acceleration behavior in WZ 1 is likely attributable to a decrease in drivers' urgency to maintain their following distance. Practically speaking, when there's a work zone with a lane closure, there is no parallel traffic in a neighboring lane; therefore, no opportunity to pass a slower moving vehicle and reduced probability of being cut off by an aggressive driver.

A similar comparison of acceleration behavior on different road types in uncongested conditions is not presented here as the trends are much less prevalent as shown in the following section.

4.2 Driver Behavior by Congestion Level

As part of this study, car-following events were split into two traffic condition categories: congested and uncongested. This section identifies trends in driver acceleration behavior between these traffic conditions and presents statistically significant evidence of acceleration differences in congested and uncongested conditions for regions within the $dV - dX$ plane for each roadway functional classification and operational condition. TABLE 3 provides the t-test results, as described in Section 3.3, to compare the same functional classification and operational condition in congested and uncongested conditions.

TABLE 3 T-Test Comparison of Functional Classifications and Operational Conditions in Congested and Uncongested Conditions

Region Location & Number		FW1 v. FW2	FW3 v. FW4	FW5 v. FW6	FW7 v. FW8	FW9 v. FW10	FW11 v. FW12
7-8 Car-Lengths | 0-4.5mph Slower	26		0.937			0.844	
7-8 Car-Lengths | 0-4.5mph Faster	25	0.985	0.374			0.058	
6-7 Car-Lengths | 4.5-9mph Slower	24	0.481	0.003			0.027	
6-7 Car-Lengths | 0-4.5mph Slower	23	0.000	0.067	0.910		0.981	0.236
6-7 Car-Lengths | 0-4.5mph Faster	22	0.000	0.010	0.774		0.130	0.990
5-6 Car-Lengths | 4.5-9mph Slower	21	0.101	0.117			0.004	
5-6 Car-Lengths | 0-4.5mph Slower	20	0.000	0.325	0.289		0.006	0.000
5-6 Car-Lengths | 0-4.5mph Faster	19	0.351	0.659	0.002		0.022	0.250
4-5 Car-Lengths | 4.5-9mph Slower	18	0.599	0.035	0.057		0.411	0.243
4-5 Car-Lengths | 0-4.5mph Slower	17	0.109	0.321	0.557	0.001	0.263	0.001
4-5 Car-Lengths | 0-4.5mph Faster	16	0.117	0.467	0.762		0.462	0.954
4-5 Car-Lengths | 4.5-9mph Faster	15	0.031	0.376				
3-4 Car-Lengths | 4.5-9mph Slower	14	0.054	0.000			0.801	0.108
3-4 Car-Lengths | 0-4.5mph Slower	13	0.075	0.000	0.003	0.041	0.033	0.302
3-4 Car-Lengths | 0-4.5mph Faster	12	0.027	0.044	0.733	0.969	0.588	0.001
3-4 Car-Lengths | 4.5-9mph Faster	11	0.051	0.065	0.296			
2-3 Car-Lengths | 4.5-9mph Slower	10	0.650	0.240			0.020	
2-3 Car-Lengths | 0-4.5mph Slower	9	0.000	0.000	0.006	0.003	0.193	0.000
2-3 Car-Lengths | 0-4.5mph Faster	8	0.000	0.633	0.003		0.174	0.000
2-3 Car-Lengths | 4.5-9mph Faster	7	0.148	0.094				
1-2 Car-Lengths | 4.5-9mph Slower	6	0.173	0.119				
1-2 Car-Lengths | 0-4.5mph Slower	5	0.002	0.001	0.003		0.206	0.023
1-2 Car-Lengths | 0-4.5mph Faster	4	0.194	0.488	0.062		0.789	0.036
1-2 Car-Lengths | 4.5-9mph Faster	3	0.027	0.005				
0-1 Car-Lengths | 0-4.5mph Slower	2		0.197				
0-1 Car-Lengths | 0-4.5mph Faster	1	0.887	0.061				

* # Car Lengths (6m) from lead vehicle | # mph speed difference between the lead and following vehicle.
** Results of a Two-Tailed, Paired T-Test. Cells indicate P-Value. At Alpha = 0.05 (95% confidence level)
*** Highlighted cells indicate a significant difference exists between the mean accelerations in that region.
**** Blank cells & regions not included on the table indicate insufficient data to complete analysis

FIGURE 5 illustrates the aggregated acceleration behavior for freeway (FW1 and FW2) and interstate (FW3 and FW4) car-following events in congested and uncongested conditions, for each functional classification.

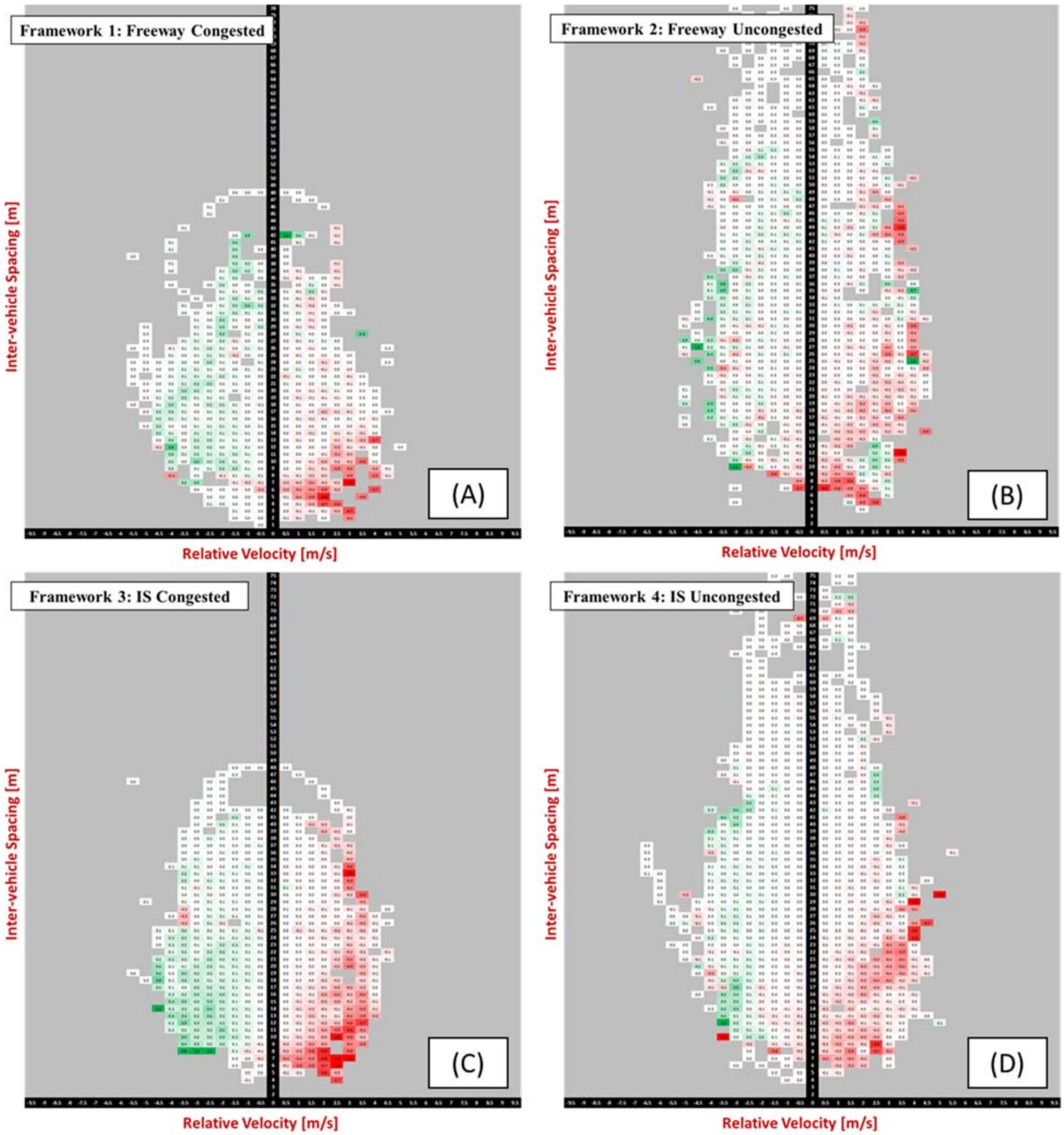

FIGURE 5 Aggregated car-following behavior acceleration behavior on a psychophysical plane, representing frameworks 1-4: freeway and interstate, congested and uncongested conditions.

Initial inspection of FIGURE 5 indicates a distinct difference in trend clarity between freeway and interstate driving. Similar to the finding discussed in the previous section, both congested and uncongested interstate frameworks (FIGURE 5C&D) are cleaner—illustrating more prevalent spiral trends—than their corresponding frameworks in freeway conditions (FIGURE 5A&B).

Uncongested conditions are substantially more dispersed over the $dV - dX$ plane resulting in the generation of acceleration bins extending to the cut-off following distance of 80m in both freeway and interstate uncongested conditions (FIGURE 5B&D). Using the video data as corroborating ground truth, this trend can be attributed to the fact that drivers prefer much shorter gaps between themselves and their leading vehicle in congested conditions—likely a byproduct of a reduced gap at lower travel speeds, as well as an attempt to avoid cut-in behavior by more aggressive drivers in adjacent lanes.

The uncongested freeway framework (FIGURE 5B) illustrates substantially more dispersed acceleration behavior, with few clear discernable trends, when compared to the congested freeway framework (FIGURE 5A). This finding is supported by results in TABLE 3 (FW1 v. FW2), which indicate statistically significant differences in acceleration behavior in regions 8 and 9 of the $dV - dX$ plane. Similarly, the uncongested interstate framework (FIGURE 5D) does not replicate the clear, succinct trends found in the congested interstate framework (FIGURE 5C, FW3 vs. FW4).

This decrease in discernable trends is anticipated for uncongested conditions because drivers' desired acceleration is less likely to be restricted by surrounding traffic and a lead vehicle. When approaching a lead vehicle, drivers are more likely to have an opportunity to overtake the leading vehicle, without making large behavioral adjustments; therefore, car-following spirals are less prominent.

Similarly, FIGURE 6 illustrates the aggregated acceleration behavior for WZ1 and WZ2 in congested and uncongested conditions. The most apparent distinction between uncongested WZ1 (FIGURE 6B) and uncongested WZ2 (FIGURE 6D) is that no acceleration behavior is observed beyond a 50m separation distance for WZ1. Thus, uncongested WZs with a lane closure share acceleration behavioral characteristics with different roadway types and operational conditions experiencing congested conditions; this is in direct contrast to all other frameworks in uncongested conditions, which have data reaching the 80m cutoff. This finding is also shown in TABLE 3, where only 32% of regions on the *dV—dX* plane indicate significant differences between WZ1 congested and uncongested conditions. Comparatively, 50% of regions indicate significant differences between congested and uncongested conditions in WZ2. This difference can be directly attributed to the lane closure in WZ1, which shifts driver behavioral tendencies to more closely match those in congested conditions; in essence, this is forcing drivers to react in response to their perception of the lead vehicle without the option to overtake the lead vehicle, which results in more consolidated driving behavior and the production of more car-following spirals. Conversely, the uncongested WZ2 behavior closely reflects the behavior seen in uncongested freeway and interstate conditions (FIGURE 5B&D).

Heavy deceleration when relative velocity is negative in both WZ1 and WZ2 uncongested conditions (FIGURE 6B&D) can be attributed to other roadway factors within the WZ that cause drivers to decelerate, even when the lead vehicle is not an imminent threat. A few of these deceleration bins can be identified in congested conditions (FIGURE 6A&C); however, the reduced frequency in their appearance is likely due to the reduced speeds attributed to congested conditions and the consistency of behavioral adjustments relative to the lead vehicle. Statistical evidence of this observation is prevalent when comparing congested and uncongested conditions in WZ2. Results in TABLE 3 (FW11 vs. FW 12) indicate that significant differences in acceleration behavior are prevalent for regions 5 and 9.

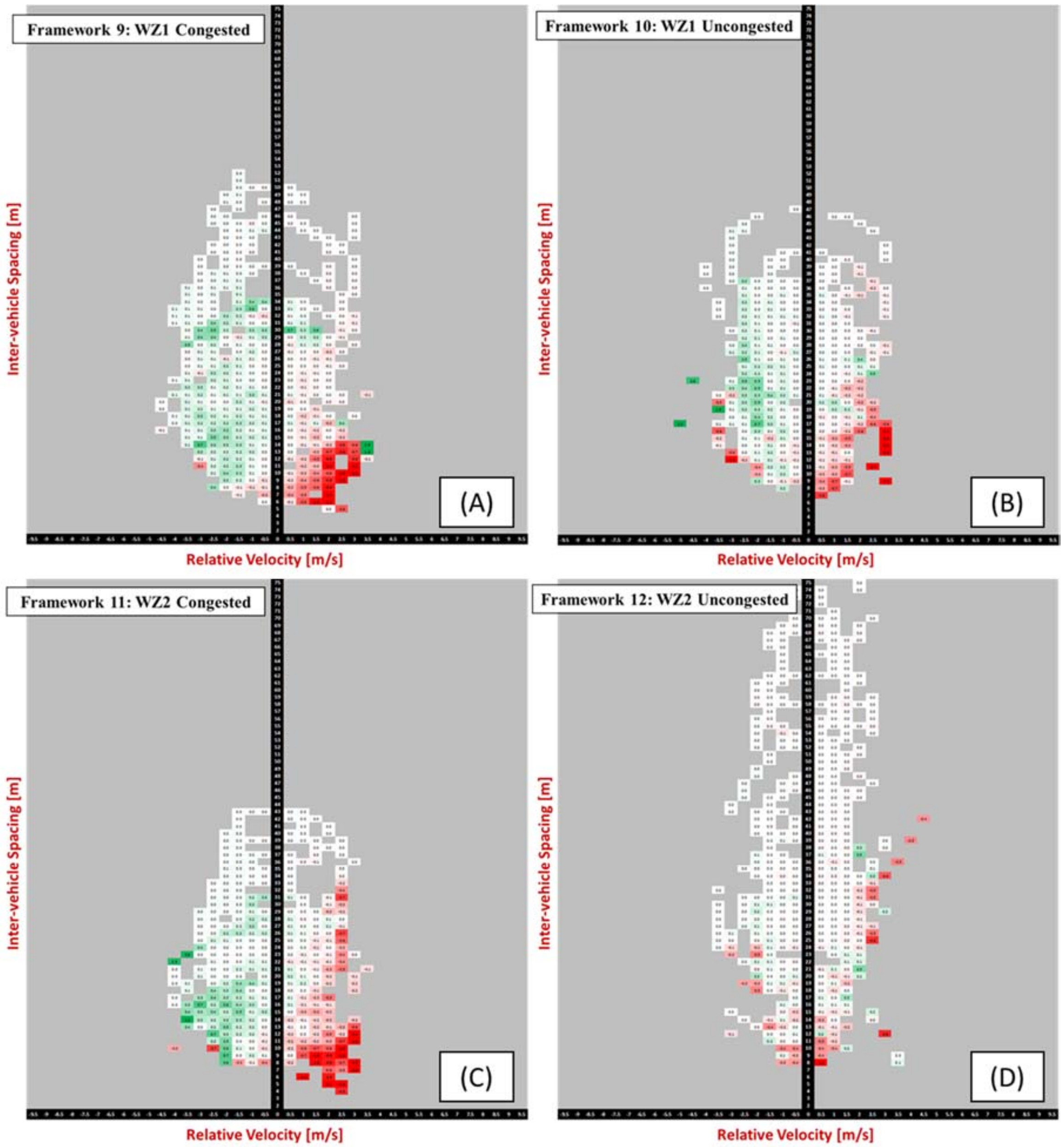

FIGURE 6 Aggregated car-following acceleration behavior on a psychophysical plane, representing frameworks 9-12: work zone with lane closure and work zone without lane closure, congested and uncongested conditions.

Acceleration behavior trends in congested and uncongested conditions for advanced warning zones are similar to the previously stated findings: uncongested conditions show significantly fewer trends than those in congested conditions. While a visual is not provided, this finding is indicated in TABLE 3 (FW5 and FW6), where the statistical analysis shows that significant differences in regions 5, 8, 9, 13, and 19 exist at a 99% confidence level. Acceleration trends in the taper zone are less notable in this study, as sufficient data for uncongested taper zones was not available in the data.

4.3 Result Summary

The qualitative and quantitative analysis presented in this section provides evidence of heterogeneity in driving behavior as a function of various driving environments. Car-following behavior for different roadway functional classifications and operational conditions with congested traffic conditions were compared, as congested traffic conditions proved to illustrate the clearest car-following trends. The analysis showed that non-WZ interstate conditions are the cleanest, with the most discernable car-following spirals, while acceleration behavior in taper zones is the most sporadic. Strong acceleration trends were identified in WZ frameworks, indicating drivers' motivation to maintain a closer following distance, especially in the advanced warning zone. The results identified regions within the psychophysical plane where driving behavior is significantly different between WZ types and differing levels of congestion. For this analysis, congestion was considered a binary variable, congested or uncongested; however, future analyses will further examine the impact of surrounding traffic conditions at a higher resolution, as studies have shown heterogeneity in desired time gap in differing levels of congestion (*19*).

5. CONCLUSIONS AND RECOMMENDATIONS

Given the necessity of microsimulation models to optimally evaluate investment decisions, the accuracy of microsimulation models in depicting traffic conditions is of upmost importance. The precision of a microsimulation model reflects the accuracy of each embedded sub-model, including car-following models. To achieve this accuracy, car-following models must be calibrated using appropriate and high-quality data sources.

This research presents conclusive evidence—generated from a robust, trajectory-level dataset—that drivers' car-following actions are different while traveling in different driving environments (intra-driver heterogeneity). This finding is presented in an innovative manner, which aggregates car-following acceleration behavior from 62 drivers participating in the 2013 FHWA Living Laboratory IRV study, to account for inter-driver heterogeneity and enable the identification and calibration of global trends in driver behavior.

The findings serve as the foundation for continued research into the development of predictive car-following and driver behavior models capable of representing heterogeneous intra-driving behavior in various driving environments. Current and future research is focused on developing the global trends portrayed in this paper to calibrate the FHWA Driver Model car-following framework.

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