Freeway Guide Sign Performance at Complex Interchanges: Reducing Information Overload

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FOREWORD

The authors conducted this research under transportation pooled fund study TPF-5(361): *SHRP 2 Naturalistic Driving Study Pooled Fund: Advancing Implementable Solutions*, whose goal is to develop novel, multidisciplinary solutions based on recorded natural behavior of vehicle operators interacting with infrastructure and other vehicles. Complex freeway interchanges can be difficult to navigate and may require multiple navigation decisions within a limited time. A sign design issue sometimes seen on urban freeways is the use of complex guide signs. In such cases, the signs give a large amount of information to drivers within a short period of time, possibly resulting in information overload that may lead to unsafe maneuvers. The 2009 *Manual on Uniform Traffic Control Devices* (MUTCD) recognizes the importance of avoiding traffic information overload in the design and installation of traffic signs and control devices. However, MUTCD provides limited information for guide sign design at complex freeway interchanges.(1)

The authors analyzed SHRP2 naturalistic driving study data to better understand correlations between driver behaviors relevant to safety and freeway guide signs at interchange areas. Agencies develop sign complexity thresholds for freeway interchange areas to ensure driver safety and make associated recommendations for practitioners. Based on observations that sign complexity affects drivers unfamiliar with an interchange much more than it does familiar drivers, the research study identified considerations for guide sign design. The research may be of interest to roadway designers, safety professionals, and others with an interest in the mitigation of disruptions to vehicle flow through complex freeway interchanges.

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16. Abstract
Complex freeway interchanges are difficult to navigate in many cases. Poorly designed signs at such locations, along with contributing roadway and traffic factors, frequently lead to increased crash risks. A sign design issue typically seen on urban freeways is the use of complex guide signs. The 2009 *Manual on Uniform Traffic Control Devices* sets forth the minimum standards for guide sign design.(1) Though the manual identifies the issue of information overload on signs and the need to spread out information on a sign, it lacks detailed provisions on how to design signs and how to space signing to rectify the issue, including a way to identify the maximum amount of information to provide on freeway guide signs at any one location. During this project, the research team analyzed a large set of the Second Strategic Highway Research Program Naturalistic Driving Study data in an effort to learn the correlations between driver behaviors relevant to safety and freeway guide signs at interchange areas.(2) Based on the correlations, the research team developed sign complexity thresholds at freeway interchange areas to ensure driver safety. The primary sign complexity variable, "Number of Words on Subject Sign," significantly correlated with a large number of driver behavior variables at the analysis segments. Overall, the sign complexity models showed that sign complexity negatively affected drivers unfamiliar with an interchange much more than it did familiar drivers. Based on the research findings, the research team suggests that a guide sign not contain more than nine words when used for right ramps requiring at least one lane change for exiting traffic to be in the correct exit lane. In addition, the research team suggests that a guide sign not contain more than 10 words for right ramps requiring no lane changes for exiting traffic already in the rightmost lane to be in the correct exit lane. The report also includes a large number of other relevant suggestions that could potentially improve the sign design process for safer freeways.

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or “metric ton”)	Mg (or “t”)
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or “t”)	megagrams (or “metric ton”)	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway Transportation Officials
ADT	average daily traffic
CAV	connected and automated vehicle
FHWA	Federal Highway Administration
GPS	Global Positioning System
HOV	high-occupancy-vehicle
HPMS	Highway Performance Monitoring System
LOS	level of service
MUTCD	*Manual on Uniform Traffic Control Devices*
NCHRP	National Cooperative Highway Research Program
NDS	Naturalistic Driving Study
RID	Roadway Information Database
SHRP2	Second Strategic Highway Research Program
VMT	vehicle miles traveled
VTTI	Virginia Tech Transportation Institute

CHAPTER 1. INTRODUCTION

BACKGROUND

Complex freeway interchanges are difficult to navigate in many cases, as travelers need to make multiple navigation decisions within a limited time. Poorly designed signs at interchanges, along with contributing roadway and traffic factors, frequently lead to increased crash risks.[3] One sign design issue frequently seen on urban freeways is the use of complex guide signs. In such cases, signs provide a large amount of information for travelers within a short period of time, resulting in information overload that may lead to unsafe maneuvers. Agencies design signs to be seen within a certain distance, but even clearly seen, complex signs require time for drivers to process the information and make appropriate decisions, which drivers do while traveling at high speeds.

The 2009 *Manual on Uniform Traffic Control Devices* (MUTCD) recognizes the importance of avoiding traffic information overload in the design and installation of traffic signs and control devices.[1] In addition to basic provisions for the designs (e.g., font, size, color, and retroreflectivity) of freeway guide signs, MUTCD contains high-level provisions for the use of guide signs to safely meet travelers' information needs. However, the manual does not include detailed provisions for guide sign design at complex freeway interchanges. Its limited provisions allow significant flexibility for practitioners in the field and create the potential for unsafe freeway guide sign designs. In particular, the manual does not provide guidelines or measurements with regard to how much information is to be allowed on guide signs to avoid information overload—due partly to lack of research that would lead to the development of such guidelines. Practitioners typically design freeway signs based on certain roadway constraints and installation cost considerations—a practice that often leads to locations with sign clusters and/or complex signs that can cause information overload and increase crash risk.

To date, a fair amount of research has been conducted nationwide relevant to freeway guide signs. A literature review the research team conducted showed that:

- Most, if not all, previous studies were based on simulations, laboratory studies, and/or experimental studies involving participants at selected sites. For obvious reasons, those studies typically involved limited scenarios and limited data.

- Participants generally either had no specific destinations or had only hypothetical destinations in past experimental studies of freeway guide signs.

- Most of the experimental studies neither realistically nor comprehensively incorporated traffic, environmental, and roadway conditions.

- Many studies focused on identifying the effectiveness of a limited number of signs or sign combinations based on MUTCD scenarios. Few studies evaluated multiple real-world field sign combinations and sequences at complex interchanges.

- Few studies linked sign locations and designs with driver behaviors relevant to safety at freeway interchanges.

This project involved an indepth analysis of driver behaviors relevant to freeway guide sign complexity in an effort to identify correlations between driver behaviors relevant to safety and the amount of information provided on guide signs at freeway interchanges. Based on the correlations identified, the research team developed suggestions relevant to the maximum amount of information a guide sign can safely provide, along with other sign- and roadway-related strategies to facilitate freeway signing—particularly at complex interchanges. The project used a large amount of data from the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) to achieve the research goal.[(4)]

The SHRP2 NDS is a nontraditional source of roadway and driver behavior information, with a vast number of trips occurring on freeways. The availability of the database makes feasible a comprehensive study of driver behavior and safety performance relevant to freeway interchange signing practices, thereby advancing the state of knowledge regarding this fundamental safety and operations topic.

PROJECT OBJECTIVES

The main objectives of the project were as follows:

- To quantify the effects of different guide sign configurations at complex freeway interchanges on driver behaviors relevant to safety.
- To identify thresholds for the maximum amount of information on guide signs at freeway interchanges, with consideration of roadway and traffic scenarios for maximizing safety and reducing information overload.
- To suggest guidelines and potential changes to relevant standards, manuals, and tools.

ORGANIZATION OF THIS REPORT

The remaining chapters of this report are as follows:

- Chapter 2. Literature Review. This chapter summarizes relevant background information from the literature on such topics as freeway interchange design, factors contributing to interchange complexity, visual performance of traffic signs, existing freeway signing guidelines, and traffic signs in the era of automation.
- Chapter 3. Data Collection and Methodology. This chapter describes in detail the data the project used, the data processing steps, the data analysis methods, and the variables used in the data modeling.
- Chapter 4. Driver Behavior and Guide Sign Correlations. This chapter presents the data analysis results, with a focus on correlations between driver behaviors and variables related to guide signs.

- Chapter 5. SHRP2 Event Data Analysis Results. This chapter summarizes the findings of a qualitative analysis of SHRP2 safety events—including crashes and near crashes—relevant to guide sign design practices. From such events the results draw lessons learned that have the potential to improve sign and related roadway design practices.

- Chapter 6. Summary, Discussion, and Suggestions. This chapter summarizes the major findings of the entire research effort, along with discussions and suggestions.

CHAPTER 2. LITERATURE REVIEW

OVERVIEW OF FREEWAY INTERCHANGES

Basic Interchange Design

Freeways provide higher levels of safety and mobility for a significant amount of traffic. In 2020, the United States registered 983 billion vehicle miles traveled (VMT) on the 67,128 mi of freeway and expressway networks, which translated to a national average daily traffic (ADT) figure of approximately 40,000 vehicles per day on any freeway (approximately 63,000 vehicles per day on urban freeways and 20,000 vehicles per day on rural freeways).(1) In the same year, 5,872 fatal crashes (or greater than 16 percent of all fatal crashes) occurred on freeways and expressways, including almost 1,000 in interchange areas.

Freeways are fully access controlled, with connections to other roadways and among themselves via interchanges. In the latest edition of *A Policy on Geometric Design of Highways and Streets*, the American Association of State Highway Transportation Officials (AASHTO) defines freeway interchanges as "a system of interconnecting roadways in conjunction with one or more grade separations that provides for the movement of traffic between two or more roadways or highways on different levels."(1) The policy lists eight types of common interchanges (figure 1).

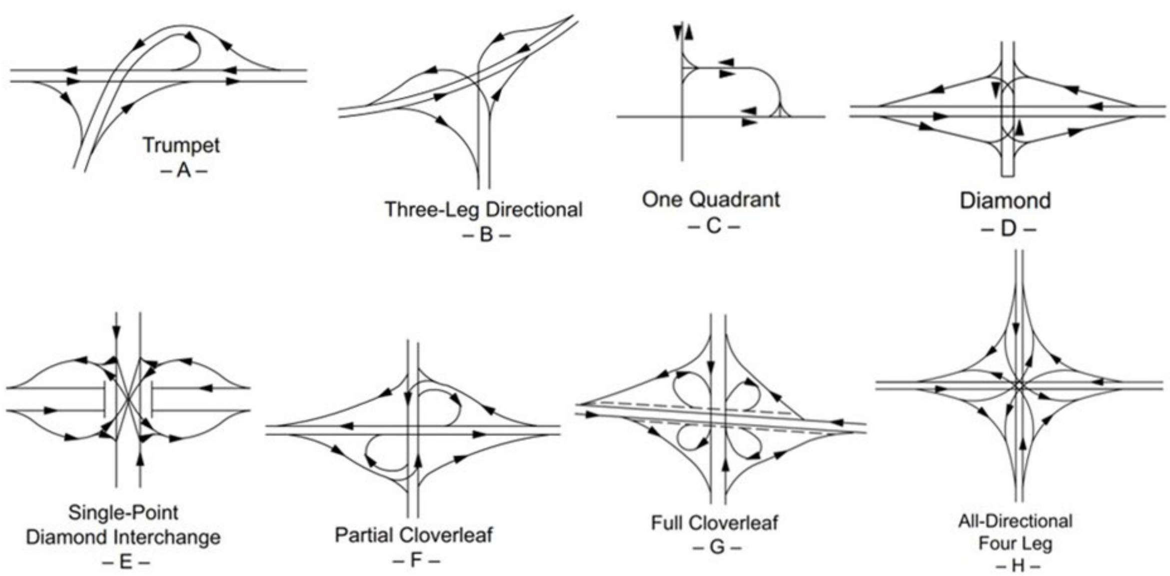

Figure 1. Diagram. Typical interchange configurations listed in AASHTO design guide.(5)

Based on their functionality, interchanges can be broadly classified as system interchanges and service interchanges.(1) The former carry traffic from one freeway to another via a network of ramps and connectors (e.g., type H in figure 1). The latter connect a freeway with local surface streets or arterials (e.g., type D in figure 1.)

In addition, MUTCD further classifies interchanges as follows:(1)

- Major interchanges, which are interchanges between two or more freeways and expressways and interchanges with principal arterials wherein interchange traffic volume is high or includes many road users unfamiliar with the area.

- Intermediate interchanges, which involve major urban and rural routes that are not in the major or minor interchange categories.

- Minor interchanges, which are roadways where traffic is local and light (i.e., roadways whose volumes for an exit ramp are fewer than 100 vehicles a day).

Diamond, cloverleaf, and partial cloverleaf interchanges are typical examples of service interchanges. Both system and service interchanges must provide appropriate balance between regional mobility and local road access.

Interchanges, particularly those in an urban area that are closely spaced and carry large amounts of traffic, can be extremely difficult to navigate. When traveling through an interchange, drivers must make a series of decisions and maneuvers, including merging, diverging, and exiting—all while traveling at high speeds.

Many design factors can therefore affect interchanges' safety and operational performance, such as the following:(5)

- Interchange and ramp spacing: Ramp spacing depends considerably on interchange spacing and local roadway density. Densely located entrance and exit ramps require drivers to make multiple decisions and maneuvers within a short period and therefore significantly increase the difficulty of navigation. AASHTO recommends a minimum interchange spacing of 1 mi in urban areas and 2 mi in rural areas. When such minimal spacing is impractical, agencies may use grade-separated ramps or collector−distributor roads to improve safety and operations.

- Sight distance: Sight distance issues frequently come up due to the horizontal and vertical alignments of a freeway and the presence of overhead structures preceding or at the interchange. Sight distance at an interchange should be at least as long as needed for stopping—and, preferably, longer. When exits are involved, decision sight distance at an interchange should be at least as long as needed for stopping—and, preferably, longer.

- Geometric alignment: In addition to potentially affecting sight distances, horizontal curves at interchanges and on ramps further complicate drivers' navigation tasks and increase difficulty in lane changes as well as in merging and diverging actions. Horizontal curves and gradients also make speed control challenging, which increases risks of crashes.

- Lane configuration: Poorly designed lane configurations at interchange areas—such as inadequate merging distance, improper lane reduction, short or lack of weaving lanes, and poor maintenance of lane consistency and balance—can all significantly affect freeway operations and safety.

- Uncommon design features: Many other interchange design features that are not consistent with drivers' expectations can also negatively affect freeway interchange safety. For example, unexpected lane reductions, ramps on the left without sufficient signage, and multilane ramps contribute in many cases to the complexity of an interchange and therefore negatively affect operations and safety.

- Signing: Freeway guide sign design directly affects drivers' ability to follow their intended paths at interchanges. The locations of and minimum distances between ramp junctions heavily influence the accommodation of sufficient signing to inform, warn, and control drivers. In conjunction with guide signs, pavement markings and delineators are elements for communicating vital navigational information to drivers at interchanges.

Complex Freeway Interchanges

In the case of complex interchanges, layouts are usually either completely customized based on access and connectivity needs, right-of-way availability, and operational and safety demands or ramps that assemble multiple types of typical interchange layouts. However, unique routing and traffic needs at complex interchanges result in major challenges for design and signing.

Previous studies have identified a variety of characteristics that users usually associate with interchange complexity. (See references 6, 7, 8, and 9.)

- Interchange as a system interchange.
- Multiple or successive option lanes, splits, or exits.
- Short weaving sections.
- Collector–distributor roads.
- On- and off-ramps for high-occupancy vehicles and managing and signing access.
- Lane continuity violations.
- Ramps on the left side.
- Narrow lateral clearances and shoulders.
- Roadside commercial developments.

A systematic look at freeway interchange complexity shows that a large number of factors can contribute to complexity with regard to the design and operations of freeway interchanges. For example, an earlier Federal Highway Administration (FHWA) project further developed a catalog of 210 factors that contribute to interchange complexity.[7]

The project organized the factors into the following groups and categories:

- Impacts and outcomes group, including factors in the traffic operations, increased congestion, crashes, and inconvenience categories.
- User characteristics group, including factors in the violated expectations, user profile, commercial motor vehicle operator, and environmental characteristics categories.
- System design group, including factors in the interchange configuration and system configuration categories.
- Roadway geometric design group, including factors in the lane configuration, ramp-terminal-spacing, geometric design, and cross-section categories.
- Traffic control devices group, including factors in the traffic-signing and pavement-marking categories.
- Management and operations group, including factors in the restricted- and managed-facilities, system management, information systems, active traffic management system, pricing, tolling, and incidence response categories.
- Institutional factors group, including factors in the institutional factors category.

VISUAL PERFORMANCE OF TRAFFIC SIGNS

Freeway Guide Sign Visibility Basics

Because freeways carry large amounts of traffic at higher speeds compared with other roadways, safe operation of the freeway system is a major challenge. In addition to safety-oriented roadway designs, traffic control is critical when it comes to freeway operations and management. Freeway signage is a fundamental component of freeway traffic control. MUTCD specifies that the freeway and expressway signing system be primarily for the benefit and direction of road users who are not familiar with the route or area.[(1)] The visual performance of traffic signs correlates closely to traffic signs' legibility and detectability. The former refers to the capability of a sign to be read at a given distance, and the latter is the sign's ability to be identified from the sign's visual background.[(5)]

A number of factors can affect both the legibility and detectability of traffic signs:[(1,5)]

- Characters on freeway signs: In addition to contents (e.g., inclusion of complex place names) and spacing, the size of the characters on a freeway or expressway sign may be an important factor in sign legibility. MUTCD's chapter 2E, "Guide Signs–Freeways and Expressways," requires a minimum letter height of 8 inches on freeway and expressway guide signs (see table 1 through table 4 for detailed size information), with larger lettering required in many instances, such as on major guide signs for all overhead signs that are at or appear in advance of interchanges. To determine letter sizes on freeway signs, MUTCD assumes a minimum specific ratio of 1 inch of letter height per 30 ft of legibility distance for letter size selection. In addition, freeway guide signs generally use a set of fonts commonly referred to as the FHWA Standard Alphabet series.

- Sign colors: MUTCD specifies that guide signs on freeways and expressways have white letters, symbols, arrows, and borders on a green background.

- Retroreflectivity and illuminance: MUTCD requires that letters, numerals, symbols, arrows, and borders on all guide signs be retroreflectorized. The background of all guide signs that are not independently illuminated should also be retroreflective.

- lists the minimum retroreflectivity levels applicable to freeway guide signs specified in chapter 2A, "General," of MUTCD. The manual also requires that overhead signs on freeways and expressways be lit unless an engineering study shows that retroreflectorization alone would perform effectively. The AASHTO *Roadway Lighting Design Guide* further recommends that overhead signs have minimum luminance levels ranging from 2.5 cd/m^2 for level 1 visual complexity (i.e., minimal objects and light sources at low traffic) and 25 cd/m^2 for level 5 visual complexity (i.e., heavy commercial activity with illuminated signs and businesses; high traffic volume and glare from opposing vehicles).

Table 1. Minimum letter and numeral sizes in inches for freeway guide signs by interchange type (modified from MUTCD).(1)

Type of Sign	Major Interchange: Category A	Major Interchange: Category B	Intermediate Interchange	Minor Interchange	Overhead Signs
Exit number plaques: Words	10	10	10	10	10
Exit number plaques: Numerals and letters	15	15	15	15	15
Interstate route signs: Numerals	24/18	—	—	—	18
Interstate route signs: One- or two-digit shields	48 × 48/36 × 36	—	—	—	36 × 36
Interstate route signs: Three-digit shields	60 × 48/45 × 36	—	—	—	45 × 36
U.S. or State route signs: Numerals	24/18	18	18	12	18
U.S. or State route signs: One- or two-digit shields	48 × 48/36 × 36	36 × 36	36 × 36	24 × 24	36 × 36
U.S. or State route signs: Three-digit shields	60 × 48/45 × 36	45 × 36	45 × 36	30 × 24	45 × 36
U.S. or State route text identification (e.g., U.S. 56): Numerals and letters	18	18/15	15	12	15
U.S. or State route text identification (e.g., US 56): Cardinal directions: First letters	18	15	15	10	15
U.S. or State route text identification (e.g., US 56): Cardinal directions: Rest of words	15	12	12	8	12

Type of Sign	Major Interchange: Category A	Major Interchange: Category B	Intermediate Interchange	Minor Interchange	Overhead Signs
Auxiliary and alternative route legends (e.g., JCT, To, ALT, BUSINESS): Words	15	12	12	8	12
Names of destinations: Uppercase letters	20	20	16	13.33	16
Names of destinations: Lowercase letters	15	15	12	10	12
Names of destinations: Distance numbers	18	18/15	15	12	15
Names of destinations: Distance fraction numerals	12	12/10	10	8	10
Names of destinations: Distance words	12	12/10	10	8	10
Names of destinations: Action message words	12	12/10	10	8	10
Gore signs: Words	12	12	12	8	—
Gore signs: Numeral and letters	18	18	18	12	—

— = No data.
ALT = alternate; JCT = junction.

Table 2. Minimum letter and numeral sizes for freeway guide signs by sign type.(1)

Type of Sign	Type of Information	Minimum Size (inches)
Pull-through signs	Destinations: Uppercase letters	16
Pull-through signs	Destinations: Lowercase letters	12
Pull-through signs	Route signs: One- or two-digit shields	36 × 36
Pull-through signs	Route signs: Three-digit shields	45 × 36
Pull-through signs	Cardinal directions: First letter	15
Pull-through signs	Cardinal directions: Rest of word	12
Supplemental guide signs	Exit number words	10
Supplemental guide signs	Exit number numerals and letters	15
Supplemental guide signs	Place names: Uppercase letters	13.33
Supplemental guide signs	Place names: Lowercase letters	10
Supplemental guide signs	Action messages	8
Supplemental guide signs	Route signs: Numerals	12
Supplemental guide signs	Route signs: One- or two-digit shields	24 × 24
Supplemental guide signs	Route signs: Three-digit shields	30 × 24
Interchange sequence or community interchanges identification signs	Words: Uppercase letters	13.33
Interchange sequence or community interchanges identification signs	Words: Lowercase letters	10
Interchange sequence or community interchanges identification signs	Numerals	13.33
Interchange sequence or community interchanges identification signs	Fraction numerals	10
Interchange sequence or community interchanges identification signs	Route signs: Numerals	12
Interchange sequence or community interchanges identification signs	Route signs: One- or two-digit shields	24 × 24

Type of Sign	Type of Information	Minimum Size (inches)
Interchange sequence or community interchanges identification signs	Route signs: Three-digit shields	30 × 24
Next XX exits signs	Place names: Uppercase letters	13.33
Next XX exits signs	Place names: Lowercase letters	10
Next XX exits signs	Next XX exits: Words	10
Next XX exits signs	Next XX exits: Number	15
Distance signs	Words: Uppercase letters	8
Distance signs	Words: Lowercase letters	6
Distance signs	Numerals	8
Distance signs	Route signs: Numerals	9
Distance signs	Route signs: One- or two-digit shields	18 × 18
Distance signs	Route signs: Three-digit shields	22.5 × 18
General services signs	Exit number words	10
General services signs	Exit number numerals and letters	15
General services signs	Services	10
Rest area, scenic area, and roadside area signs	Words	12
Rest area, scenic area, and roadside area signs	Distance numerals	15
Rest area, scenic area, and roadside area signs	Distance fraction numerals	10
Rest area, scenic area, and roadside area signs	Distance words	10
Rest area, scenic area, and roadside area signs	Action message words	12
Reference location signs	Words	4
Reference location signs	Numerals	10
Boundary and orientation signs	Words: Uppercase letters	8
Boundary and orientation signs	Words: Lowercase letters	6
Next exit and next services signs	Words and numerals	8
Exit-only signs	Words	12

XX = placeholder for sign exit number.

Table 3. Minimum letter and numeral sizes in inches for expressway guide signs by interchange classification.[1]

Type of Sign	Major Interchange Category A	Major Interchange Category B	Intermediate Interchange	Minor Interchange	Overhead
Exit number plaques: Words	10	10	10	8	10
Exit number plaques: Numerals and letters	15	15	15	12	15
Interstate route signs: Numerals	18	—	—	—	18
Interstate route signs: One- or two-digit shields	36 × 36	—	—	—	36 × 36
Interstate route signs: Three-digit shields	45 × 36	—	—	—	45 × 36
U.S. or State route signs: Numerals	18	18	18	12	18
U.S. or State route signs: One- or two-digit shields	36 × 36	36 × 36	36 × 36	24 × 24	36 × 36
U.S. or State route signs: Three-digit shields	45 × 36	45 × 36	45 × 36	30 × 24	45 × 36
U.S. or State route text identification (e.g., US 56): Numerals and letters	18	15	15	12	15
Cardinal directions: First letters	18	15	12	10	15
Cardinal directions: Rest of words	15	12	10	8	12
Auxiliary and alternative route legends (e.g., JCT, TO, ALT, BUSINESS): Words	15	12	10	8	12
Names of destinations: Uppercase letters	20	16	13.33	10.67	16
Names of destinations: Lowercase letters	15	12	10	8	12
Names of destinations: Distance numbers	18	15	12	10	15
Names of destinations: Distance fraction numerals	12	10	10	8	10
Names of destinations: Distance words	12	10	10	8	10
Names of destinations: Action message words	10	10	10	8	10
Gore signs: Words	10	10	10	8	—
Gore signs: Numerals and letters	12	12	12	10	—

— = No data.

Notes: Major interchange category A comprises interchanges with other expressways or freeways. Major interchange category B comprises interchanges with high-volume multilane highways, principal urban arterials, and major rural routes whose volumes of interchanging traffic are heavy or include many road users unfamiliar with the area.[1]

Table 4. Minimum letter and numeral sizes for expressway guide signs by sign type.[1]

Type of Sign	Type of Information	Minimum Size (inches)
Pull-through	Destinations: Uppercase letters	13.33
Pull-through	Destinations: Lowercase letters	10
Pull-through	Route signs: One- or two-digit shields	36 × 36

Type of Sign	Type of Information	Minimum Size (inches)
Pull-through	Route signs: Three-digit shields	45 × 36
Pull-through	Cardinal directions: First letters	12
Pull-through	Cardinal directions: Rest of word	10
Supplemental guide	Exit number: Words	8
Supplemental guide	Exit number: Numerals and letters	12
Supplemental guide	Place names: Uppercase letters	10.67
Supplemental guide	Place names: Lowercase letters	8
Supplemental guide	Action messages	8
Supplemental guide	Route signs: Numerals	12
Supplemental guide	Route signs: One- or two-digit shields	24 × 24
Supplemental guide	Route signs: Three-digit shields	30 × 24
Interchange sequence or community interchanges identification	Words: Uppercase letters	10.67
Interchange sequence or community interchanges identification	Words: Lowercase letters	8
Interchange sequence or community interchanges identification	Numerals	10.67
Interchange sequence or community interchanges identification	Fraction numerals	8
Interchange sequence or community interchanges identification	Route signs: numerals	12
Interchange sequence or community interchanges identification	Route signs: One- or two-digit shields	24 × 24
Interchange sequence or community interchanges identification	Route signs: Three-digit shields	30 × 24
Next XX exits	Place names: Uppercase letters	10.67
Next XX exits	Place names: Lowercase letters	8
Next XX exits	Next XX exits: Words	8
Next XX exits	Next XX exits: Number	12
Distance	Words: Uppercase letters	8
Distance	Words: Lowercase letters	6
Distance	Numerals	8
Distance	Route signs: Numerals	9
Distance	Route signs: One- or two-digit shields	18 × 18
Distance	Route signs: Three-digit shields	22.5 × 18
General services	Exit number: Words	8
General services	Exit number: Numerals and letters	12
General services	Services	8
Rest area, scenic area, and roadside area	Words	10
Rest area, scenic area, and roadside area	Distance numerals	12
Rest area, scenic area, and roadside area	Distance fraction numerals	8
Rest area, scenic area, and roadside area	Distance words	8
Rest area, scenic area, and roadside area	Action message words	10
Reference location	Words	4
Reference location	Numerals	10
Boundary and orientation	Words: Uppercase letters	8
Boundary and orientation	Words: Lowercase letters	6
Next exit and next services	Words and numerals	8
Exit only	Words	12
Pull-through	Destinations: Uppercase letters	13.33
Pull-through	Destinations: Lowercase letters	10

Type of Sign	Type of Information	Minimum Size (inches)
Pull-through	Route signs: One- or two-digit shields	36 × 36
Pull-through	Route signs: Three-digit shields	45 × 36
Pull-through	Cardinal Directions: First letters	12
Pull-through	Cardinal Directions: Rest of word	10
Supplemental guide	Exit number: Words	8
Supplemental guide	Exit number: Numerals and letters	12
Supplemental guide	Place names: Uppercase letters	10.67
Supplemental guide	Place names: Lowercase letters	8
Supplemental guide	Action messages	8
Supplemental guide	Route signs: Numerals	12
Supplemental guide	Route signs: One- or two-digit shields	24 × 24
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Interchange sequence or community interchanges identification	Words: Uppercase letters	10.67
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Interchange sequence or community interchanges identification	Numerals	10.67
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Next XX exits	Place names: Lowercase letters	8
Next XX exits	Next XX exits: Words	8
Next XX exits	Next XX exits: Number	12
Distance	Words: Uppercase letters	8
Distance	Words: Lowercase letters	6
Distance	Numerals	8
Distance	Route signs: Numerals	9
Distance	Route signs: One- or two-digit shields	18 × 18
Distance	Route signs: Three-digit shields	22.5 × 18
General services	Exit number: Words	8
General services	Exit number: Numerals and letters	12
General services	Services	8
Rest area, scenic area, and roadside area	Words	10
Rest area, scenic area, and roadside area	Distance numerals	12
Rest area, scenic area, and roadside area	Distance fraction numerals	8
Rest area, scenic area, and roadside area	Distance words	8
Rest area, scenic area, and roadside area	Action message words	10
Reference location	Words	4
Reference location	Numerals	10
Boundary and orientation	Words: Uppercase letters	8
Boundary and orientation	Words: Lowercase letters	6
Next exit and next services	Words and numerals	8
Exit Only	Words	12

Table 5. Minimum maintained retroreflectivity levels for freeway guide signs.[1]

Sheeting Type	Beaded Sheeting: I	Beaded Sheeting: II	Beaded Sheeting: III	Prismatic Sheeting: III, IV, VI, VII, VIII, IX, X
Overhead	W*; G ≥ 7	W*; G ≥ 15	W*; G ≥ 25	W ≥ 250; G ≥ 25
Post mounted	W*; G ≥ 7	W ≥ 120; G ≥ 15	W ≥ 120; G ≥ 15	W ≥ 120; G ≥ 15

*This sheeting type is not used for white color for the specific sign type.
G = green; W = white.
Note: Retroreflectivity levels are in units of candelas per lux per square meter.

Freeway Sign Performance in a Dynamic Driving Environment

Vehicle speeds and driving environments involve dynamic visual tasks that significantly affect driving and navigation on freeways. As the driving environment (e.g., traffic, roadway, and atmospheric conditions) becomes more complex, drivers naturally concentrate less on detecting and understanding guide signs due to competing visual information that they must attend. That reduced concentration is consistent with Wickens' multiple resource theory that information must be processed in sequence when different tasks require the same cognitive resource—in this case, visual perception.[5] In addition, a driver's peripheral vision degrades as speed increases, and the driver also has less time to comprehend a traffic sign. In general, navigating through freeway interchanges requires a number of tasks, including sign detection and reading, decision making and responding, and maneuvering. Theoretically, agencies should locate freeway sign such that drivers have sufficient time and distance to complete all of the sign's tasks. Repeating the same signs at multiple locations may also give drivers more time to read signs and maneuver accordingly.

Sign Detection and Reading Time

A number of previous studies have researched the topic of sign effectiveness and required reading times. (See references 10–16.) For example, Seyfried found that eye dwell time (i.e., the amount of time spent looking at a particular area of interest) spent on a guide sign was a function of a number of factors, such as time or advance distance of the first glance, traffic density, the driver's specific informational need, length of message, relevancy of information to the driver, and route familiarity.[17] Seyfried suggested an average eye dwell time of 2.6 s per sign in low-density traffic to as little as 0.9 s during vehicle following. Further, the study showed that drivers read signs at, on average, half the distance at which the signs are first legible in moderate-density traffic. A study by Mitchell and Forbes found the following relationship between the number of words on a sign (N) and sign-reading time (T in s) when incorporating a safety margin:[18]

$$T = N/3 \text{ or } \mathrm{T} = 2N/3$$

According to that relationship, road users require about 1/3 s (or 2/3 s with a safety margin) to read each word on a sign. Another study, by McNees and Messer, based on simulated signs showed that sign-reading time increased as the amount of information and number of signs collocated increased (table 6).[19] Based on the McNees and Messer study, a user would travel a distance of 350 ft on a freeway with a speed limit of 60 mph while reading three collocated overhead signs with four units of information, on average, in a simulated environment. A later study, by Hall, McDonald, and Rutley, based on nonfreeway signs, found that sign-reading time could vary from 1.6 to 2.9 s depending on the sign's number of words and type of information (table 7).[20] An FHWA study found that changeable message signs with more than five words required significantly longer times to read, and the study suggested in most conditions a minimum distance of 800 ft (included in the 2009 MUTCD) between consecutive guide signs on freeways.[1,21]

Table 6. Minimum reading times for collocated overhead guide signs.[19]

Units of Information per Panel	Condition	Reading Times for Two Panels (s)	Reading Times for Three Panels (s)	Reading Times for Four Panels (s)	Reading Times for Five Panels (s)
2	Desirable	3.1	3.5	3.9	4.4
2	Minimum	2.7	2.7	3	3.3
4	Desirable	3.6	4.2	5	5.7
4	Minimum	2.7	3.2	3.7	4.2
6	Desirable	3.8	4.5	—	—
6	Minimum	2.8	3.4	—	—
8	Desirable	3.9	—	—	—
8	Minimum	2.9	—	—	—
10	Desirable	4	—	—	—
10	Minimum	3	—	—	—

— = No data.

Table 7. Reading times for nonfreeway guide signs.[20]

Type of Information	Number of Words (2–4)	Number of Words (4–10)
Mileage to a specific destination (s)	1.6–2.2	2.2–2.3
Destination information that was present on the sign (s)	1.7–2.2	2.2–2.4
Destination information that was not present on the sign (s)	1.65–2.6	2.6–2.9

Decision, Reaction, and Maneuvering

Based on a previous literature review, a study by Hooper and McGee found that the 85th-percentile decision time for a braking situation ranged from 0.7 to 2.6 s (table 8).[22] The same literature review also showed a 50th-percentile decision time for a braking situation of 0.5 s and an 85th-percentile decision time of 0.85 s. A study based on 401 simulated lane changes on a multilane highway showed an average of 5.14 s for a single lane change.[23] McGee suggested a set of values for decision and maneuvering based on a literature review validated with a controlled experiment (table 9) in a decision reached in a hazard avoidance situation.[24]

Table 8. 85th-percentile decision time in a braking situation.[22]

Information (bits)	Decision Time Expected (s)	Decision Time Unexpected (s)
1	0.7	1.0
2	1.3	1.6
3	2.0	2.6

Table 9. Decision and maneuvering times in a hazard avoidance situation.[24]

Design Speed (mph)	Decision and Initiation of Response (s)	Lane Change (s)
49.7	4.2–6.5	4.5
62.1	4.7–7.0	4.3
74.6	4.7–7.0	4.0
86.9	4.7–7.0	4.0

For drivers combining decision, reaction, and maneuvering, AASHTO's latest book, *A Policy on Geometric Design of Highways and Streets*—commonly referred to as the Green Book—recommends durations ranging from 10 to 15 s based on design speeds and maneuvers required (table 10 derived based on decision distances).[5]

Table 10. AASHTO decision and maneuvering times in a hazard avoidance situation.[5]

Situation	Design Speed (mph)				
	55	60	65	70	75
Speed/path/direction change on rural road (s)	10.72	11.25	11.01	10.76	10.73
Speed/path/direction change on suburban road or street (s)	12.15	12.78	12.80	12.42	12.41
Speed/path/direction change on urban, urban, urban core, or rural town road or street (s)	14.07	14.55	14.32	14.07	14.05

Driver Information Overload

The 2009 MUTCD recognizes the importance of avoiding traffic information overload in the design and installation of traffic signs and control devices.[1] A careful review of relevant MUTCD requirements confirmed a lack of detailed guidelines for the design of guide signs at complex freeway interchanges. Although MUTCD requires that guide signs placed in advance of an interchange deceleration lane be spaced at least 800 ft apart, the manual does not contain requirements with regard to either minimum spacing between traffic signs in general, including overhead signs and signs placed on the side of a roadway, or minimum sign sight distance, in that sign sight distances at interchanges are usually affected by other overhead signs, bridges, and elevated ramps. Partly due to lack of research that would lead to such needed guidelines, neither does the manual offer guidelines or measurements regarding how much information to allow so as to avoid information overload. MUTCD's provisions therefore allow significant flexibility in practitioners' locations of signs in the field, which could result in more complicated guide sign designs that could, potentially, affect safety.

Two National Cooperative Highway Research Program (NCHRP) efforts—Projects 3-50 and 3-50(2)—involved a national initiative to understand driver information overload and develop a model to understand and assess driver information overload scenarios.[25] Based on laboratory and participant data, the projects developed a lookup table containing sign complexity ratings, which was found to be fairly consistent with participants' perceptions.

The projects also used two ways to compute combined information load ratings for sign arrays:

- Adding the highest information load to the square root of the information load of the remaining signs.

- Using a linear regression (i.e., array value = 0.94 (maximum value + square root of others) + 0.08).

Both methods, however, assumed that the most complex sign had the greatest impact on mental workload. That assumption may not necessarily be applicable to this study, since, in a real roadway environment, drivers would search—in an array—for the sign most relevant to their navigation needs. In addition, the lookup table was based on the 2000 edition of MUTCD.[26] Therefore, the table needs an update to reflect the newest MUTCD if used in practice.

Recently, FHWA conducted a study to better understand the effectiveness of freeway interchange signing in six scenarios: signing for option lanes, signing for three destinations when two interstates exist, signing for exits at Y-splits, single sign with supplemental way-finding information versus spreading information among multiple signs, effectiveness of sign spreading instead of collocating, and signing for left exits.[7] The study was valuable by leading to better understanding of drivers' reactions and of scenarios' sign effectiveness, but it did not provide quantitative performance measures and therefore implementable sign spacing or design recommendations.

GUIDELINES FOR FREEWAY SIGNING

Freeway and Expressway Guide Sign Function and Classification

MUTCD recognizes that signing is primarily for the benefit and direction of roadway users who are not familiar with a route or area. Therefore, guide signs at freeway interchanges should serve the following functions for roadway users:[1]

- Provide—at ramps—directions to destinations and major connected roadways.
- Give advance notice of approaching intersections or interchanges.
- Direct traffic on lane usage and connectivity in advance of merging or diverging points.
- Notify route and direction of travel at strategic mainline points.
- Inform distances to major destinations and points of interest.
- Provide other information of value.

In accordance with those functions, MUTCD classifies freeway and expressway guide signs into 16 categories:[1]

A. Route signs and Trailblazer Assemblies.
B. At-Grade Intersection signs.
C. Interchange signs.
D. Interchange Sequence signs.
E. Community Interchanges Identification signs.
F. NEXT XX EXITS signs, for which XX is the placeholder for sign exit number.

G. Weigh Station signing.
H. Miscellaneous Information signs.
I. Reference Location signs.
J. General Service signs.
K. Rest and Scenic Area signs.
L. Tourist Information and Welcome Center signs.
M. Radio Information signing.
N. Carpool and Ridesharing signing.
O. Specific Service signs.
P. Recreational and Cultural Interest Area signs.

Among the signs, categories C, D, E, and F are most commonly used on freeway mainlines at interchange areas and are therefore of particular interest to this research.

Freeway and Expressway Interchange Sign Design and Installation

In urban areas with densely spaced interchanges and ramps, MUTCD recommends the use of interchange sequence signs, sign spreading, overhead signs, overhead arrow-per-lane or diagrammatic signs (required for all splits or multilane exit ramps with option lanes at major interchanges), and street names as the principal messages to improve signing effectiveness.(1)

In particular, MUTCD includes the following guidelines relevant to the design and installation of guide signs at freeway interchanges:(1)

- Amount of legend on guide signs: MUTCD requires that no more than two destination names or street names be displayed on any advance guide sign or exit direction sign, that a place name and a street name not be on the same sign, that the total number of destinations or names of signs on the same support not exceed three, and that sign legends not exceed three lines, excluding exit number and action or distance information.

- Number of signs on an overhead installation: MUTCD recommends that no more than three signs be located on the same overhead structure and that regulatory signs not be collocated with guide signs.

- Sign spreading: MUTCD recognizes the need for spacing overhead signs at busy urban interchanges to prevent information overload. To achieve sign spreading, the manual requires that exit direction signs be the only signs used near the gore and that advance guide signs be placed separately near the crossroad location.

- Advance guide signs: MUTCD recommends that advance guide signs be placed 0.5 mi and 1 mi in advance of an exit, with a third advance guide sign placed at 2 mi in advance, if possible, at major and intermediate interchanges. In addition, when the distance between interchanges is less than 2 mi, the first advance guide sign may be closer than 2 mi. MUTCD recommends the use of interchange sequence signs when the distance is less than 800 ft between interchanges. MUTCD also requires that advance guide signs for closely spaced interchanges show information for only one interchange.

- Use of pavement-marking guidance: MUTCD suggests the use of elongated pavement markings of highway route shield signs and lane-use arrow markings for additional guidance for roadway users. MUTCD does not, however, provide detailed guidance on when and how the markings should be used at complex freeway interchanges. Previous research recommended that pavement-marking guidance be considered based on such factors as crashes, lane usage, traffic, and level of service (LOS).[27]

Some States have developed their own MUTCD based on or supplementary to the FHWA MUTCD. Review of a sample of State MUTCDs for the six States involved in the SHRP2 NDS data collection effort, however, showed that none included major revisions relevant to where and how guide signs be installed at freeway interchanges.[28,29,30]

Signing Practices Contributing to Interchange Complexity

Complex interchanges typically share common characteristics, such as serving as system interchanges, multiple or successive option lanes and ramps, weaving lanes, and closely spaced interchanges. Practitioners typically design freeway signs based heavily on roadway constraints and installation cost considerations. Such practices lead to locations with sign clusters that often cause information overload and increase crash risks. Ambiguities in signing guidelines, unique roadway geometric and lane configuration features, and differing engineering preferences frequently lead to different signing practices, which can be challenging when it comes to safety and operations at complex interchanges.

A previous study identified a number of examples of different signing practices and practices that deviate from the 2009 MUTCD requirements:[1,7]

- Inconsistent option lane signing: Such as the use of so-called discrete arrow signs versus MUTCD arrow-per-lane signs.

- Varying sign distance to a painted gore causing different signing methods for option lanes: for example, an option lane that may be signed as either an option lane or two separate lanes, with one as exit only depending on how close the sign structure is located from the gore.

- Signing for exit-only lanes at or past the painted gore of an interchange: MUTCD does not permit this practice because the practice may violate a driver's expectation of the amount of space needed to change out of exit-only lanes.

- Signing for exit-only lanes at an exit where an option lane continues for a short distance after the ramp: An example is the escape lane at an exit ramp, which certain States use and which creates a situation in which the exit lane is signed as an exit-only lane but appears to be an option lane.

- Omission of advance guide signs: For example, some States omit the 0.5-mi advance guide sign even when MUTCD clearly recommends such a sign.

- Omission of distance information on advance guide signs: In some cases, advance guide signs do not contain distance information—possibly to reduce sign sizes and therefore costs.

- Inconsistent arrow designs: Such inconsistencies are common when a sign uses diagonal arrows instead of curved arrows.

- Omission of interchange sequence signs: In many cases, agencies omit interchange sequence signs due to such factors as cost, design preferences, and space availability.

- Signing issues for lane reductions: Practitioners commonly use lane-ends signs for exit-only lanes, through-traffic-merge-left signs in place of lane-ends signs, and/or lane-ends signs without distance information.

TRAFFIC SIGNS IN THE AUTOMATED ERA

Overview of Connected and Automated Vehicle Technologies

Automation and connectivity have become two major trends in the development of transportation. Highly connected and automated vehicle (CAV) technologies are becoming increasingly mature and implementable. Based on the SAE Levels of Driving Automation™, many vehicle models on today's roadways have already been equipped with functions falling into level 2 (Partial Automation) and level 3 (Conditional Automation).(31) While providing a multitude of opportunities for improved safety, efficiency, and comfort, such technologies also impose unique needs and requirements on transportation infrastructure.

CAV functions use a variety of sensors to detect, recognize, and track obstacles surrounding a vehicle. Recent advances in software and hardware technologies combined with increasingly affordable costs have led to a boom in vehicle vision applications, thereby propelling the development of highly automated vehicle features. Most modern vehicle vision systems rely on a combination of technologies, such as camera-, lidar-, and radar-based systems.(32) Currently, mostly camera-based systems achieve sign recognitions of CAV features. Such systems generally use machine-learning techniques to read sign contents. Previous applications suggested correct detection rates greater than 90 percent for most learning-based methods: 99.94 percent for traffic sign recognition (at a distance up to 164 ft), 99 percent for pedestrian recognition, 95 percent for human face recognition, and 93 percent for vehicle detection. (See references 33, 34, 35, and 36.) Mobileye®, a leading camera-based vehicle vision system manufacturer, has claimed that its systems could reach a detection accuracy of 99 percent for a collection of vehicles, pedestrians, cyclists, lane markings, and speed limit signs.(37)

Although CAV technologies are maturing fast, they are hardly expected to replace human drivers in the near future. Based on a survey conducted in Texas, for example, a study estimated the following adoption rates for various CAV technologies by 2045, assuming a 10-percent annual technology cost reduction rate:(38)

- Blind-spot monitoring and emergency automated braking: 59.4 percent of vehicles would have these functions.

- Connectivity (for basic safety messaging): 57.9 percent of vehicles would have this function.
- Full self-driving: 38.5 percent of vehicles would have this function.
- Traffic sign recognition: 38.4 percent of vehicles would have this function.

Foreseeing whether those estimations are accurate reflections of future CAV adoption would prove difficult; however, the projections clearly indicate that CAVs, even if adopted, would experience a significant period of coexistence with human-driven vehicles in the Nation's transportation system.

Signing for CAVs

In an ideal CAV environment, traffic signs as well as most, if not all, other traffic control devices currently in use may become completely replaced by digital navigation data and traffic control information communicated individually and wirelessly to drivers in need. However, the technology and infrastructure developments would still face challenges due to the gradual implementation nature of CAV technologies and the foreseeable prolonged coexistence of autonomous and human-driven vehicles.

Currently, research and development focus mostly on the following areas, which are highly likely to merge in the future as CAVs become dominant:

- Image recognition based on traditional signs: Relevant research experience and informal conversations with vehicle technology vendors point to a practitioner opinion that infrastructure improvements good for human drivers are also good for CAVs. Based on that opinion, traditional traffic signs with standardized design and installation; improved retroreflectivity, size, and legibility; and better illumination would likely play significant roles in the transportation system for the foreseeable future to benefit both human drivers and automated vehicles.
- Machine-vision-oriented signs: Current autonomous vehicles use image recognition to read road signs. However, a much more reliable approach would produce machine-readable signs. Examples of such signs are those designed with radiofrequency identification systems or machine-readable codes (e.g., QR codes) that use special sheeting designs to enable short-range sign–vehicle communication or to facilitate machine vision systems.(39,40,41)
- Digital and virtual signs: All traffic information that traditional signs convey can, theoretically, be communicated wirelessly to CAVs in the future. Advances in cellular and short-range communication technologies combined with geospatial sensing and analysis techniques enable the communication of traffic sign information to individual vehicles in need. When receiving such information, onboard processors would process the information based on the kinds of driving and navigation decisions made. The visualization of digital or virtual sign information in the vehicle to benefit passengers is optional. Another optional measure is to place physical transmitters and receivers

(e.g., via 5G cellular communications to or from vehicles and control centers) at strategic locations along roadways to meet different technology needs. In such cases, low-cost transmitters may replace physical signs by transmitting via internet the needed sign information either to vehicles in the vicinity or to all vehicles regardless of their locations. A central location (i.e., no physical objects of any type installed at sign locations) may also provide georeferenced, virtual sign information for vehicles in need.

To improve CAV operations, studies also found a number of areas for improvement in current traffic signs as follows:(42,43,44)

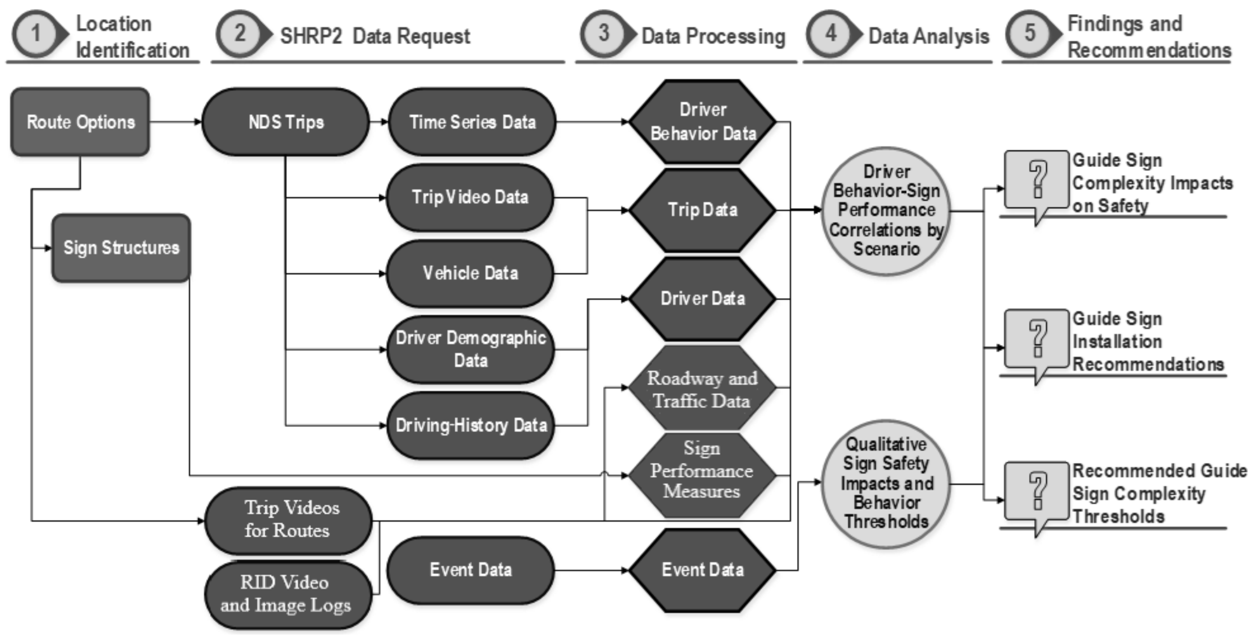
- Establish national sign uniformity.
- Install regulatory signs in a manner such that signs are clearly associated with applicable lanes.
- Use pictograms instead of text signs.
- Clear visual obstructions from signs.
- Maintain and/or improve sign retroreflectivity.
- Adopt a standard refresh or flicker rate for electric signs.
- Develop a digital database of sign types and placements.

In the foreseeable future, when human drivers and traditional roadway infrastructure still constitute major components of the transportation system, freeway guide signs will likely continue in their importance to ensure safety and operational efficiency. This project, therefore, centered on the 2009 MUTCD and human drivers with limited machine-vision assistance.(1)

CHAPTER 3. DATA COLLECTION AND METHODOLOGY

OVERVIEW OF PROJECT APPROACH

The primary goal of this project was to find correlations between freeway guide sign complexity and driver behaviors that are relevant to safety. Based on those correlations, the project can identify and suggest potential improvements to current freeway guide sign design and installation practices at interchange areas. To fulfill that goal, the team designed a systematic approach that reflected careful consideration of the data and the data analysis methodology used for achieving anticipated project outcomes. Figure 2 is an overview of the approach the project took. The figure illustrates the steps and activities involved—from identifying study sites to developing final project outcomes. The project used SHRP2 NDS data, a rich source of driver behavioral and safety event data collected at six sites across the Nation.[4]



RID = Roadway Information Database.

Figure 2. Diagram. Overview of project approach.

The entire project approach involved the following key steps:

- Identification of study sites: The project team identified for study a large number of sign locations at freeway interchanges. The team made its site identifications based on the SHRP2 Roadway Information Database (RID), a geographic information system database of roadway and related datasets that links roadway locations and SHRP2 NDS data.[45,46] At each location, the project team collected detailed roadway and sign information based on a variety of sources.

- SHRP2 data request: After identifying study locations, the project team requested detailed driver and vehicle behavioral data for a large number of NDS trips at the identified locations, including associated vehicle, driver, and roadway data. In addition to driver behavior data, the project team requested detailed data for all safety events occurring at freeway interchange areas in the SHRP2 database.

- Data processing: This step integrated SHRP2 driver behavior data with roadway and sign data for each study location. The project team then calculated a large number of driver behavioral variables, which the team combined with driver, roadway, trip level, and sign variables into an integrated dataset. Each data row included such information for each trip segment at each analysis area.

- Data analysis: This step analyzed the processed data in an effort to identify significant correlations between driver safety behaviors and sign complexity levels. The team also analyzed safety event data to obtain qualitative information on how sign design issues, including sign complexity issues, could affect driver behavior and cause crashes at freeway interchanges.

- Conclusion and recommendation: Based on data analysis findings, the project team developed certain suggestions—including potential sign-related improvements—that could lead to safety and operations improvements at freeway interchange locations.

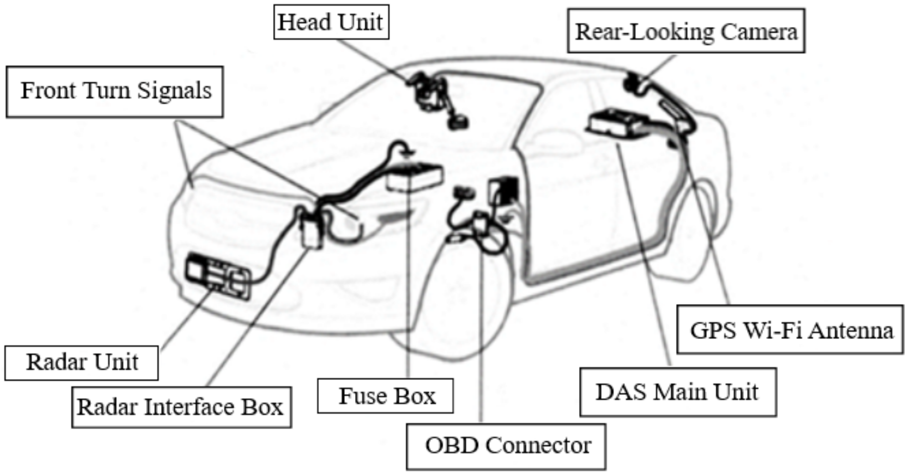
The following sections of this chapter detail the data and the data analysis methodology.

DATA COLLECTION

Data Collection Overview

SHRP2 launched the NDS project from 2010 to 2013 to investigate driver behavior and performance relevant to safety in real-world scenarios.[47] With more than 3,500 participating drivers recruited, the study collected naturalistic-driving data and related data surrounding six sites across the country: Buffalo, NY; Durham-Raleigh, NC; Indianapolis, IN; Seattle-Tacoma, WA; State College, PA; and the Tampa, FL, region.

The SHRP2 NDS used an onboard data acquisition system for vehicle kinematic and driver behavior data collection. The data acquisition system consisted of a forward radar, four video cameras (observing driver’s face and hands, passenger side, forward roadway, and rear roadway), accelerometers, Global Positioning System (GPS) receivers, computer vision lane-tracking capability, and data storage equipment (figure 3).[48] The final NDS database contained information on more than 5 million trips and 41,000 events, with additional events and data added as data processing continued.[2] Events in the SHRP2 database are epochs of NDS trips that involved either a crash or a near crash (a near miss in which abrupt vehicle maneuvers avoided a crash outcome) or a period of normal driving that the team sampled statistically for comparison with the crash and near-crash events.[46] As part of the same effort, the SHRP2 project also developed the RID with relatively detailed traffic and roadway information for the six participating sites. The RID incorporated both data originated at the State transportation agencies and data collected by instrumented vehicles.[45] The linkage between the SHRP2 driving data and roadway data gives researchers an opportunity to effectively identify driving data on specific roadway segments of interest.[49]



DAS = data acquisition system; OBD = onboard diagnostics port.

Figure 3. Diagram. Components of the SHRP2 DAS.[48]

The project involved two major types of data analyses: the SHRP2 safety event analysis and the driver behavior analysis. For SHRP2 safety event data, the project team collected detailed data about SHRP2 safety events that had occurred on ramps or in interchange areas. Due to the rare nature of safety events collected during the initial SHRP2 project, most such events were not committed by drivers and/or at the locations studied in the driver behavior analysis. The team could not, therefore, link event data with sign data collected for the driver behavior data analysis. The driver behavioral data analysis, however, involved a considerably more significant data collection and processing effort, which is the focus of the remaining sections of this chapter.

Identification of Locations for Driver Behavior Analysis

The goal of location identification was to identify route–guide sign combinations for which the team could study correlations between guide sign performance measures and driver behaviors for the subject route. The identification process therefore involved three steps:

- Identify interchanges: During this project and based on RID data, the team identified 192 urban area system interchanges at the six SHRP2 sites. During site identification, the team focused on system interchanges where two or more major freeways connect, with multiple major highways located in the near vicinity and with at least three through lanes in each direction. For comparison purposes and for use as baselines, the team also included interchanges that appeared to be less complex.

- Identify route options: At each interchange, the team manually identified a varying number of route options based on the RID, satellite images on the Esri® ArcGIS™ platform, and satellite images and street views in Google® Maps™.[50,51] For this project, the team defined each route option as a sequence of links that led to a lane choice as specified on applicable guide signs. To ensure the RID link sequence for each route option covered at least one overhead guide sign structure, each selected link sequence was at least 1 mi long from the center of the interchange. In total, the team identified 629 route options it used for the SHRP2 data request.

- Identify applicable signs for each route option: Based on satellite images, Google Street Views, and SHRP2 video log data, the team identified applicable guide sign structures for each route option or link sequence. The step initially resulted in a total of 773 sign structures. Figure 4 illustrates route options and sign structures identified at a sample system interchange.

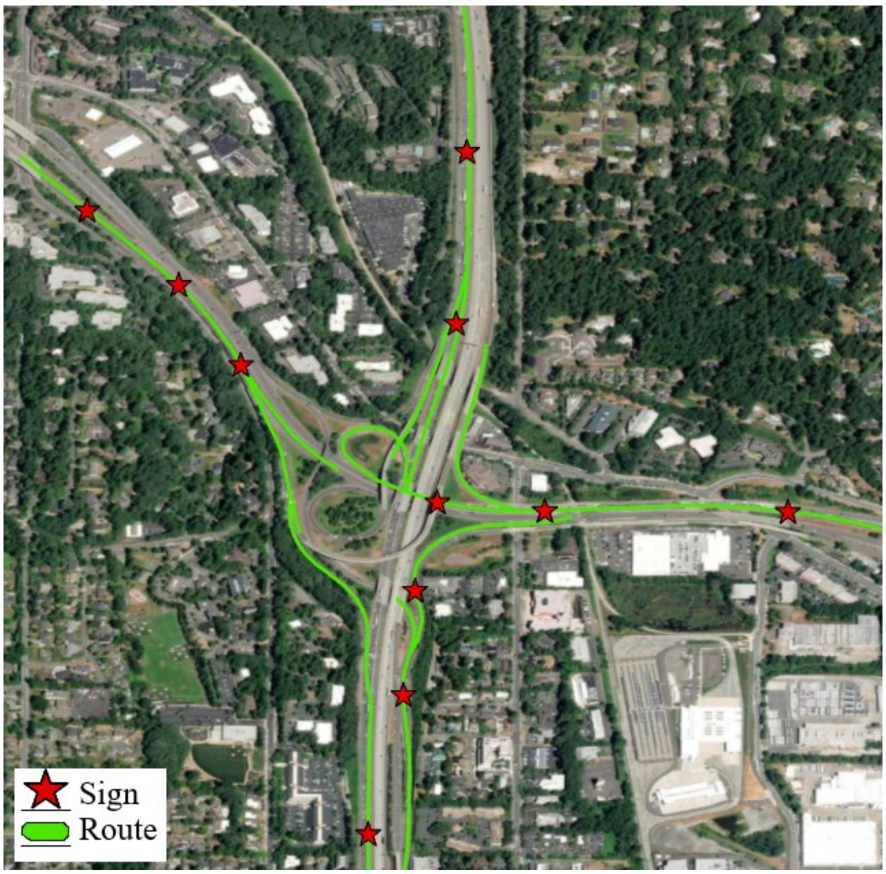


Figure 4. Map. Route options and sign structures at a system interchange.[52]

SHRP2 Data Request and Collection

For the purpose of this project, the team requested time series data items from the SHRP2 data team. For each route option, the team requested up to 20 trip segments meeting the criteria specified in table 11. Due to data extraction and processing cost considerations, the team capped the total number of trips at a random sample of 10,000 from available trip segments meeting the selection criteria.

During the sampling of the 10,000 trip segments, the team maximized the total number of route options represented in the sample data. In addition, the selection criteria for the trips in table 11 considered such factors as time (night versus day), driver age, and route familiarity. During this study, a driver was considered to be familiar with a studied route option if the driver traversed the same individual link sequence 10 or more times during the entire SHRP2 data collection period (i.e., 2011–13). The team considered a driver to be unfamiliar with a studied route option if the driver traversed the same link sequence fewer than four times in total during the entire data collection period. Drivers familiar with the route options are referred to hereinafter as "familiar drivers," and drivers unfamiliar with the route options are referred to as "unfamiliar drivers."

Table 11. Criteria used for SHRP2 trip data request for each route option.

	Trip Time and Driver Age				
Criteria	**9–11:30 a.m. or 1:30–4 p.m., 64 yr or Younger**	**9–11:30 a.m. or 1:30–4 p.m., 65 yr or Older**	**8:30 p.m.–12 a.m., 64 yr or Younger**	**8:30 p.m.–12 a.m., 65 yr or Older**	**Total**
Unfamiliar driver (total traversals for the same link combo < 6)	6	3	4	2	**15**
Familiar driver (total traversals for the same link combo > 9)	2	1	1	1	**5**
Total	**8**	**4**	**5**	**3**	**20**

Note: Values are the number of trip segments by criteria for each link combination.

- Trip videos: The team requested two types of trip videos during the data collection effort:
    - Forward-facing and cabin-view videos for all time series data trip segments previously selected: The team requested these video files primarily for two purposes: collecting information that described the driver, the traffic, and the environmental conditions during each trip, which is used in the data analysis, and screening each trip for eligibility for data analysis. Examples that would disqualify a trip for data analysis were major weather or surface conditions that would significantly affect driver behaviors (e.g., heavy rain, fog, or snow), lighting conditions affecting sign visibility (e.g., glare), and driver distraction (e.g., using a cell phone). Virginia Tech Transportation Institute's (VTTI's) SHRP2 video reduction team processed the video files in secure data reduction labs.[(53)] More information about the variables collected from the trips is available in the remaining sections of this chapter.
    - Sample forward-facing videos for each route option: For each route option, the team requested forward-facing videos for two trip segments: one for daytime and one for nighttime. Neither video was necessarily associated with a trip segment for which the team requested time series data. The video files verified whether roadway and/or subject guide signs were altered after the SHRP2 data collection period. If altered, team used the videos for collecting roadway and sign information during the SHRP2 study. The team also used the videos for collecting visual background complexity information for each sign structure.

- Vehicle detail data for all vehicles involved in the trip segments: These data included vehicle classification, site name, factory navigation, and navigation display location. The major purpose of vehicle data was to verify whether a vehicle had an onboard navigation system.

- Driver age in the SHRP2 driver demographic questionnaire dataset for all drivers involved in the trip segments selected.[(53)]

- Driving history questionnaires data for all drivers involved in the trip segments selected, including numbers of crashes and violations for 3 yr before the SHRP2 NDS study, driving years, and average annual mileage driven.[(53)]

- Visual and cognitive tests for all drivers involved in the trip segments selected, including day far acuity both eyes, day near acuity both eyes, color score first circle, color score second circle, color score third circle, color score fourth circle, color score fifth circle, and color score sixth circle.

- Each driver's total traversals during the SHRP2 data collection period for the subject route option for all drivers involved in the trip segments selected.[(53)]

- Detailed event data, event video data, and time series data for crashes and near crashes at freeway interchange areas: The objectives of the event data were to learn qualitatively how guide signs affect safety and driver behavior at interchange areas and to potentially identify vehicle kinematic thresholds for risky driver behaviors. For this purpose, the project requested data for SHRP2 safety events that met the following criteria: relation to junction = "Interchange area or entrance/exit ramp" and event severity = "Crashes" or "Near crashes."[(53)]

Final Trip Selection for Driver Behavior Data Analysis

SHRP2 trip segments involving the following conditions were not used in analyses during this project:

- Non-free-flow traffic conditions (traffic conditions clearly affected vehicle maneuverability).

- Construction zones.

- Adverse weather conditions that clearly affected visibility.

- Drivers' performing of complex secondary tasks.

- Sign visibility obstruction (e.g., by sun glare, significant windshield obstructions, or obstructions due to roadway or roadside objects or large vehicles).

The team based final trip selection primarily on trip video screening performed by SHRP2 video reductionists in secure data labs. Appendix A contains more detailed information on the variables and conditions the team used in trip qualification.

Driver Behavior Data Analysis Areas

Analysis areas were roadway segments whose SHRP2 driver behavioral data the team analyzed.[53] The driver behavior data analysis consisted of two 500-ft analysis areas (figure 5): one at the sign location (ending at the sign structure) and the other at the ramp location (ending at the physical gore nose). The 500-ft segment length provides 5–6 s of driver behavior data, assuming speeds of 60–70 mph. The analysis area at the sign location was intended to capture driver behaviors when drivers read and reacted to the subject signs, while the analysis area at the ramp location was intended to learn how drivers navigate routes after reading signs.

The team determined analysis area length based on a number of observations and considerations:

- Legibility range of freeway guide signs: Freeway guide signs in most cases use letters and numerals with heights of 8–20 inches (table 1 through table 4). Assuming a conservative ratio of 1 inch of letter height per 30 ft of legibility distance, as used by MUTCD, freeway guide signs are legible to most drivers for a distance ranging from 240 to 600 ft based on letter size.[1] The analysis area should not include driver behaviors that may not be responses to the subject traffic signs.

- SHRP2 data collection frequencies: The area had to be long enough to include sufficient driver behavioral information for analysis. The SHRP2 data were collected at different frequencies based on data and sensor types. The team collected vehicle dynamics data in the SHRP2 time series dataset at a frequency of 10 hertz and GPS location data at 1 hertz. At those frequencies, a vehicle traveling at 65 mph (i.e., 95 ft/s) would let approximately 10 vehicle dynamics data points and 1 GPS location be collected for each 100 ft of distance.[53]

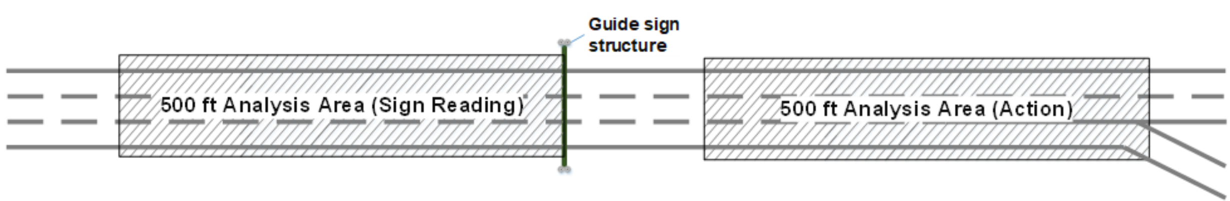


Figure 5. Illustration. Data analysis area.

Data Processing and Variables for Driver Behavior Analysis

Driver Behavioral Variables

This study used several driver behavioral variables to learn how different levels of sign complexity could affect driver behaviors relevant to safety. The variables were used as dependent variables in the statistical data modeling process. The team calculated all driver behavioral variables based on SHRP2 time series data for each trip segment at each sign location over the entire analysis segment.[53]

Following are the driver behavioral variables the study used:

- Relative speed: Speed and speed-related measures are commonly considered major contributing factors with regard to crash and crash severity. (See references 54, 55, 56, 57, 58, 59, and 60). Studies have suggested that overall crash involvement as a function of travel speed generally follows a U-shaped curve, with crash likelihood increasing quadratically with increase in absolute difference between one's travel speed and the predominant speed on a roadway.[61] For this study, the team considered the following speed-related variables:

    - Mean relative speed, which is speed relative to posted speed (ΔV-μ) in mph.
    - Relative speed standard deviation (ΔV-σ) in mph.
    - Minimum speeding amount (i.e., difference between speed and speed limit) in mph, denoted as ΔV-Min.
    - Maximum speeding amount (ΔV-Max) in mph.

- Longitudinal acceleration: The team used measures related to longitudinal acceleration to learn the magnitude and frequency of speed changes as functions of independent variables. Studies have found that crash-involved drivers frequently engaged in abrupt deceleration behavior.[59] A previous SHRP2 NDS study also used longitudinal acceleration as a major indicator of crashes and near crashes.[4] The longitudinal acceleration variables were:

    - Mean longitudinal acceleration rate (along-μ) in g.
    - Longitudinal acceleration standard deviation (along-σ) in g.
    - Maximum longitudinal acceleration (in absolute value) (along-Max) in g.

In the SHRP2 time series data, longitudinal acceleration was a vector variable, with acceleration being positive and deceleration being negative (figure 6).

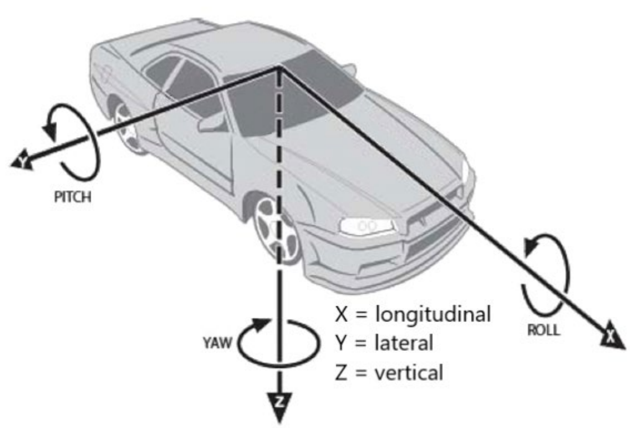


Figure 6. Diagram. Vehicle dynamics variable axes used by SHRP2 NDS data.[46]

- Lateral acceleration: Lateral acceleration rate can provide information about a vehicle's lane-changing behavior and evasive maneuvers that are closely related to crash risks. Previous studies have used lateral acceleration as an indicator of near crashes and crashes.[4] Lateral acceleration was also a vector variable, with acceleration to the right being positive and acceleration to the left being negative (figure 6). During this study, the team used:

    - Mean lateral acceleration rate (a_{lat}-μ) in g.
    - Lateral acceleration standard deviation (a_{lat}-σ) in g.
    - Minimum lateral acceleration rate (a_{lat}-*Min)* in g.
    - Maximum lateral acceleration rate (*alat-Max*) in g.

- Jerk: Jerk is a measurement of how fast an object accelerates.[62] Jerk-related metrics are frequently used as indicators of driver comfort and crash risks. For this study, the team used a number of variables for both longitudinal and lateral jerk rates:

    - Mean longitudinal jerk (j_{long}-μ) in g/s.
    - Standard deviation of longitudinal jerk (j_{long}-σ) in g/s.
    - Minimum longitudinal jerk (j_{long}-*Min*) in g/s.
    - Maximum longitudinal jerk (j_{long}-*Max*) in g/s.
    - Mean lateral jerk (j_{lat}-μ) in g/s.
    - Standard deviation of lateral jerk (j_{lat}-σ) in g/s.
    - Minimum lateral jerk (j_{lat}-*Min*) in g/s.
    - Maximum lateral jerk (j_{lat}-*Max*) in g/s.

The project team initially attempted to identify harsh braking actions as well as sudden lane changes based on lateral and longitudinal acceleration rates. However, a preliminary analysis of the time series data obtained showed that events involving sudden longitudinal or lateral acceleration that would be considered out of the normal range are generally rare and did not constitute a large enough sample to enable meaningful statistical analysis. For this attempt, harsh braking actions or lateral movements were defined as momentary values for longitudinal and lateral acceleration rates that exceeded 0.3 g or 1 standard deviation of the variable observations. A previous study, for example, summarized a number of criteria in vehicle dynamics, as illustrated in figure 7.[63] In addition, previous studies used a range of longitudinal acceleration values (e.g., $a_{long} = -0.3$ g or 1–4 σ) that would be considered harsh braking.[47,64] To identify maximum acceleration and jerk values, the team smoothed the time series data by using the moving averages of three adjacent data points.

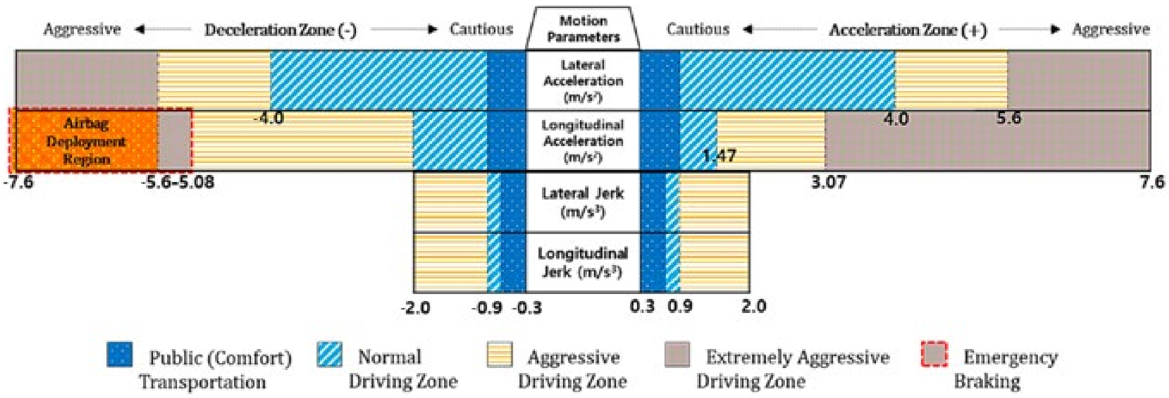


Figure 7. Diagram. Acceleration and jerk criteria to categorize driver behaviors.[63]

The SHRP2 time series data facilitate the computation of measures related to lane offset (i.e., the distance between the center of a subject vehicle and the center of a lane) and distance from a leading vehicle (based on which measures such as time to collision could be derived). SHRP2 collected lane position data based on machine vision and distance to leading vehicles based on radar. The project team randomly compared these time series data elements with trip videos for a number of SHRP2 trips and found that both data elements exhibited limited reliability when used for identifying lane changes and traffic conditions. In addition, such measures are better suited to driver behavior analyses of straight segments—as opposed to ramp locations, where frequent merging and diverging behaviors are expected. Therefore, those measures were not considered further during this study.

Guide Sign Variables

The team collected guide sign data based primarily on Google Street Views, with supplemental information obtained from sample trip videos and SHRP2 video logs to ensure that sign data reflected the time that original SHRP2 data were collected.[51,53] For each guide sign, the team collected the following information during this project:

- Number of words for each sign and for the entire sign structure (excluding symbols but including numerals).

- Units of information for the subject sign and other signs at each sign structure: Following are examples (in parentheses) of units of information:[19]

    - Place name (Denver).
    - Street name (Lamar Street).
    - Route number (I–95).
    - Cardinal direction (North).
    - Exit number (Exit 243A).
    - Command (Exit).
    - Distance (0.5 mi).
    - Lane-use arrow (↓).
    - Junction (Jct).

    - Exit only.

- Number of words and units of information for additional applicable signs at the subject sign location: Additional signs considered here are signs that provide regulatory or warning information applicable to route users in close vicinity of a subject sign structure. Examples of such signs are speed limit signs and high-occupancy-vehicle (HOV) signs.

Table 12 lists the guide sign complexity metrics used in this study.

Table 12. Guide sign complexity variables used in this study.

No.	Variable Name	Variable Values	Data Source (Collection Method)
1	Units of information for subject sign	Continuous number	Google, SHRP2 videos (manual)[51,46]
2	Units of information per s for subject sign	Continuous number	Other variables (calculate)
3	Units of information for other signs on structure	Continuous number	Google, SHRP2 videos (manual)
4	Units of information for other applicable signs	Continuous number	Google, SHRP2 videos (manual)
5	Number of words for subject sign	Continuous number	Google, SHRP2 videos (manual)
6	Number of words per s for subject sign	Continuous number	Other variables (calculate)
7	Number of words for other signs on structure	Continuous number	Google, SHRP2 videos (manual)
8	Number of words for other applicable signs	Continuous number	Google, SHRP2 videos (manual)
9	Subject sign arrow-per-lane indicator	Yes, no	Google, SHRP2 videos (manual)
10	Subject sign diagrammatic indicator	Yes, no	Google, SHRP2 videos (manual)

Note that the team originally considered using sign complexity ratings developed by two previous NCHRP efforts. However, that method relied on a lookup table based on the 2000 edition of MUTCD.[26] Using the lookup table in practice can be challenging for practitioners because use of the complexity rating would require an update of the table to reflect the latest MUTCD, and updated ratings that use current sign designs might not be consistent with driver perceptions without additional evaluations.[1] Some previous studies proposed using sign LOS based on assessments of three aspects of sign performance: navigation, workload, and response.[10,65] That method was found to be cumbersome for use in practice and therefore was not used in this study.

Roadway, Traffic, and Sign Structure Data Collection

The project team collected a number of variables relevant to roadway, traffic, and sign structure at the study locations. The data collection used various sources:

- SHRP2 RID: The RID contains basic lane configuration and traffic data for public roadways at all of the study sites.[45] In addition, the database includes historical satellite images of the six NDS States. In cases in which traffic- and roadway-related information was incomplete, the project team used historical Highway Performance Monitoring System (HPMS) data as a supplement source.[66]

- Sample NDS trip videos for identified route options: The team requested forward-facing videos for a nighttime trip and a daytime trip for each route option. The videos were used for verifying whether current roadway and sign conditions changed after the SHRP2

NDS.[53] In addition, the videos also formed the basis for collection of sign background complexity levels.

- Satellite images and street views from Google Maps and Esri ArcGIS: These images were used for collecting more detailed roadway information that was not available in the RID.[51,50] Such information included lane changes required for each route option, auxiliary lanes, and ramp speed limits.

For roadway and traffic data available in a feature class format, the team used automatic spatial joins to collect data and match them to the study sign structures. For information available only via video files and satellite images, the team collected variables manually.

For each SHRP2 trip segment extracted for analysis, the team screened associated videos and collected a variety of information. The major purposes of that activity were to ensure the eligibility of each trip for analysis and to identify the environmental and traffic conditions during the trip. During the process, the team deleted trips that took place in construction zones, trips during adverse weather conditions that clearly affected visibility, and trips in traffic conditions that clearly affected vehicle maneuverability. For qualified trips, the team collected the following information (appendix A):

- Traffic density (e.g., LOS A, B, and C).
- Lighting condition (e.g., darkness without lighting or darkness lighted).
- Surface condition (e.g., dry or wet).
- Visual obstruction (e.g., windshield impairment or glare): Trips with significant visual obstructions were disqualified for analysis.
- GPS indication.
- Driver distraction (e.g., simple, moderate, and complex): Trips with identified complex secondary tasks were disqualified for analysis.

Table 13 lists the roadway, traffic, driver, trip, and sign structure variables used in this study.

Table 13. List of roadway, traffic, driver, trip, and sign structure variables.

Variable Type	Variable Name	Variable Values	Data Source (Collection Method)
Trip	Traffic density	LOS A, B, C	Trip videos (manual)
Trip	Weather	None, other (no or minor effect)	Trip videos (manual)
Trip	Lighting	E.g., day, darkness lighted	Trip videos (manual)
Trip	Surface condition	Dry, other (no or minor effect)	Trip videos (manual)
Trip	GPS usage	Yes or likely, no	Trip videos (manual)
Trip	Task engagement	Simple, moderate, complex	Trip videos (manual)
Driver	Age	64 yr or younger, 65 yr or older	SHRP2 driver data (request)[46]
Driver	Driving years	2 or fewer, 3 or more	SHRP2 driver data (request)

Variable Type	Variable Name	Variable Values	Data Source (Collection Method)
Driver	Crashes in past 3 yr	0 or 1, 2 or more	SHRP2 driver data (request)
Driver	Violations in past 3 yr	0 or 1, 2 or more	SHRP2 driver data (request)
Driver	Annual miles driven	<5,000; 5,000–10,000; >10,000	SHRP2 driver data (request)
Driver	Total traversals	5 or fewer, 10 or more	SHRP2 driver data (request)
Driver	Day far acuity both eyes	20/20 or better, lower than 20/20	SHRP2 driver data (request)
Driver	Color score first–sixth plates[1]	6 numerals or higher, 5 or lower	SHRP2 driver data (request)
Driver	Night contrast sensitivity rows A–C[2]	5 or higher, 4 or lower	SHRP2 driver data (request)
Driver	Night contrast glare sensitivity rows A–C[2]	3 or higher, 2 or lower	SHRP2 driver data (request)
Roadway and traffic	Interchange layout type	See figure 1	Esri, Google, RID (manual)[(50,51,45)]
Roadway and traffic	Ramp geometry	See figure 8	Esri, Google, RID (manual)
Roadway and traffic	Mainline alignment	Tangent versus curve	Esri, Google, RID (manual)
Roadway and traffic	Mainline average annual daily traffic	Continuous number	RID/HPMS (spatial matching)[(45,66)]
Roadway and traffic	Mainline truck average annual daily traffic	Continuous number	RID/HPMS (spatial matching)
Roadway and traffic	Mainline total lanes	Continuous number	Esri, Google, RID (manual)
Roadway and traffic	Mainline through lanes	Continuous number	RID/HPMS (spatial matching)
Roadway and traffic	Number of weaving lanes	Continuous number	Esri, Google, RID (manual)
Roadway and traffic	Mainline speed limit	Whole number in mph	RID/HPMS (spatial matching)
Roadway and traffic	Ramp speed limit	Whole number in mph	Google, SHRP2 videos (manual)[(51,46)]
Roadway and traffic	If exit, side of ramp	Left, right	Esri, Google, RID (manual)
Roadway and traffic	Next movement after sign movement	Diverge, merge, right and left turns	Esri, Google, RID (manual)
Roadway and traffic	Maximum number of lane changes required	Continuous number	Esri, Google, RID (manual)
Roadway and traffic	Minimum number of lane changes required	Continuous number	Esri, Google, RID (manual)
Roadway and traffic	Route guidance on pavement	Yes, no	Esri, Google, RID (manual)
Roadway and traffic	Distance from previous interchange	Continuous number in feet	Esri, Google, RID (manual)
Roadway and traffic	Distance from previous on-ramp within 1 mi	Continuous number in feet	Esri, Google, RID (manual)
Roadway and traffic	Distance from previous off-ramp within 1 mi	Continuous number in feet	Esri, Google, RID (manual)
Roadway and traffic	Distance to diverging point	Continuous number in feet	Esri, Google, RID (manual)

Variable Type	Variable Name	Variable Values	Data Source (Collection Method)
Roadway and traffic	Prior ramp distance in time	Continuous number in seconds	Other variables (calculate)
Roadway and traffic	Next ramp distance in time	Continuous number in seconds	Other variables (calculate)
Sign structure	Number of signs on the structure	Continuous number	Google, SHRP2 videos (manual)
Sign structure	Sign visual background complexity	See figure 9 to figure 13	SHRP2 videos (manual)
Sign structure	Number of route options on sign structure	Continuous number	Google, SHRP2 videos (manual)
Sign structure	Number of route options on subject sign	Continuous number	Google, SHRP2 videos (manual)
Sign structure	Number of lanes for route option	Continuous number	Esri, Google, RID (manual)
Sign structure	Distance from previous applicable advance sign	Continuous number in feet <1 mi	Esri, Google, RID (manual)
Sign structure	Advance signs <1 mi prior to subject sign	Continuous number	Esri, Google, RID (manual)

[1]SHRP2 used an Optec® 6500P Vision Analyzer for vision and cognitive data collection.(67) The device uses six Ishihara test plates for color blindness, with a total of eight numerals, of which subjects with five out of eight numerals identified correctly are considered to have mild color deficiency.(68)

[2]Eye contrast sensitivity can negatively affect driving during adverse weather and lighting conditions. This study considered driver contrast sensitivity data for nighttime conditions with and without glare. An Optec 6500P Vision Analyzer uses the Functional Acuity Contrast Test® for contrast sensitivity tests.(68,69,70) The test contains six rows (i.e., spatial frequencies ranging from 1.5 to 18 cycles per degree), with nine cells in each row of decreasing contrast values. Contrast sensitivity for healthy eyes is a function of such factors as age, luminance, and glare. Vision problems are identified by comparing a subject's responses for all cells with standard curves. Nighttime condition was simulated at a luminance level of 3.0 cd/m^2. For simplicity, this project considered only rows A–C responses for the better performing eye of each subject.

Figure 8 lists the typical ramp layouts observed in this study.

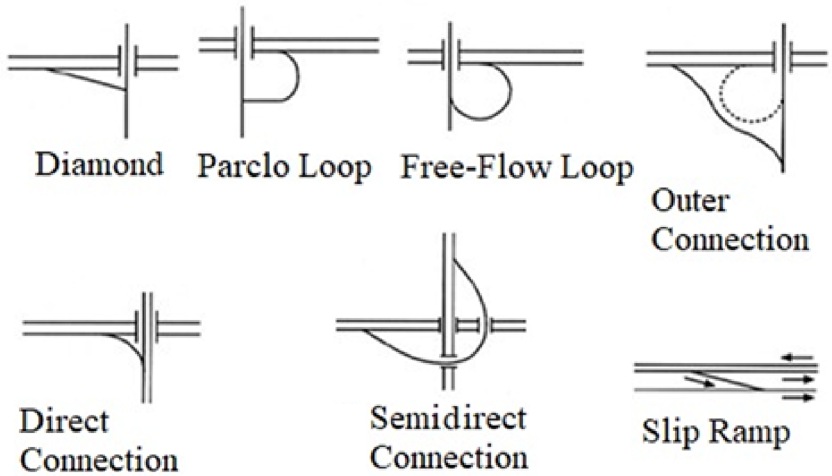


Figure 8. Diagram. Ramp geometric layout types.[5]

Figure 9. Photo. Visual complexity for overhead guide signs level 1: Minimal objects and light sources (low traffic).[71]

Figure 10. Photo. Visual complexity for overhead guide signs level 2: Low commercial activity, some nearby light sources and signs (low traffic).[71]

Figure 11. Photo. Visual complexity for overhead guide signs level 3: Illuminated commercial signs, moderate number of other signs and light sources (low to moderate traffic).[71]

Figure 12. Photo. Visual complexity for overhead guide signs level 4: Moderate commercial activity with illuminated signs and businesses (moderate to high traffic).[(71)]

Figure 13. Photo. Visual complexity for overhead guide signs level 5: Heavy commercial activity with illuminated signs and businesses and high opposing traffic volume and glare.[(71)]

Overview of the Data Collection Results

At the end of data processing for the driver behavior analysis, the project team combined the different datasets involved in the driver behavior analysis into an integrated datasheet on which each data row included values for all analysis variables for each analysis segment (e.g., location) and each SHRP2 trip. Initially, the project team requested 10,000 trip segments for the 629 original route options at 773 sign locations. After data collection and processing, the team reduced the original dataset to a total number of 7,871 trip–sign data points (i.e., a trip segment within an individual analysis segment for the subject sign) involving 99 interchanges, 540 sign structures, and 1,925 unique drivers. Appendix B has detailed descriptions of the data used in the driver behavior analysis.

The project team viewed the trip video files for all analyzed SHRP2 driver behavior trips to learn how drivers behaved relevant to traffic signs analyzed. The purpose of that effort was bifold. First, the team had to ensure the analyzed trips were qualified trips that had great potential for project success. Second, by viewing trip videos at the analysis segments, the team could learn qualitatively how drivers reacted to the analyzed signs and relevant route navigation challenges. That way, the team could better interpret the statistical analysis results later on. The team used the following two measures to rate driver behaviors based on the video files:

- Driver's attention to analyzed sign: Driver's attention to analyzed sign was a subjective rating assigned to each video measuring a subject driver's attentiveness to the analyzed signs. The observations of the rating included "Driver appeared to not look at signs," "Driver looked at signs casually," "Driver looked at signs somewhat attentively," and "Driver looked at signs attentively." Note that this information was based only on SHRP2 trip videos and not eye-tracking equipment or software. Eye attentiveness was based on judgments by the researchers and therefore involved a level of subjectivity.

- Driver's decisiveness at ramp location: This was a three-level rating score assigned to each video to measure a driver's level of hesitation at a ramp location. Observations for this rating included "No navigation issue observed when taking ramp," "Hesitation observed but no issue taking lane/ramp," and "Hesitation observed and driver switched lanes back and forth." Similarly, level of hesitation was based on judgments by the researchers and therefore involved a level of subjectivity.

As figure 14 and figure 15 show, the majority of trips involved drivers' clearly looking at signs when traversing the analysis segments during each trip. Based on the videos, however, due to the lack of facial expressions on drivers, the research team could not in many cases determine how attentively drivers were looking at signs. In addition, the videos showed that based on their facial expressions and driver reactions at the ramp locations, most drivers did not have issues in exiting freeways.

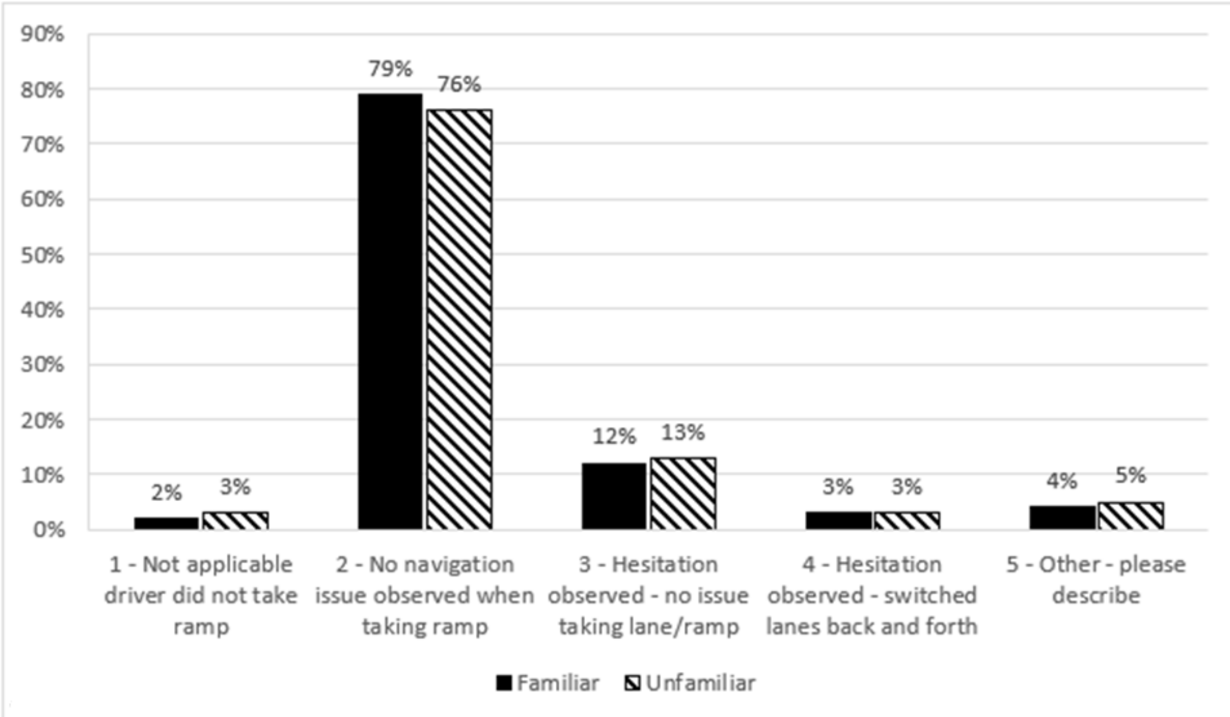


Figure 14. Graph. Analyzed SHRP2 driver behavior trips by driver attentiveness to sign.

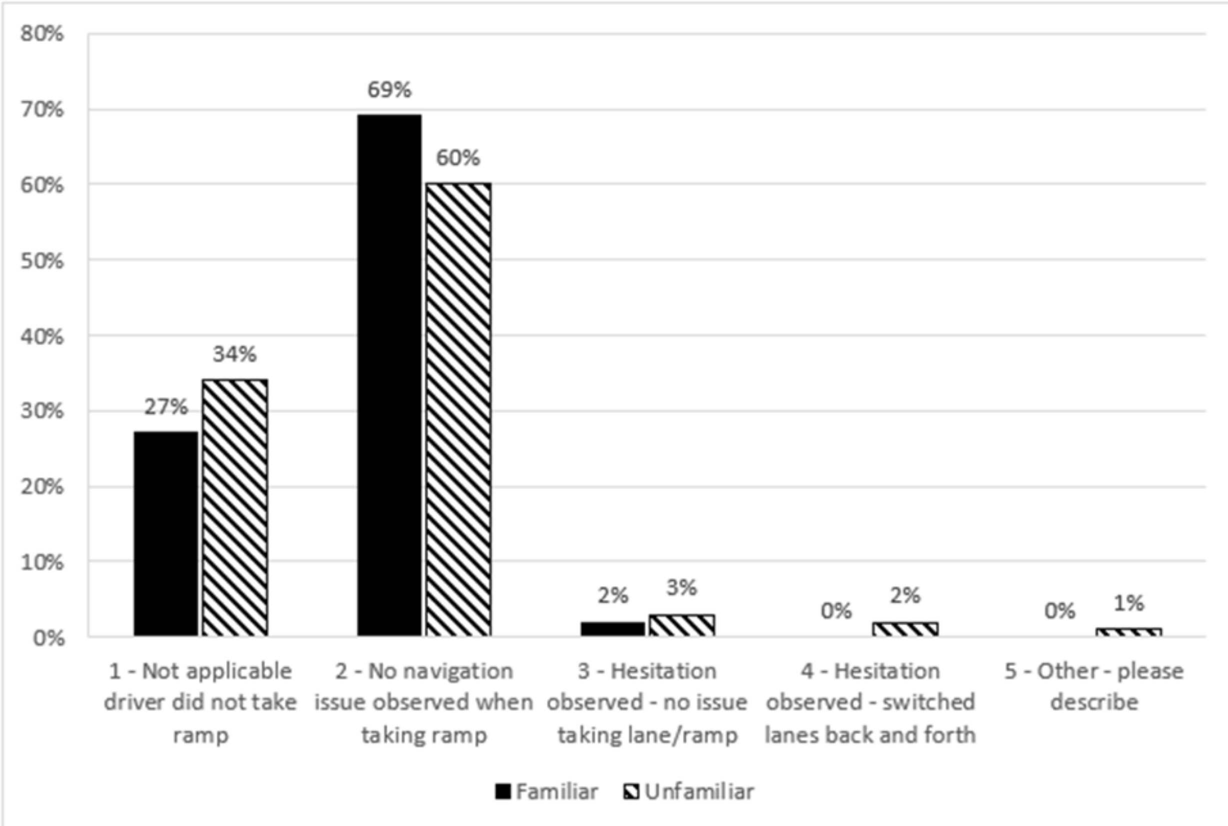


Figure 15. Graph. Analyzed SHRP2 driver behavior trips by driver hesitation at ramp location.

The event data request resulted in a total of 1,475 safety events: 83 crashes and 1,392 near crashes (table 14). This event-detailed table includes a large number of variables depicting driver, vehicle, roadway, traffic, environment, contributing factors, outcome, driver actions, and other factors involved in each safety event. The SHRP2 team developed the table based on an analysis of event video files by following an approved data reduction protocol, and the table was readily available by request of the research team. Time series data depicted vehicle kinematic information for the period of each safety event. The event video files enabled the project team to develop a comprehensive understanding of chains of events and potential roles that traffic signs in the interchange areas might have played to contribute to occurrences of safety events.

Table 14. Counts of SHRP2 safety events used for event analysis.

Event Severity	Entrance/Exit Ramp	Interchange Area	Total
Crash	24	59	83
Near crash	193	1,199	1,392
Total	**217**	**1,258**	**1,475**

DATA ANALYSIS METHODOLOGY

Driver Behavior Data Analysis Scenarios

The team conducted a driver behavior data analysis for a number of analysis scenarios to ensure a comprehensive understanding of driver behavior–sign complexity correlations in different scenarios. The project team based its selection of data analysis scenarios on the following:

- Driver characteristics: The 2009 MUTCD recognizes that freeway guide signs are designed primarily for drivers unfamiliar with the routes.(1) In addition, older drivers (i.e., drivers 65 yr or older) are generally considered to have visual performance different from that of younger drivers.

- Roadway and traffic considerations: A number of roadway and traffic variables can affect the design and installation of freeway guide signs. For example, speed limit, ADT, number of lanes, ramp location (i.e., left versus right), and freeway mainline geometric alignment (i.e., curve versus tangent) are all major factors that affect both sign design and data analysis results. Note, however, that ADT is generally highly correlated with number of lanes. In addition, to isolate the effects of traffic signs, this study considered only trips during nonpeak hours.

- Data availability considerations: For any analysis scenario to be meaningful, the sample size has to be sufficiently large to yield practically meaningful and/or statistically significant results.

- Use of a variable to define analysis scenarios versus including a variable as an independent variable in multivariate models: Analysis scenarios can be useful for simulating typical settings in which users can readily apply analysis results. In a warranting analysis or design process, such scenarios may be adapted directly as warranting or design scenarios. When including a variable in multivariate models as an independent variable, a research team would have the opportunity to identify criteria or thresholds for the variable that could be used in sign designs and analyses.

- Data analysis demand: Each analysis scenario would require a separate set of models to run.

Based on the aforementioned considerations, the team decided to use the following variables to define scenarios:

- Driver age (i.e., older versus younger).
- Route familiarity (i.e., familiar, unfamiliar, and unfamiliar using GPS).
- Ramp type (i.e., ramps on left versus ramps on right).
- Trip time (i.e., daytime versus nighttime).

Based on those variables, the project team initially divided the dataset into 24 scenarios for each of the two types of analysis segments. The team later combined or removed some scenarios due to low sample sizes. In addition, the team did not analyze trips by drivers unfamiliar with the route who were using GPS. At the end, the team analyzed the data for 10 scenarios (table 15). For each scenario, the team developed separate models for each driver variable and analysis segment.

Table 15. List of analysis scenarios and sample sizes.

No.	Age	Route Familiarity	Ramp Type	Time	Drivers (No.)	Sign Locations (No.)
1	65 yr or older	Familiar	Right ramps	Daytime	129	252
2	65 yr or older	Familiar	Right ramps	Nighttime	109	204
3	65 yr or older	Unfamiliar	Right ramps	Daytime	300	374
4	65 yr or older	Unfamiliar	Right ramps	Nighttime	131	193
5	64 yr or younger	Familiar	Right ramps	Daytime	261	333
6	64 yr or younger	Familiar	Right ramps	Nighttime	164	270
7	64 yr or younger	Unfamiliar	Right ramps	Daytime	628	420
8	64 yr or younger	Unfamiliar	Right ramps	Nighttime	460	379
9	All ages	Unfamiliar	Left ramps	Daytime	160	113
10	All ages	Unfamiliar	Left ramps	Nighttime	99	85

Statistical Approach for Driver Behavior Data Analysis

Data Analysis Approach Overview

This data analysis task involved a large number of variables that the project team classified into continuous, categorical, and discrete based on the variables' values. The team designed a multistep data analysis approach to efficiently and effectively investigate the data (figure 16):

- Identify significant driver behavioral and sign complexity variables: This study involved a large number of driver behavioral and sign complexity variables. Although the project team selected variables to depict driver behaviors and guide signs in a comprehensive manner, some variables might be more significant than others and therefore more likely to result in meaningful findings. To control data-modeling efforts yet ensure meaningful findings, the team first conducted a series of correlation tests to select the most significant driver behavioral and sign complexity variables. The team conducted the correlation analyses between each driver behavioral variable and all sign performance variables. Since both driver behavior variables and sign complexity variables were continuous variables, the team used Hoeffding's measure of dependence, Kendall's tau-b coefficient Pearson's product-moment correlation, and Spearman's rank-order correlation to test for the correlations.(See references 72, 73,74, and 75). Among the four methods, the Pearson's product-moment correlation is most robust for calculating a parametric measure of the linear relationship, while the three others are best known for detecting nonparametric measures of association. Spearman's rank-order correlation and Kendall's tau-b coefficient can be particularly suitable for paired observations, while Hoeffding's measure of dependence is designed to detect more general departures from independence. In addition, the Spearman and Kendall tests are also known to be effective for nonlinear correlations. Note that the different sign complexity variables were highly correlated with one another by nature, and therefore, using the variables simultaneously in the same models may result in unknown biases.

- Select meaningful independent variables: This study collected a large number of variables depicting roadways, traffic, trips, drivers, and sign structures. The team collected the variables to capture as much information as possible that might have played roles in correlations between driver behaviors and sign complexity levels. However, the large number of variables would inevitably complicate the data-modeling effort. The number would also make it more challenging to interpret modeling results in a meaningful and straightforward way. In particular, the large number of categorical variables would significantly reduce the sample sizes during the modeling process. To filter out insignificant independent variables prior to the multivariate modeling process, the project team conducted the same correlation screening (i.e., by using Hoeffding's measure of dependence, Kendall's tau-b coefficient, Pearson's product-moment correlation, and Spearman's rank-order correlation) to test correlations with each driver behavioral variable. The team then used only significant independent variables in the subsequent, multivariate modeling process. In addition to identifying significant variables, the team developed correlation matrices for the independent variables in the dataset to identify highly correlated independent variables prior to the modeling process by using the same four test methods for correlations. The team further treated highly correlated variables (i.e., that have correlation coefficients exceeding 0.6) by either combining the correlated pairs into a single variable or keeping the variables that were more practically available and meaningful.

- Develop detailed analysis scenarios based on significant variables and data availability: The researchers carefully examined each significant categorical or discrete variable to determine whether they should use the variable to define new scenarios or whether they should use it in a multivariate environment. The primary consideration was that a scenario be a common roadway setting requiring a sign complexity criterion that designers frequently deal with. A variable in a multivariate model, in contrast, would be a factor a sign designer has to use collectively to determine maximum sign complexity.

- Develop driver behavior–sign complexity models: For each scenario, the team developed multivariate mixed-effect linear models for each significant driver behavioral variable, with only sign-complexity-related variables as the independent variables. The modeling attempt showed that many roadway- and traffic-related variables had more significant and/or competing effects on driver behavior variables. For that reason, the inclusion of non-sign-related variables would result in less significance for the sign-related variables and, in many cases, fewer sign-related variables in the final models. In addition, using only sign-related variables resulted in fuller models (i.e., with more sign-related variables as significant independent variables), which enabled the research team to better understand the potential effects of more sign-related variables on driver behaviors. The following section describes in more detail the statistical techniques the project team used in the development of mixed-effect models.

- Develop complete multivariate models with roadway variables: The second set of multivariate models included all significant independent variables, such as those depicting roadway, driver, trip, and traffic conditions. The purpose of this modeling effort was to develop an understanding of how such variables jointly affect driver behaviors with sign complexity metrics. That understanding helped in the development of suggestions—particularly suggestions relevant to roadway and interchange design—and laid a foundation for the identification of warranting conditions relevant to sign design.

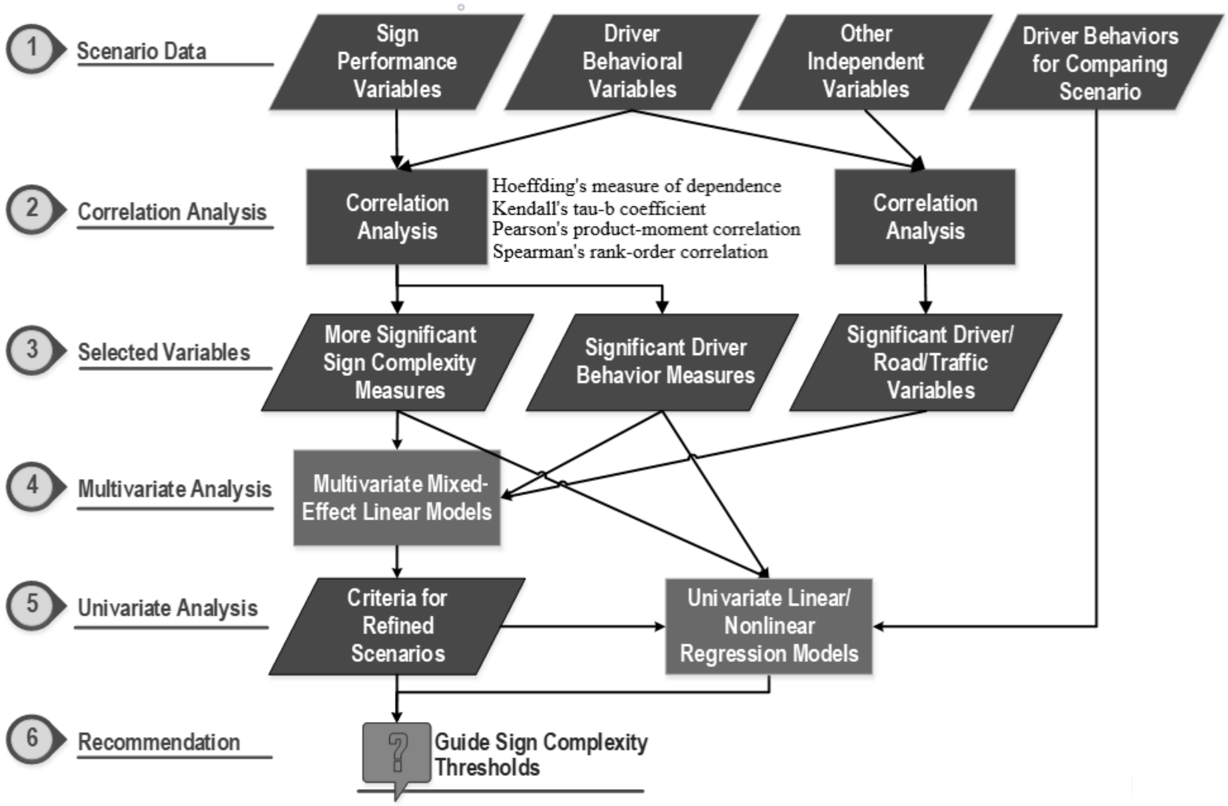


Figure 16. Diagram. Driver behavior analysis approach.

Data Modeling Methods

The involvement of both continuous and discrete or categorical variables prevented a large variety of modeling techniques specialized for categorical and count data analysis. As mentioned in a preceding section, the team developed multivariate models in this study by using mixed-effect linear regression. Linear mixed models are extensions of traditional linear models so as to allow both fixed and random effects. Linear mixed models take the following form:[76,77]

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{Z\mu} + \boldsymbol{\varepsilon}$$

Source: FHWA

Figure 17. Equation. Traditional linear mixed-model equation containing both mixed and fixed effects.

Where:

$\boldsymbol{y}$ = is the vector of observations with the mean as $X\beta$.
$\boldsymbol{\beta}$ = an unknown variable vector of fixed effects.

$\boldsymbol{\mu}$ = an unknown vector of random effects with a mean of 0 and a covariance matrix of G.
$\boldsymbol{\varepsilon}$ = an unknown vector of random errors with a mean of 0 and a variance matrix of R.
X and Z = the design matrices for the observation matrices of $\boldsymbol{\beta}$ and $\boldsymbol{\mu}$, respectively.

Compared with traditional linear regression, linear mixed models have an additional term (i.e., $\boldsymbol{Z\mu}$).

Assuming normality (i.e., $\boldsymbol{\mu \sim N(0, G), \varepsilon \sim N(0, R)}$, and Cov($\boldsymbol{\mu, \varepsilon}$) = 0), linear mixed models can be solved by maximizing the joint density over $\boldsymbol{\beta}$ and $\boldsymbol{\mu}$:

$$\begin{pmatrix} X'R^{-1}X & X'R^{-1}Z \\ Z'R^{-1}X & Z'^{R^{-1}}Z + G^{-1} \end{pmatrix} \begin{pmatrix} \hat{\beta} \\ \hat{\mu} \end{pmatrix} = \begin{pmatrix} X'R^{-1}y \\ Z'R^{-1}y \end{pmatrix}$$

Source: FHWA

Figure 18. Equation. Linear mixed-model joint density function.

SAS® uses the restricted (residual) maximum likelihood method for parameter estimation of linear mixed models.(78)

During this study, the project team selected multiple time series data trips for analysis at a fewer number of locations, which resulted in data from multiple trips collected for the same analysis locations. Such data technically are treated as hierarchical data, wherein the team collects multiple measurements (e.g., driver behavior data) from each of the same statistical units (e.g., sign locations). Mixed-effects models are particularly suitable for that kind of data structure to address the relative dependence among multiple trips at the same sign location.

A key assumption with regard to the multiple linear regression is that the dependent variables and, more important, the residuals be normally distributed. That assumption was verified by the team's plotting of the distributions of both dependent variables and residuals during the modeling process. The statistical analyses used a 0.05 significance level. Figure 19 through figure 22, for example, show the data distribution (counts of trip segments and data rows) for selected driver behavioral variables. The plots show that the dependent variables in general followed a normal distribution.

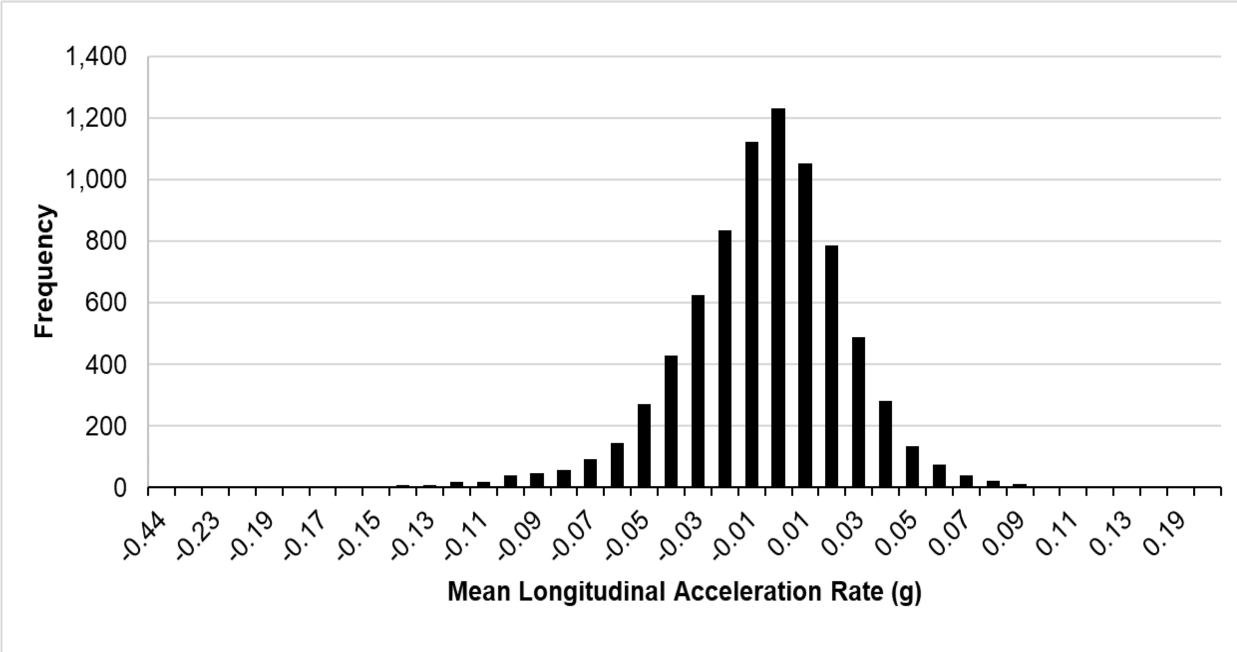


Figure 19. Graph. Data distribution by mean longitudinal acceleration rate.

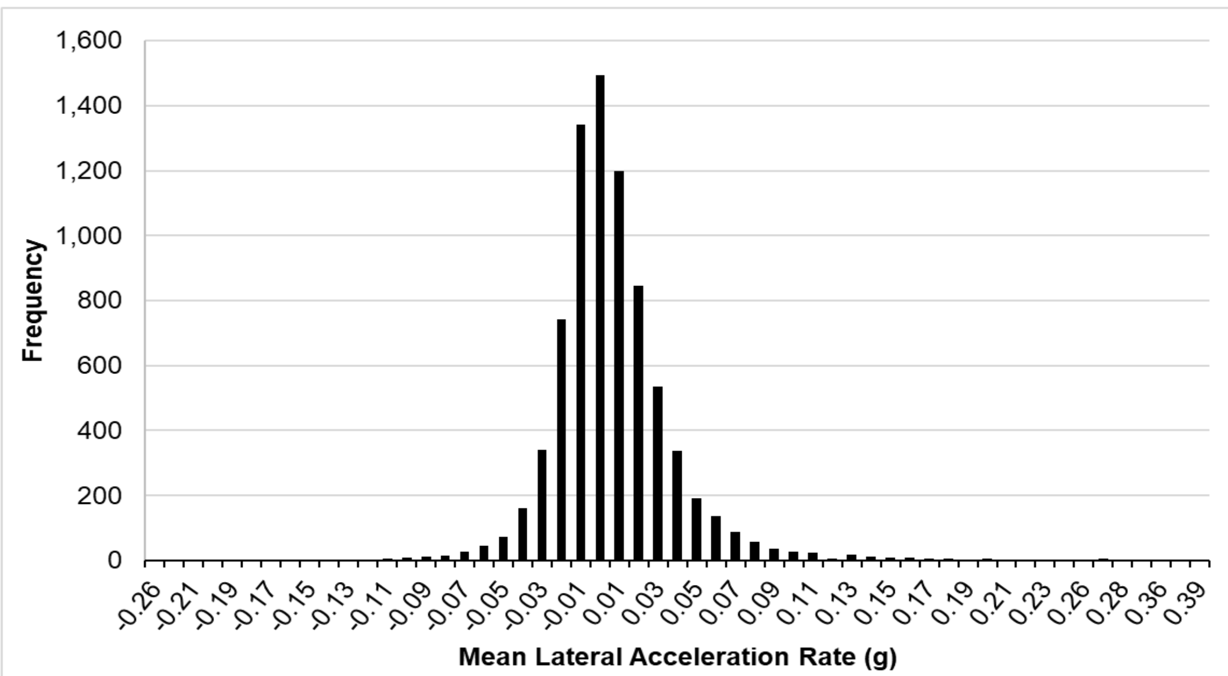


Figure 20. Graph. Data distribution by mean lateral acceleration rate.

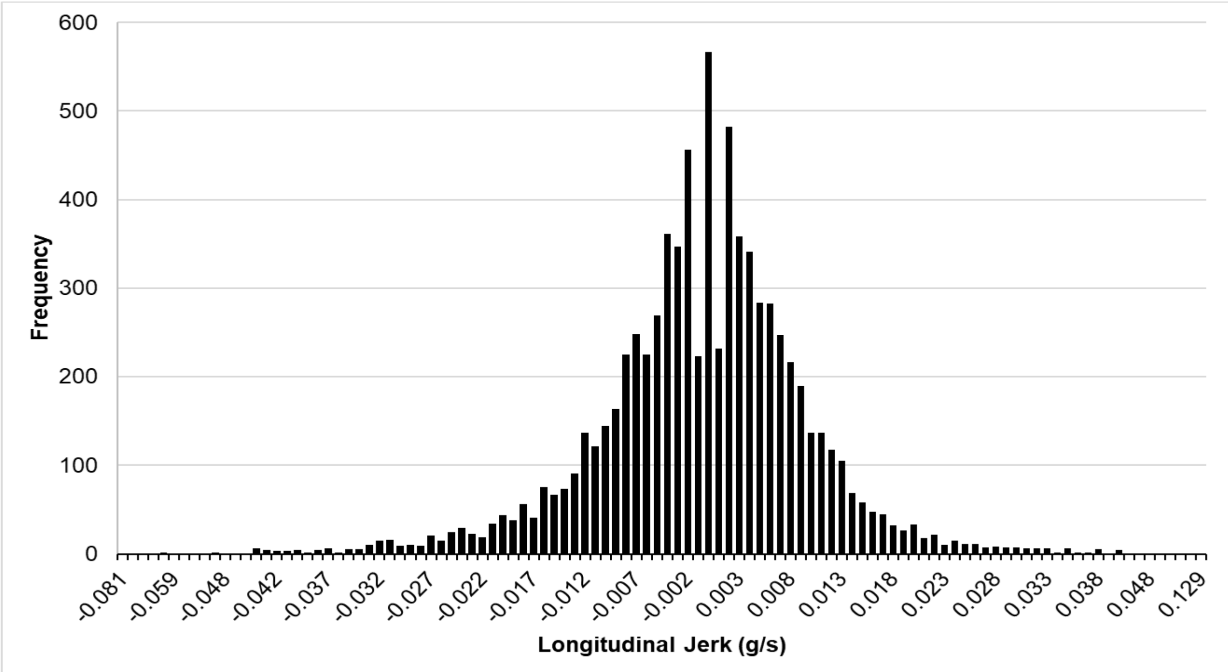


Figure 21. Graph. Data distribution by mean longitudinal jerk.

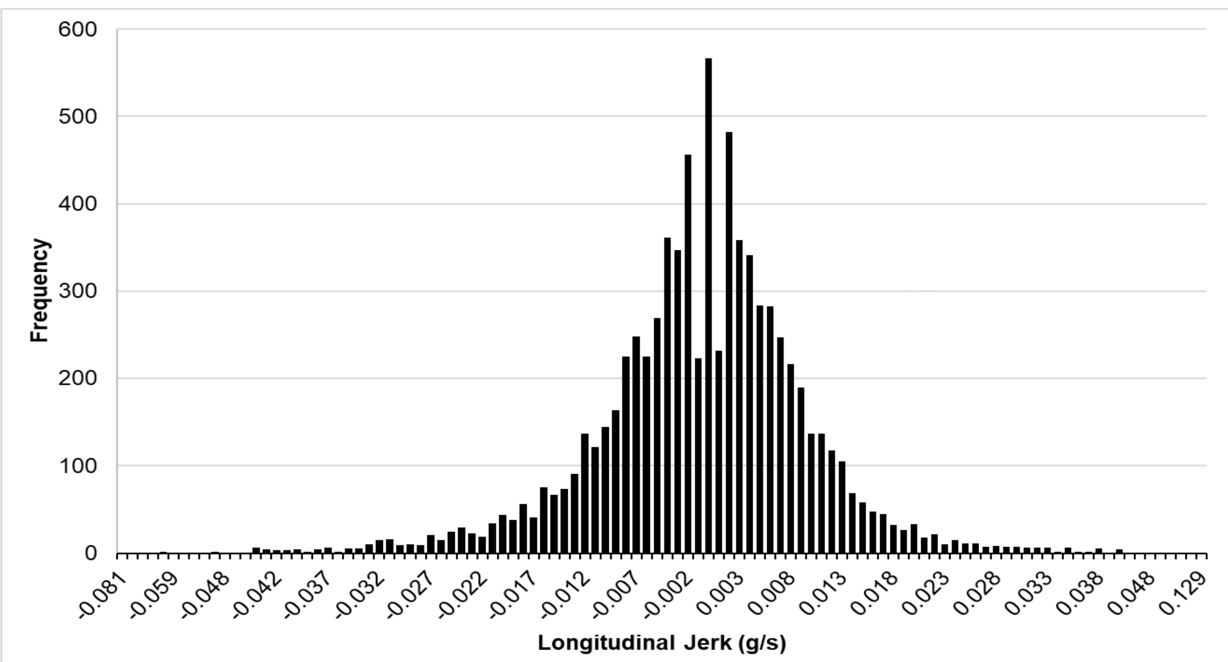


Figure 22. Graph. Data distribution by mean lateral jerk.

During the modeling process, the results showed that the mixed-effect linear modeling method was highly volatile (i.e., changing variables resulted in considerable differences among other variables in terms of *p*-values and parameter estimates) when sample sizes were small. That volatility further justified combining scenarios with smaller sample sizes to increase sample sizes.

SHRP2 Safety Event Analysis Methodology

The project team conducted the safety event data analysis primarily for the purpose of qualitatively learning how traffic signs in freeway interchange areas could contribute to safety risks. Due to the limited sample size and the lack of sign and route information at the safety event locations, the team did not conduct statistical analyses for the event data.

During the event data analysis, the project team took an iterative approach to identify the events in which traffic-sign-related factors might have played contributing roles and to document lessons learned from the safety events. The research team first analyzed the event details table for all crash and near-crash events that had occurred at interchange areas or on entrance and exit ramps, with the aim of selecting the ones that could potentially be relevant to this research. During this step, the team excluded events that had involved driver distraction, severe weather conditions, surface roadways (i.e., as opposed to access-controlled roadways), and other conditions that would have precluded the potential contribution of sign-related factors. The team then viewed the forward-facing videos on the SHRP2 Insight website to further learn how the events had occurred and whether sign-related factors could have contributed to the events.(53) Taking a case study approach, the team further analyzed in VTTI's secure data reduction labs the events selected after this step—in the forms of the detailed forward-facing, cabin-view, face-view, and rearview video files.

The project team attempted to analyze the vehicle kinematic measures of the selected SHRP2 safety events in an effort to establish thresholds for identifying unsafe behaviors (e.g., harsh braking or sudden lane change actions) that the team could use in the driver behavior analysis. However, only a limited number of trips used for the driver behavior analysis met the thresholds identified based on the safety events. For that reason, the team did not include such measures in the driver behavior data analysis task. That finding also indicated that the team not focus on risky behaviors during driver behavior data analysis.

CHAPTER 4. DRIVER BEHAVIOR AND GUIDE SIGN CORRELATIONS

CORRELATION SCREENING AND VARIABLE SELECTION

Table 16 lists the number of significant correlations (i.e., number of scenarios for which a driver behavior–sign complexity correlation was statistically significant) based on Pearson correlation test results. The table lists counts of significant correlations for the four primary sign complexity measures and for each driver behavior variable. Appendix C contains the same tables for the three other correlation test methods. Using four scenarios as examples, table 17 through table 20 further list the Pearson correlation coefficients and *p*-values for correlations for the four sign complexity variables. Overall, the analysis results showed that:

- Number of words had more significant correlations (based on both number of significant correlations and correlation coefficient values) compared with units of information. In addition, the logarithmic form of the number of words on subject sign generally had more significant correlations—judging from the equal or higher correlation coefficients in the majority of cases. Therefore, number of words and its logarithmic form were used as the sign information measures in the development of individual models.

- Among the large number of driver behavioral variables tested, acceleration and speed variables tended to be more likely to be significantly correlated with sign complexity measures. In comparisons by driver groups, jerk-related variables tended to be more frequently significant for older drivers, while acceleration-related variables tended to be more frequently significant for younger drivers.

To reduce modeling effort, the project team attempted to develop mixed models only for the number of words on subject sign variable. Compared with its logarithmic form, number of words was considered a more straightforward measure of sign complexity, which therefore better facilitates quantitative understanding of the results.

Table 16. Count of significant correlations: Pearson correlation.

Variable	Action				Sign			
	No. Words	Log No. Words	Units Info.	Log Units Info.	No. Words	Log No. Words	Units Info.	Log Units Info.
along-μ (g)	3	3	1	0	5	5	3	2
along-σ (g)	5	6	5	5	6	6	1	2
along-Max (g)	2	1	3	3	0	1	0	1
along-Min (g)	5	6	3	4	6	5	1	2
alat-μ (g)	0	0	1	1	3	3	0	1
alat-σ (g)	0	1	2	3	6	6	2	2
alat-Max (g)	0	0	1	1	3	3	2	2
alat-Min (g)	2	2	4	4	2	2	2	2
ΔV-μ (km/h)	3	4	2	3	5	5	1	2
ΔV-Max (km/h)	4	4	2	3	5	5	1	1
ΔV-Min (km/h)	4	5	3	3	6	6	1	4
ΔV-σ (km/h)	4	4	5	6	7	7	3	4
jlong-μ (g/s)	3	4	2	2	0	0	0	0
jlong-σ (g/s)	2	2	3	3	2	2	2	2
jlong-Max (g/s)	3	3	3	3	2	2	3	4
jlong-Min (g/s)	2	2	5	4	1	1	2	2
jlat-μ (g/s)	0	0	0	1	1	0	0	0
jlat-σ (g/s)	1	1	5	6	3	3	2	2
jlat-Max (g/s)	2	2	4	4	1	1	1	1
jlat-Min (g/s)	3	3	4	5	3	2	0	0
along-absμ (g)	6	6	4	4	3	5	0	2
along-absσ (g)	5	5	2	4	5	6	1	1
along-absMax (g)	4	5	4	4	5	6	3	1
alat-absμ (g)	2	2	1	1	5	5	0	0
alat-absσ (g)	0	0	1	1	4	5	2	2
alat-absMax (g)	1	2	0	2	7	6	2	1
Total	66	73	70	80	96	98	35	43

Info. = information.; No. = number.

Note: The maximum number of significant correlations possible for each cell (i.e., sign complexity–driver behavior variable combination) was 10, which was the number of scenarios analyzed.

Table 17. Pearson correlation results for unfamiliar, older drivers at ramp analysis segments (ramps on right, not using GPS, and nighttime).

Variable	Subject Sign Units of Information				Number of Words on Subject Sign				Significance
	Corr. Coef.	Prob. >|*r*|	Log: Corr. Coef.	Log: Prob. >|*r*|	Corr. Coef.	Prob. >|*r*|	Log: Corr. Coef.	Log: Prob. >|*r*|	
a_{long}-μ (g)	0.018	0.782	0.023	0.728	0.096	0.146	0.101	0.123	No
a_{long}-σ (g)	−0.015	0.823	−0.004	0.955	−0.027	0.678	−0.014	0.830	No
a_{long}-Max (g)	−0.067	0.310	−0.053	0.422	0.005	0.945	0.033	0.612	No
a_{long}-Min (g)	0.026	0.695	0.026	0.693	0.071	0.283	0.064	0.333	No
a_{lat}-μ (g)	0.004	0.951	0.012	0.857	−0.019	0.779	−0.001	0.988	No
a_{lat}-σ (g)	0.016	0.807	0.023	0.721	−0.005	0.936	0.020	0.757	No
a_{lat}-Max (g)	0.022	0.738	0.031	0.642	−0.002	0.973	0.023	0.722	No
a_{lat}-Min (g)	0.026	0.697	0.030	0.645	0.030	0.643	0.034	0.602	No
ΔV-μ (km/h)	<0.001	0.994	0.023	0.733	0.074	0.271	0.086	0.201	No
ΔV-Max (km/h)	−0.018	0.790	0.007	0.918	0.050	0.461	0.064	0.341	No
ΔV-Min (km/h)	0.012	0.861	0.030	0.659	0.088	0.191	0.095	0.160	No
ΔV-σ (km/h)	−0.063	0.350	−0.057	0.396	−0.101	0.134	−0.088	0.190	No
j_{long}-μ (g/s)	0.090	0.173	0.077	0.240	0.090	0.169	0.077	0.241	No
j_{long}-σ (g/s)	−0.059	0.370	−0.063	0.340	−0.026	0.694	−0.010	0.879	No
j_{long}-Max (g/s)	−0.149	0.023	−0.155	0.018	−0.107	0.103	−0.091	0.165	Yes
j_{long}-Min (g/s)	0.015	0.815	0.023	0.732	0.009	0.896	−0.011	0.871	No
j_{lat}-μ (g/s)	0.060	0.364	0.059	0.373	0.030	0.654	0.027	0.683	No
j_{lat}-σ (g/s)	−0.166	0.011	−0.161	0.014	−0.123	0.060	−0.098	0.135	Yes
j_{lat}-Max (g/s)	−0.113	0.084	−0.101	0.125	−0.103	0.118	−0.067	0.309	No
j_{lat}-Min (g/s)	0.233	<0.001	0.227	0.001	0.230	<0.001	0.200	0.002	Yes
a_{long}-$abs\mu$ (g)	−0.039	0.552	−0.026	0.693	−0.086	0.189	−0.078	0.235	No
a_{long}-$abs\sigma$ (g)	−0.014	0.827	−0.009	0.893	−0.044	0.502	−0.038	0.568	No
a_{long}-$absMax$ (g)	−0.035	0.590	−0.030	0.649	−0.071	0.281	−0.061	0.351	No
a_{lat}-$abs\mu$ (g)	−0.033	0.613	−0.021	0.745	−0.081	0.219	−0.056	0.398	No
a_{lat}-$abs\sigma$ (g)	−0.007	0.915	0.001	0.985	−0.025	0.700	0.002	0.978	No
a_{lat}-$absMax$ (g)	−0.024	0.713	−0.013	0.838	−0.052	0.427	−0.023	0.723	No

Coef. = coefficient; Corr. = correlation; Prob. = probability.

Table 18. Pearson correlation results for unfamiliar, younger drivers at ramp analysis segments (ramps on right, not using GPS, and nighttime).

Variable	Subject Sign Units of Information				Number of Words on Subject Sign				Significance
	Corr. Coef.	Prob. $>\lvert r\rvert$	Log: Corr. Coef.	Log: Prob. $>\lvert r\rvert$	Corr. Coef.	Prob. $>\lvert r\rvert$	Log: Corr. Coef.	Log: Prob. $>\lvert r\rvert$	
a_{long}-μ (g)	−0.014	0.666	−0.018	0.591	0.029	0.379	0.034	0.306	No
$a_{long}-\sigma$ (g)	−0.056	0.089	−0.055	0.093	−0.039	0.240	−0.031	0.347	No
a_{long}-Max (g)	−0.116	<0.001	−0.115	0.001	−0.047	0.156	−0.031	0.341	Yes
a_{long}-Min (g)	0.024	0.475	0.022	0.515	0.036	0.277	0.033	0.320	No
a_{lat}-μ (g)	0.123	<0.001	0.122	<0.001	0.063	0.057	0.052	0.114	Yes
a_{lat}-σ (g)	0.071	0.031	0.070	0.034	0.056	0.089	0.050	0.134	Yes
a_{lat}-Max (g)	0.073	0.027	0.075	0.023	0.048	0.143	0.048	0.150	Yes
a_{lat}-Min (g)	0.071	0.031	0.080	0.015	0.048	0.145	0.055	0.099	Yes
ΔV-μ (km/h)	−0.015	0.658	−0.005	0.870	0.012	0.714	0.024	0.470	No
ΔV-Max (km/h)	−0.016	0.632	−0.005	0.886	0.014	0.676	0.028	0.399	No
ΔV-Min (km/h)	−0.018	0.598	−0.010	0.775	0.007	0.844	0.015	0.643	No
ΔV-σ (km/h)	0.027	0.427	0.033	0.329	0.031	0.351	0.039	0.239	No
j_{long}-μ (g/s)	0.045	0.173	0.060	0.068	0.064	0.053	0.071	0.032	Yes
j_{long}-σ (g/s)	−0.034	0.305	−0.037	0.260	0.010	0.755	0.016	0.631	No
j_{long}-Max (g/s)	−0.025	0.458	−0.024	0.468	0.006	0.858	0.013	0.700	No
j_{long}-Min (g/s)	0.076	0.021	0.084	0.011	0.027	0.416	0.025	0.455	Yes
j_{lat}-μ (g/s)	0.056	0.090	0.056	0.088	0.063	0.057	0.064	0.054	No
j_{lat}-σ (g/s)	−0.001	0.983	−0.006	0.844	0.008	0.808	0.008	0.808	No
j_{lat}-Max (g/s)	−0.001	0.973	−0.003	0.923	−0.006	0.861	−0.006	0.866	No
j_{lat}-Min (g/s)	0.019	0.560	0.024	0.477	0.006	0.848	0.007	0.822	No
a_{long}-$abs\mu$ (g)	−0.041	0.209	−0.035	0.286	−0.045	0.170	−0.042	0.205	No
a_{long}-$abs\sigma$ (g)	−0.033	0.313	−0.030	0.365	−0.023	0.489	−0.016	0.629	No
a_{long}-$absMax$ (g)	−0.047	0.156	−0.042	0.206	−0.039	0.241	−0.031	0.351	No
a_{lat}-$abs\mu$ (g)	0.081	0.014	0.087	0.008	0.019	0.574	0.011	0.734	Yes
a_{lat}-$abs\sigma$ (g)	0.072	0.029	0.074	0.025	0.052	0.113	0.052	0.118	Yes
a_{lat}-$absMax$ (g)	0.041	0.213	0.045	0.172	0.019	0.568	0.019	0.567	No

Table 19. Pearson correlation results for unfamiliar, older drivers at sign analysis segments (ramps on right, not using GPS, and nighttime).

	Subject Sign Units of Information				Number of Words on Subject Sign				
Variable	Corr. Coef.	Prob. $>\lvert r\rvert$	Log: Corr. Coef.	Log: Prob. $>\lvert r\rvert$	Corr. Coef.	Prob. $>\lvert r\rvert$	Log: Corr. Coef.	Log: Prob. $>\lvert r\rvert$	Significance
a_{long}-μ (g)	0.046	0.489	0.057	0.387	0.098	0.136	0.096	0.145	No
a_{long}-σ (g)	−0.122	0.064	−0.110	0.096	−0.162	0.014	−0.136	0.038	Yes
a_{long}-*Max* (g)	−0.052	0.427	−0.042	0.529	−0.017	0.792	−0.007	0.920	No
a_{long}-*Min* (g)	0.114	0.082	0.114	0.084	0.154	0.019	0.136	0.039	Yes
a_{lat}-μ (g)	0.005	0.945	0.020	0.756	<0.001	0.998	0.017	0.802	No
a_{lat}-σ (g)	−0.065	0.326	−0.055	0.403	−0.096	0.143	−0.073	0.268	No
a_{lat}-*Max* (g)	−0.002	0.978	0.014	0.833	−0.028	0.667	−0.002	0.970	No
a_{lat}-*Min* (g)	0.102	0.122	0.123	0.062	0.099	0.132	0.108	0.101	No
ΔV-μ (km/h)	0.056	0.404	0.069	0.306	0.123	0.066	0.123	0.066	No
ΔV-*Max* (km/h)	0.049	0.467	0.063	0.351	0.106	0.116	0.107	0.110	No
ΔV-*Min* (km/h)	0.063	0.354	0.072	0.282	0.140	0.037	0.138	0.040	Yes
ΔV-σ (km/h)	−0.045	0.509	−0.035	0.607	−0.134	0.046	−0.121	0.073	Yes
j_{long}-μ (g/s)	0.011	0.874	−0.001	0.993	0.043	0.513	0.044	0.508	No
j_{long}-σ (g/s)	−0.092	0.161	−0.104	0.113	−0.056	0.395	−0.041	0.537	No
j_{long}-*Max* (g/s)	−0.153	0.020	−0.161	0.014	−0.094	0.152	−0.078	0.238	Yes
j_{long}-*Min* (g/s)	0.061	0.356	0.071	0.284	0.027	0.682	0.015	0.823	No
j_{lat}-μ (g/s)	−0.033	0.614	−0.017	0.795	−0.025	0.709	0.003	0.965	No
j_{lat}-σ (g/s)	−0.181	0.006	−0.192	0.003	−0.145	0.028	−0.131	0.046	Yes
j_{lat}-*Max* (g/s)	−0.153	0.020	−0.151	0.021	−0.116	0.078	−0.086	0.192	Yes
j_{lat}-*Min* (g/s)	0.125	0.058	0.121	0.067	0.107	0.103	0.087	0.186	No
a_{long}-*abs*μ (g)	−0.090	0.170	−0.073	0.266	−0.162	0.014	−0.138	0.036	Yes
a_{long}-*abs*σ (g)	−0.095	0.150	−0.085	0.199	−0.141	0.031	−0.116	0.077	Yes
a_{long}-*absMax* (g)	−0.134	0.042	−0.122	0.063	−0.173	0.008	−0.147	0.026	Yes
a_{lat}-*abs*μ (g)	−0.021	0.745	−0.002	0.979	−0.119	0.070	−0.098	0.136	No
a_{lat}-*abs*σ (g)	−0.049	0.457	−0.035	0.595	−0.100	0.131	−0.072	0.275	No
a_{lat}-*absMax* (g)	−0.056	0.397	−0.041	0.537	−0.124	0.059	−0.094	0.155	No

Table 20. Pearson correlation results for unfamiliar, younger drivers at sign analysis segments (ramps on right, not using GPS, and nighttime).

Variable	Subject Sign Units of Information				Number of Words on Subject Sign				Significance
	Corr. Coef.	Prob. >|*r*|	Log: Corr. Coef.	Log: Prob. >|*r*|	Corr. Coef.	Prob. >|*r*|	Log: Corr. Coef.	Log: Prob. >|*r*|	
a_{long}-μ (g)	−0.006	0.859	−0.004	0.906	0.027	0.419	0.032	0.327	No
a_{long}-σ (g)	−0.049	0.134	−0.048	0.142	−0.048	0.142	−0.045	0.176	No
a_{long}-Max (g)	−0.057	0.083	−0.055	0.095	−0.022	0.515	−0.013	0.690	No
a_{long}-Min (g)	0.035	0.294	0.040	0.227	0.052	0.118	0.056	0.088	No
a_{lat}-μ (g)	0.057	0.083	0.070	0.033	−0.014	0.682	−0.009	0.788	Yes
a_{lat}-σ (g)	−0.047	0.152	−0.048	0.142	−0.094	0.004	−0.099	0.003	Yes
a_{lat}-Max (g)	0.021	0.521	0.032	0.334	−0.054	0.101	−0.050	0.129	No
a_{lat}-Min (g)	0.097	0.003	0.110	0.001	0.070	0.034	0.079	0.017	Yes
ΔV-μ (km/h)	0.052	0.116	0.059	0.074	0.094	0.005	0.105	0.002	Yes
ΔV-Max (km/h)	0.046	0.168	0.054	0.107	0.082	0.014	0.093	0.005	Yes
ΔV-Min (km/h)	0.056	0.090	0.062	0.065	0.103	0.002	0.112	0.001	Yes
ΔV-σ (km/h)	−0.028	0.396	−0.018	0.594	−0.067	0.044	−0.057	0.085	Yes
j_{long}-μ (g/s)	0.027	0.409	0.030	0.362	0.020	0.552	0.016	0.624	No
j_{long}-σ (g/s)	−0.038	0.248	−0.038	0.246	0.003	0.926	0.012	0.715	No
j_{long}-Max (g/s)	−0.053	0.108	−0.056	0.091	−0.025	0.449	−0.021	0.531	No
j_{long}-Min (g/s)	0.036	0.271	0.040	0.229	0.004	0.895	−0.004	0.915	No
j_{lat}-μ (g/s)	−0.021	0.518	−0.024	0.471	−0.053	0.111	−0.056	0.089	No
j_{lat}-σ (g/s)	0.032	0.337	0.022	0.503	0.021	0.527	0.015	0.643	No
j_{lat}-Max (g/s)	0.040	0.220	0.029	0.382	0.008	0.797	−0.004	0.906	No
j_{lat}-Min (g/s)	−0.012	0.708	−0.001	0.971	−0.001	0.977	0.012	0.708	No
a_{long}-$abs\mu$ (g)	−0.035	0.292	−0.024	0.464	−0.056	0.089	−0.049	0.138	No
a_{long}-$abs\sigma$ (g)	−0.040	0.223	−0.038	0.255	−0.041	0.214	−0.036	0.273	No
a_{long}-$absMax$ (g)	−0.047	0.155	−0.045	0.173	−0.049	0.137	−0.045	0.171	No
a_{lat}-$abs\mu$ (g)	−0.013	0.696	<0.001	0.994	−0.091	0.006	−0.087	0.008	Yes
a_{lat}-$abs\sigma$ (g)	−0.049	0.138	−0.045	0.176	−0.097	0.003	−0.095	0.004	Yes
a_{lat}-$absMax$ (g)	−0.047	0.156	−0.038	0.249	−0.114	0.001	−0.110	0.001	Yes

SIGN–DRIVER BEHAVIOR CORRELATION MODELING RESULTS

This section presents results of the multivariate modeling to identify correlations between the sign complexity variables and the driver behavior variables. The modeling process developed multivariate mixed-effect linear models for each driver behavior variable as the dependent variable and the following sign-related variables as the independent variables:

- Number of words on subject sign.
- Guide on pavement.
- Number of words on applicable signs on the same sign structure.
- Number of words on other signs on the same sign structure.
- Subject sign arrow-per-lane indicator.
- Subject sign diagrammatic indicator.
- Sign lighting indicator.
- Visual background complexity for sign.

Due to the large number of mixed-effect models developed during this analysis, listing all models in detail was not realistic. The summarized results in this section are organized by analysis segment (i.e., sign segment versus ramp segment). The section for each analysis segment type discusses the correlations between the number of words on subject sign variable and the driver behavior variables in more detail, followed by summarized results relevant to the other sign-related variables.

Sign Analysis Segment

Overview of Modeling Results

Table 21 shows the counts of significant mixed-effect models developed using only the sign-related variables for the sign analysis segment. The project team developed a total of 56 significant (i.e., at least one sign-related variable is significant in addition to the intercept) models for the analysis scenarios. Among the 10 analysis scenarios modeled, the scenario defined by all ages, unfamiliar, with no GPS, left ramp, and nighttime did not result in any significant models. As the table indicates, the scenario for younger, unfamiliar drivers (not using GPS) during daytime had the most significant models (i.e., 13 driver behavior variables), followed by older, familiar drivers during daytime for right ramps and then by older, unfamiliar drivers not using GPS during daytime for right ramps. Based on an overall examination of the significant models, the results showed the following:

- Drivers 65 yr or older versus younger drivers: Overall, the younger (26 models) and older (25 models) driver groups had similar numbers of significant models. A look at the models in more detail, during daytime, showed that the younger driver group that was familiar with the analyzed routes had only one significant model, while unfamiliar younger drivers were responsible for the majority of the daytime models. For older drivers during daytime, however, both familiar and unfamiliar drivers had comparable numbers of models (i.e., 10 models versus 8). During nighttime, on the other hand, older, unfamiliar drivers had considerably more (six versus one) significant models compared with older drivers who were familiar with the routes, while younger drivers had the same number of significant models for both those familiar with and those unfamiliar with the routes. The number of models or the number of significantly correlated driver behavior variables may be considered an indicator of how strong the correlations were for the different driver group scenarios.

- Nighttime versus daytime: As the table indicates, the analysis showed more daytime significant models between driver behaviors and sign variables compared with nighttime scenarios. More specifically, daytime scenarios had a total of 37 significant models compared with 19 nighttime models, which thereby appeared to indicate that traffic signs had more effect on driver behavior during daytime.

- Familiar drivers versus unfamiliar drivers not using GPS: Overall, unfamiliar drivers were responsible for considerably more (38 versus 18) significant models between sign and driver behavior variables.

Table 21. Count of models for significant sign–driver behavior correlations: Sign segments.

Age and Route Familiarity	Left Ramp Daytime	Left Ramp Nighttime	Right Ramp Daytime	Right Ramp Nighttime	Total	Significance
64 yr or younger, all	—	—	14	12	26	Yes
64 yr or younger, familiar	—	—	1	6	7	No
64 yr or younger, unfamiliar, no GPS	—	—	13	6	19	No
65 yr or older, all	—	—	18	7	25	Yes
65 yr or older, familiar	—	—	10	1	11	No
65 yr or older, unfamiliar, no GPS	—	—	8	6	14	No
All ages, unfamiliar, no GPS	5	0	—	—	5	Yes
Total	**5**	**0**	**32**	**19**	**56**	Yes

— = No data.
Note: Each cell represents an analysis scenario for which a total of 26 models (i.e., 26 driver variables) were developed.

Table 22 shows the count of significant mixed-effect linear models by driver behavior variables based on sign segment analysis results. As the table confirms once again, acceleration-related variables were among the variables that had the most models (and therefore significant correlations) with the sign variables.

Table 22. Count of scenarios for which driver behavior variable had significant model: sign segments.

Variable	Variable Description	Count of Significant Scenarios
a_{lat}-$abs\mu$ (g)	Mean absolute lateral acceleration rate	5
a_{long}-μ (g)	Mean longitudinal acceleration rate	5
a_{long}-$absMax$ (g)	Maximum absolute longitudinal acceleration rate	4
a_{lat}-$absMax$ (g)	Maximum absolute lateral acceleration rate	4
a_{long}-Min (g)	Minimum longitudinal acceleration rate	4
a_{long}-$abs\sigma$ (g)	Standard deviation of absolute longitudinal acceleration rate	4
a_{lat}-$abs\sigma$ (g)	Standard deviation of absolute lateral acceleration rate	4
a_{long}-σ (g)	Standard deviation of longitudinal acceleration rate	4
a_{lat}-σ (g)	Standard deviation of lateral acceleration rate	4
j_{long}-Max (g/s)	Maximum longitudinal jerk rate	3
a_{lat}-Max (g)	Maximum lateral acceleration rate	3
a_{long}-$abs\mu$ (g)	Mean absolute longitudinal acceleration rate	2
ΔV-μ (km/h)	Mean speeding amount	2
ΔV-Min (km/h)	Minimum speeding amount	2
j_{lat}-μ (g/s)	Mean lateral jerk rate	1
a_{lat}-μ (g)	Mean lateral acceleration rate	1
ΔV-Max (km/h)	Maximum speeding amount	1
j_{long}-Min (g/s)	Minimum longitudinal jerk rate	1
a_{lat}-Min (g)	Minimum lateral acceleration rate	1
j_{long}-σ (g/s)	Standard deviation of longitudinal jerk rate	1
Total	**Total count of all significant scenarios**	**56**

Note: For each driver behavior variable, the maximum count of significant scenarios possible is 10 (i.e., 10 analysis scenarios in total as listed in table 15).

Results Pertaining to Number of Words on Subject Sign Variable

Table 23 lists the parameter estimates by scenario for the variable called “Number of Words on Subject Sign” in the fitted significant mixed-effect models for the sign analysis segment. For the linear models, the parameter estimates can be considered elasticities (i.e., changes to the driver behavior variable corresponding to each unit change in the number of words on subject signs). The parameter estimates are coded based on correlation directions. Numbers with negative signs indicate negative correlations, and the absence of a sign indicates positive correlations. Based on the summarized results listed in the table, more words on traffic signs consistently correlated with less acceleration activity. That observation seems to suggest that drivers were driving with more caution, possibly taking time to read and understand signs.

Table 23. Correlations of number of words on subject sign with driver behavior variables: sign segments.

Variable	Older Drivers, Ramps on Right				Younger Drivers, Ramps on Right				All Drivers, Left Ramps
	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Unfamiliar, No GPS, Day
ΔV-μ (km/h)	—	—	5.3E-01	—	—	—	—	2.9E-01	—
ΔV-*Max* (km/h)	—	—	5.0E-01	—	—	—	—	—	—
ΔV-*Min* (km/h)	—	—	6.1E-01	—	—	—	—	4.3E-01	—
a_{long}-μ (g)	9.9E-04	—	—	—	1.7E-03	1.2E-03	1.4E-03	—	1.1E-03
a_{long}-σ (g)	−5.2E-04	—	—	−7.2E-04	—	—	−4.8E-04	—	−6.7E-04
a_{long}-*Min* (g)	2.4E-03	—	—	2.8E-03	—	—	3.1E-03	—	—
a_{long}-*abs*μ (g)	−8.7E-04	—	—	−8.2E-04	—	—	—	—	—
a_{long}-*abs*σ (g)	−5.4E-04	—	—	−5.8E-04	—	—	−3.4E-04	—	−6.8E-04
a_{long}-*absMax* (g)	−2.5E-03	—	—	−2.8E-03	—	−1.5E-03	−1.4E-03	—	—
j_{long}-σ (g/s)	—	—	—	—	—	—	−2.7E-03	—	—
j_{long}-*Max* (g/s)	−1.2E-02	—	—	−1.3E-02	—	—	−1.3E-02	—	—
j_{long}-*Min* (g/s)	1.3E-02	—	—	—	—	—	—	—	—
a_{lat}-μ (g)	—	—	—	—	—	—	−7.9E-04	—	—
a_{lat}-σ (g)	—	—	−3.8E-04	—	—	−5.6E-04	−4.9E-04	−4.0E-04	—
a_{lat}-*Max* (g)	—	—	−1.9E-03	—	—	—	−1.8E-03	—	−3.2E-03
a_{lat}-*Min* (g)	—	—	—	—	—	2.3E-03	—	—	—
a_{lat}-*abs*μ (g)	−1.2E-03	−1.3E-03	−1.3E-03	—	—	—	−9.2E-04	−7.8E-04	—
a_{lat}-*abs*σ (g)	—	—	−4.0E-04	—	—	−4.6E-04	−4.0E-04	−3.2E-04	—
a_{lat}-*absMax* (g)	—	—	−2.0E-03	—	—	−1.8E-03	−2.3E-03	−1.5E-03	—
j_{lat}-μ (g/s)	—	—	—	—	—	—	—	—	−4.9E-04

— = No data.

The driver behavior–sign correlations show the following:

- Negative correlations are dominant for acceleration-related variables. With regard to longitudinal acceleration activity, the correlations suggest increased longitudinal acceleration rates but decreased absolute longitudinal acceleration rates (deceleration rates are negative values, while acceleration rates are positive values in the SHRP2 data), which indicates that the acceleration values became closer to 0 (i.e., less accelerating and decelerating activity) as the number of words on a sign increased. Note that locations with more complex lane configurations typically have lower posted speeds.

- Longitudinal jerk rates show mostly negative correlations. For trips dominated by deceleration activity, smaller longitudinal jerk rates indicate faster deceleration activity correlated with locations with more complex signs. However, in a combination of the correlations with speed and lateral acceleration rates, the results seem to indicate hesitation or caution in deceleration behaviors (e.g., fast tapping of brakes without actually affecting speeds or prolonged deceleration rates).

- With regard to lateral acceleration variables, correlations were dominantly negative, indicating less lane-changing behavior to the right. In addition, positive correlations dominated for relative speed-related variables (correlations significant only for unfamiliar drivers), indicating the possibility that unfamiliar drivers were not adjusting speeds as much as were drivers familiar with the route.

- With regard to familiar drivers versus unfamiliar drivers, based on the results, sign complexity appeared to have particular effects on the speeds of unfamiliar drivers and the lateral acceleration activity of unfamiliar drivers during daytime. Overall, unfamiliar younger drivers had considerably more significant correlations with sign complexity during daytime at the sign analysis segment.

The correlations previously discussed strongly suggest that drivers—especially unfamiliar drivers—were not taking actions such as deceleration and lane changes as much as were drivers familiar with the routes at the sign analysis segments. Not making the needed maneuvers as early as possible could result in greater safety risks because such actions would have to be completed in a shorter period prior to the ramp locations.

Results for Other Sign-Related Variables

In addition to the number of words on subject sign variable, the following list summarizes the results based on sign–driver behavior models relevant to the other sign-related variables. Readers should note that the results discussed in this section are based only on the models for which the number of words on subject sign variable was significant (i.e., a total of 56 models). Models for which the number of words on subject sign variable was not significant were discarded in the modeling process and were not discussed. The table following each discussion lists the parameter estimates by scenario for each sign-related variable in the fitted significant mixed-effect models. Similarly, numbers with negative signs indicate negative correlations, and the absence of a sign indicates positive correlations.

Guide on Pavement (0 = No/1 = Yes)

Guide on pavement appeared as a significant variable in 8 of the 56 models (table 24). The presence of guidance on pavement overall correlated with higher deceleration rates and standard deviation, which indicates that the use of on-pavement guidance increased driver activity at the sign analysis segment.

Table 24. Driver behavior models and analysis scenarios for pavement guidance.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, unfamiliar, no GPS, night	j_{lat}-*Max* (g/s)	0.113	Positive
Younger, right, familiar, day	a_{long}-μ (g)	−0.007	Negative
Younger, right, familiar, night	a_{lat}-*Min* (g)	−0.011	Negative
Younger, right, unfamiliar, no GPS, day	a_{long}-μ (g)	−0.008	Negative
Younger, right, unfamiliar, no GPS, day	a_{long}-σ (g)	0.002	Positive
Younger, right, unfamiliar, no GPS, day	a_{long}-*Min* (g)	−0.012	Negative
Younger, right, unfamiliar, no GPS, day	a_{lat}-*abs*μ (g)	0.005	Positive
All, left, unfamiliar, no GPS, day	a_{long}-μ (g)	−0.014	Negative

Number of Words on Applicable Signs at the Same Sign Structure

This variable appeared to be significant in 16 of the 56 models (table 25). More words on other relevant signs correlated in general with slower speeds (i.e., lower speeding amounts) but also with higher acceleration activity. For younger drivers, other applicable signs on the same sign structure seemed to have particularly affected their nighttime driver behaviors.

Table 25. Driver behavior models and analysis scenarios for number of words on applicable signs.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, familiar, day	j_{long}-*Min* (g/s)	−1.2E-02	Negative
Older, right, unfamiliar, no GPS, day	ΔV-μ (km/h)	−7.9E-01	Negative
Older, right, unfamiliar, no GPS, day	ΔV-*Max* (km/h)	−6.9E-01	Negative
Older, right, unfamiliar, no GPS, day	ΔV-*Min* (km/h)	−9.1E-01	Negative
Older, right, unfamiliar, no GPS, night	a_{long}-*Min* (g)	−2.6E-03	Negative
Older, right, unfamiliar, no GPS, night	j_{long}-*Max* (g/s)	2.2E-02	Positive
Older, right, unfamiliar, no GPS, night	a_{long}-*absMax* (g)	3.1E-03	Positive
Younger, right, familiar, day	a_{long}-μ (g)	−1.5E-03	Negative
Younger, right, familiar, night	a_{lat}-σ (g)	5.7E-04	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-*abs*μ (g)	5.8E-04	Positive
Younger, right, unfamiliar, no GPS, night	a_{lat}-σ (g)	8.2E-04	Positive
Younger, right, unfamiliar, no GPS, night	ΔV-μ (km/h)	−5.6E-01	Negative
Younger, right, unfamiliar, no GPS, night	ΔV-*Min* (km/h)	−5.6E-01	Negative
Younger, right, unfamiliar, no GPS, night	a_{lat}-*abs*σ (g)	5.7E-04	Positive
Younger, right, unfamiliar, no GPS, night	a_{lat}-*absMax* (g)	1.4E-03	Positive
All, left, unfamiliar, no GPS, day	j_{lat}-μ (g/s)	−8.5E-04	Negative

Number of Words on Other Signs on the Same Sign Structure

This variable appeared to be significant in 4 of the 56 models (table 26). The amount of information on other signs on the same structure mainly affected lateral acceleration activity for unfamiliar drivers. Results found that the more words on other signs on the same structure (also an indicator of number of other signs at the same structure), the less the lateral acceleration activity, which occurred, possibly, because unfamiliar drivers tended to stay in the right lanes at complex ramp locations (i.e., with more lanes and route choices), thereby reducing the need for sudden or faster lane changes to the right.

Table 26. Driver behavior models and analysis scenarios for number of words on other signs.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, unfamiliar, no GPS, day	a_{lat}-$abs\mu$ (g)	−5.1E-04	Negative
Younger, right, unfamiliar, no GPS, day	a_{lat}-μ (g)	−4.4E-04	Negative
Younger, right, unfamiliar, no GPS, day	a_{lat}-σ (g)	2.0E-04	Positive
Younger, right, unfamiliar, no GPS, night	a_{lat}-$abs\mu$ (g)	−4.4E-04	Negative

Subject Sign Arrow-per-Lane Indicator

This variable was a significant variable in 29 of the 56 models (table 27). The variable overwhelmingly correlated with higher lateral and longitudinal acceleration activity, seemingly indicating more confident and decisive driving behaviors at the sign location. Again, this variable had more significant models with unfamiliar drivers compared with familiar drivers, thereby indicating that the variable is a measure that benefits unfamiliar drivers considerably. Since drivers react to arrow-per-lane signs, the significance may be an indicator to locate such signs at locations with sufficient space available for lane changes.

Table 27. Driver behavior models and analysis scenarios for arrow-per-lane indicator.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, familiar, day	a_{long}-μ (g)	−0.012	Negative
Older, right, familiar, day	a_{long}-σ (g)	0.004	Positive
Older, right, familiar, day	a_{long}-Min (g)	−0.024	Negative
Older, right, unfamiliar, no GPS, day	a_{lat}-σ (g)	0.004	Positive
Older, right, unfamiliar, no GPS, day	a_{lat}-Max (g)	0.019	Positive
Older, right, unfamiliar, no GPS, day	a_{lat}-$abs\sigma$ (g)	0.003	Positive
Older, right, unfamiliar, no GPS, day	a_{lat}-$absMax$ (g)	0.012	Positive
Older, right, unfamiliar, no GPS, night	a_{long}-$abs\mu$ (g)	0.007	Positive
Younger, right, familiar, day	a_{long}-μ (g)	−0.009	Negative
Younger, right, familiar, night	a_{long}-μ (g)	−0.011	Negative
Younger, right, familiar, night	a_{lat}-σ (g)	0.005	Positive
Younger, right, familiar, night	a_{lat}-$abs\sigma$ (g)	0.005	Positive
Younger, right, familiar, night	a_{lat}-$absMax$ (g)	0.018	Positive
Younger, right, unfamiliar, no GPS, day	a_{long}-μ (g)	−0.010	Negative
Younger, right, unfamiliar, no GPS, day	a_{long}-σ (g)	0.003	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-μ (g)	0.006	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-σ (g)	0.008	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-Max (g)	0.023	Positive

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Younger, right, unfamiliar, no GPS, day	a_{long}-*absμ* (g)	0.002	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-*absμ* (g)	0.009	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-*absσ* (g)	0.006	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-*absMax* (g)	0.023	Positive
Younger, right, unfamiliar, no GPS, night	a_{lat}-*σ* (g)	0.007	Positive
Younger, right, unfamiliar, no GPS, night	Δ*V*- *μ* (km/h)	−3.286	Negative
Younger, right, unfamiliar, no GPS, night	Δ*V-Min* (km/h)	−4.109	Negative
Younger, right, unfamiliar, no GPS, night	a_{lat}-*absμ* (g)	0.008	Positive
Younger, right, unfamiliar, no GPS, night	a_{lat}-*absσ* (g)	0.005	Positive
Younger, right, unfamiliar, no GPS, night	a_{lat}-*absMax* (g)	0.019	Positive

Subject Sign Diagrammatic Indicator (Yes = 1 and No = 0)

Whether a guide sign is a diagrammatic sign or not was a less significant factor affecting driver behaviors compared with other sign variables analyzed. The team included only two significant models in this variable (table 28). Both models suggested that diagrammatic signs correlated with higher lateral acceleration variances, seemingly suggesting that drivers increased their lateral acceleration activity at sign locations if signs were diagrammatic.

Table 28. Driver behavior models and analysis scenarios for diagrammatic sign indicator.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, unfamiliar, no GPS, day	a_{lat}-*σ* (g)	0.012	Positive
Older, right, unfamiliar, no GPS, day	a_{lat}-*absσ* (g)	0.007	Positive

Sign Lighting Indicator (Yes = 1 and No = 0)

This variable was significant in 7 of the 56 models (table 29). The presence of sign lighting was a significant factor only for unfamiliar drivers and correlated mainly with reduced speed and longitudinal acceleration activity. Interestingly, this variable was found significant in more daytime models than in nighttime models. Sign lighting tended to be used during high ADT (e.g., at system interchanges and/or urban interchanges), and in this case, it possibly served as a surrogate of more complex lane configurations.

Table 29. Driver behavior models and analysis scenarios for sign lighting indicator.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, unfamiliar, no GPS, day	ΔV-μ (km/h)	−5.830	Negative
Older, right, unfamiliar, no GPS, day	ΔV-*Max* (km/h)	−5.825	Negative
Older, right, unfamiliar, no GPS, day	ΔV-*Min* (km/h)	−5.752	Negative
Older, right, unfamiliar, no GPS, night	j_{long}-*Max* (g/s)	−0.090	Negative
Younger, right, unfamiliar, no GPS, day	a_{long}-σ (g)	−0.002	Negative
Younger, right, unfamiliar, no GPS, day	a_{long}-*abs*μ (g)	−0.002	Negative
Younger, right, unfamiliar, no GPS, night	ΔV-μ (km/h)	−5.452	Negative

Visual Background Complexity for Sign (1–5, With 5 Indicating Most Complex Background)

The results showed that visual background complexity of signs affected mainly speed and longitudinal acceleration activity—particularly for older drivers who were more familiar with the routes during daytime (table 30). In addition, correlations were mostly positive, indicating that more complex sign background correlated with higher speed and longitudinal acceleration activity. Complex visual background in many cases indicates that drivers were approaching an urban environment with significant commercial developments in the vicinity.

Table 30. Driver behavior models and analysis scenarios for visual background complexity.

Scenario (Driver Age, Ramp Side, Route Familiarity, GPS Usage, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, right, familiar, day	a_{long}-σ (g)	0.001	Positive
Older, right, familiar, day	j_{long}-*Max* (g/s)	0.031	Positive
Older, right, familiar, day	a_{long}-*abs*μ (g)	0.001	Positive
Older, right, familiar, day	a_{long}-*absMax* (g)	0.007	Positive
Older, right, unfamiliar, no GPS, night	j_{long}-*Max* (g/s)	0.038	Positive
Younger, right, familiar, day	a_{long}-μ (g)	0.004	Positive
Younger, right, unfamiliar, no GPS, day	a_{long}-μ (g)	0.003	Positive
Younger, right, unfamiliar, no GPS, day	a_{lat}-*abs*μ (g)	−0.002	Negative
Younger, right, unfamiliar, no GPS, night	ΔV-μ (km/h)	1.890	Positive

Ramp Analysis Segment

Overview of Modeling Results

Table 31 lists the counts of significant mixed-effect models that the team developed for the ramp analysis segment. The team included a significant model when a driver behavior variable significantly correlated with the number of words on subject sign variable in a multivariate setting involving all sign-related variables. Similar to the sign analysis segment, analysis of the ramp segment resulted in 56 significant models, with the scenarios having the most number of significant models being younger, unfamiliar drivers during daytime at right-side ramp locations (16 models); older, unfamiliar drivers during daytime at right-side ramp locations (14 models); and younger, familiar drivers during nighttime at right-side ramp locations (8 models). The model counts suggest the following:

- Younger driver versus older drivers: The results showed 30 significant models for younger drivers compared with 24 models for older drivers, indicating that sign complexity has more impact on the behaviors of younger drivers.

- Nighttime versus daytime: Overall, 43 models were fitted for daytime trips, while 13 models were fitted for nighttime trips. The considerably larger number of daytime models appears to indicate more evident effects of sign complexity on driver behavior during daytime. For unfamiliar drivers in particular, a majority of significant models were for daytime trips regardless of driver age.

- Drivers familiar with routes versus those who were unfamiliar: Overall, the team developed a larger number of models for unfamiliar drivers compared with the number developed for familiar drivers. In particular, the results showed a much larger number of significant models for unfamiliar drivers during daytime compared with those for familiar drivers. This was true for both younger and older drivers.

Table 31. Count of models for sign–driver behavior correlations: Ramp segments.

Age and Route Familiarity	Left Ramp Daytime	Left Ramp Nighttime	Right Ramp Daytime	Right Ramp Nighttime	Total	Significance
64 yr or younger, all	0	0	21	9	30	Yes
64 yr or younger, familiar	0	0	5	8	13	No
64 yr or younger, unfamiliar, no GPS	0	0	16	1	17	No
65 yr or older, all	0	0	21	3	24	Yes
65 yr or older, familiar	0	0	7	2	9	No
65 yr or older, unfamiliar, no GPS	0	0	14	1	15	No
All ages, unfamiliar, no GPS	1	1	0	0	2	Yes
Total	1	1	42	12	56	Yes

Note: Each cell represents an analysis scenario for which a total of 26 models (i.e., 26 driver variables) were developed.

Table 32 ranks driver behavior variables for which the team developed significant models based on the number of scenarios for which a significant model was fitted. The driver behavior variables that most frequently significantly correlated with sign complexity measures were overwhelmingly longitudinal acceleration indicators. In addition, the list has a large number of jerk-related variables.

Table 32. Count of scenarios for which driver behavior variable had significant model: Ramp segments.

Variable	Variable Description	Count of Significant Scenarios
a_{long}-$abs\mu$ (g)	Mean absolute longitudinal acceleration rate	6
a_{long}-σ (g)	Standard deviation of longitudinal acceleration rate	6
a_{long}-$absMax$ (g)	Maximum absolute longitudinal acceleration rate	4
a_{long}-Min (g)	Minimum longitudinal acceleration rate	4
a_{long}-$abs\sigma$ (g)	Standard deviation of absolute longitudinal acceleration rate	4
j_{long}-μ (g/s)	Mean longitudinal jerk rate	3
a_{long}-μ (g)	Mean longitudinal acceleration rate	3
ΔV-σ (km/h)	Standard deviation of speeding amount	3
a_{lat}-$abs\mu$ (g)	Mean absolute lateral acceleration rate	2
a_{lat}-$absMax$ (g)	Maximum absolute lateral acceleration rate	2
j_{long}-Max (g/s)	Maximum longitudinal jerk rate	2
ΔV-Max (km/h)	Maximum speeding amount	2
ΔV-μ (km/h)	Mean speeding amount	2
j_{long}-Min (g/s)	Minimum longitudinal jerk rate	2
j_{lat}-Min (g/s)	Mean lateral jerk rate	2
ΔV-Min (km/h)	Minimum speeding amount	2
j_{long}-σ (g/s)	Standard deviation of longitudinal jerk rate	2
j_{lat}-μ (g/s)	Mean lateral jerk rate	1
j_{lat}-Max (g/s)	Maximum lateral jerk rate	1
a_{lat}-Min (g)	Minimum lateral acceleration rate	1
j_{lat}-σ (g/s)	Standard deviation of lateral jerk rate	1
a_{lat}-σ (g)	Standard deviation of lateral acceleration rate	1
Total	**Total count of all significant scenarios**	**56**

Note: For each driver behavior variable, the maximum count of significant scenarios possible is 10 (i.e., 10 analysis scenarios in total as listed in table 15).

Results Pertaining to Number of Words on Subject Sign Variable

Table 33 lists parameter estimates for the variable called "Number of Words on Subject Sign" in the significant models and indicates both the direction of the correlations and their elasticities. The table shows relatively mixed directions of the correlations with more negative correlations. Similarly, numbers with negative signs indicate negative correlations, and the absence of a sign indicates positive correlations. A look at the correlations in detail shows the following about the variables:

- Speed-related variables: The results showed higher speeds (indicating speeds closer to speed limits as most drivers traveled below speed limits at such locations) and decreased speed variation when drivers approached the ramps. Those positive correlations seemed to suggest that unfamiliar drivers—particularly during daytime—drove through the ramp analysis segments at higher speeds overall immediately prior to exiting the ramps.

- Longitudinal acceleration variables: Similar to those for the sign analysis segment, correlations for longitudinal acceleration variables indicate less deceleration activity. This phenomenon may indicate that drivers became more cautious at locations with signs that have more words.

- Lateral acceleration variables: Overall, the correlations for lateral acceleration variables similarly indicated less lane-changing behavior at locations with more complex signs. Note that the number of significant correlations for lateral acceleration variables is considerably smaller than that for the sign segment, indicating that the impact of sign complexity on driver behavior at this point became smaller compared with the sign segment.

- Familiar drivers versus unfamiliar drivers: Unfamiliar drivers had considerably more significant correlations than did familiar drivers during daytime. In particular, drivers unfamiliar with roadways during daytime had significant correlations for speed and lateral acceleration variables during daytime, while familiar drivers had limited correlations with those driver behavior variables.

Table 33. Correlations of number of words on subject sign with driver behavior variables: Ramp segments.

Variable	Older Drivers, Ramps on Right				Younger Drivers, Ramps on Right				All Drivers, Left Ramps	
	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night
ΔV-μ (km/h)	—	—	5.1E-01	—	—	—	3.0E-01	—	—	—
ΔV-σ (km/h)	—	—	−8.1E-02	—	—	−1.1E-01	−9.2E-02	—	—	—
ΔV-*Max* (km/h)	—	—	3.8E-01	—	—	—	—	—	−7.4E-01	—
ΔV-*Min* (km/h)	—	—	6.3E-01	—	—	—	4.6E-01	—	—	—
a_{long}-μ (g)	—	—	—	—	1.3E-03	2.2E-03	1.2E-03	—	—	—
a_{long}-σ (g)	−8.3E-04	−7.4E-04	−7.8E-04	—	−6.2E-04	—	−6.3E-04	—	—	−1.3E-03
a_{long}-*Min* (g)	—	—	1.9E-03	—	2.5E-03	3.0E-03	2.5E-03	—	—	—
a_{long}-*abs*μ (g)	−1.5E-03	−9.9E-04	−9.6E-04	—	−7.3E-04	−1.1E-03	−7.3E-04	—	—	—
a_{long}-*abs*σ (g)	−6.0E-04	—	−5.6E-04	—	—	−5.4E-04	−4.7E-04	—	—	—
a_{long}-*absMax* (g)	−2.9E-03	—	−2.1E-03	—	—	−2.7E-03	−2.2E-03	—	—	—
j_{long}-μ (g/s)	—	—	—	—	—	6.1E-04	3.2E-04	2.1E-04	—	—
j_{long}-σ (g/s)	−5.2E-03	—	—	—	—	—	−2.2E-03	—	—	—
j_{long}-*Max* (g/s)	−1.7E-02	—	—	—	—	—	−8.3E-03	—	—	—
j_{long}-*Min* (g/s)	1.1E-02	—	—	—	—	—	9.1E-03	—	—	—
a_{lat}-σ (g)	—	—	—	—	—	—	−6.3E-04	—	—	—
a_{lat}-*Min* (g)	—	—	—	—	—	1.6E-03	—	—	—	—
a_{lat}-*abs*μ (g)	—	—	−8.1E-04	—	—	—	−8.4E-04	—	—	—
a_{lat}-*absMax* (g)	—	—	−2.3E-03	—	—	—	−2.0E-03	—	—	—
j_{lat}-μ (g/s)	—	—	—	—	−6.3E-04	—	—	—	—	—
j_{lat}-σ (g/s)	—	—	−2.2E-03	—	—	—	—	—	—	—
j_{lat}-*Max* (g/s)	—	—	−1.0E-02	—	—	—	—	—	—	—
j_{lat}-*Min* (g/s)	—	—	1.3E-02	1.9E-02	—	—	—	—	—	—

— = No data.

In addition to the number of words on subject sign variable, the following summarizes modeling results for other sign-related variables. Similarly, the results are based only on models for which the number of words on subject sign variable was significant (i.e., a total of 56 models). Models for which the number of words on subject sign variable was not significant were discarded in the modeling process and were not discussed here.

Guide on Pavement

This variable was significant for 8 of the 56 models. Table 34 shows the scenario–driver behavior variable combinations for which the guide on pavement variable was significant. For familiar drivers, the correlations were all for longitudinal acceleration variables, and all correlations were negative—meaning, increased deceleration activity. For unfamiliar drivers, however, most correlations were for lateral acceleration variables and positive, indicating that the presence of guide on pavement increased the lateral acceleration activity of drivers who were not familiar with the route options.

Table 34. Correlations and parameter estimates for guide on pavement: Ramp segment.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, familiar, right, night	a_{long}-σ (g)	−0.006	Negative
Younger, familiar, right, night	a_{long}-μ (g)	−0.015	Negative
Younger, familiar, right, night	a_{long}-*Min* (g)	−0.018	Negative
Younger, unfamiliar, no GPS, right, day	a_{long}-μ (g)	−0.008	Negative
Younger, unfamiliar, no GPS, right, day	a_{lat}-σ (g)	0.006	Positive
Younger, unfamiliar, no GPS, right, day	j_{long}-μ (g/s)	0.002	Positive
Younger, unfamiliar, no GPS, right, day	a_{lat}-*abs*μ (g)	0.007	Positive
Younger, unfamiliar, no GPS, right, day	a_{lat}-*absMax* (g)	0.014	Positive

Number of Words on Other Applicable Signs

The team included this variable in a large number of driver behavior models (23 of the 56 models). In addition, the majority of models were for speed- or longitudinal-acceleration-related variables. Correlations and parameter estimates for number of words on other applicable signs at ramp segments are shown in table 35. Examples of commonly observed other applicable signs mounted at the same sign gantries are a ramp-speed-limit sign and a vehicle-type-restriction sign. Therefore, driver behaviors, such as vehicle speed and acceleration, are particularly affected by accompanying signs mounted on the same gantry.

Table 35. Correlations and parameter estimates for number of words on other applicable signs: Ramp segments.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Unfamiliar, No GPS, left, day	ΔV-*Max* (km/h)	*−0.946*	Negative
Older, unfamiliar, no GPS, right, day	a_{long}-σ (g)	0.001	Positive
Older, unfamiliar, no GPS, right, day	a_{long}-*Min* (g)	−0.003	Negative
Older, unfamiliar, no GPS, right, day	ΔV-μ (km/h)	−0.797	Negative
Older, unfamiliar, no GPS, right, day	ΔV-*Max* (km/h)	−0.679	Negative
Older, unfamiliar, no GPS, right, day	ΔV-*Min* (km/h)	−0.983	Negative
Older, unfamiliar, no GPS, right, day	ΔV-σ (km/h)	0.103	Positive
Older, unfamiliar, no GPS, right, day	j_{lat}-σ (g/s)	0.002	Positive
Older, unfamiliar, no GPS, right, day	j_{lat}-*Max* (g/s)	0.013	Positive
Older, unfamiliar, no GPS, right, day	j_{lat}-*Min* (g/s)	−0.010	Negative
Older, unfamiliar, no GPS, right, day	a_{long}-*abs*μ (g)	0.001	Positive
Older, unfamiliar, no GPS, right, day	a_{long}-*abs*σ (g)	0.001	Positive
Older, unfamiliar, no GPS, right, day	a_{long}-*absMax* (g)	0.004	Positive
Younger, familiar, right, day	a_{long}-*Min* (g)	−0.002	Negative
Younger, familiar, right, night	a_{lat}-*Min* (g)	−0.002	Negative
Younger, unfamiliar, no GPS, right, day	a_{long}-σ (g)	4.2E-04	Positive
Younger, unfamiliar, no GPS, right, day	ΔV-μ (km/h)	−0.815	Negative
Younger, unfamiliar, no GPS, right, day	ΔV-*Min* (km/h)	−0.886	Negative
Younger, unfamiliar, no GPS, right, day	ΔV-σ (km/h)	0.063	Positive
Younger, unfamiliar, no GPS, right, day	j_{long}-σ (g/s)	0.002	Positive
Younger, unfamiliar, no GPS, right, day	j_{long}-*Max* (g/s)	0.008	Positive
Younger, unfamiliar, no GPS, right, day	j_{long}-*Min* (g/s)	−0.007	Negative
Younger, unfamiliar, no GPS, right, day	a_{lat}-*absMax* (g)	0.002	Positive

Number of Words on Other Signs

The number of words on other signs was significant in 6 of the 56 driver behavior models. Of the six models, five were negative correlations, and all were for speed or longitudinal acceleration variables (table 36). That pattern is similar to correlations for the number of words on subject sign, with a much smaller number of correlations though.

Table 36. Correlations and parameter estimates for number of words on other signs: Ramp segments.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Unfamiliar, no GPS, left, night	a_{long}-σ (g)	−0.001	Negative
Older, familiar, right, day	j_{long}-σ (g/s)	−0.002	Negative
Older, familiar, right, day	j_{long}-*Min* (g/s)	0.007	Positive
Older, unfamiliar, no GPS, right, day	ΔV-σ (km/h)	−0.036	Negative
Older, unfamiliar, no GPS, right, day	a_{long}-*abs*σ (g)	−2.4E-04	Negative
Younger, familiar, right, night	j_{long}-μ (g/s)	−2.1E-04	Negative

Subject Sign Arrow-per-Lane Indicator

Compared with correlations at the sign analysis segment, this variable correlated with evidently fewer driver behavior variables for the 10 analysis scenarios (table 37). The limited correlations are mixed, with positive and negative directions, which is similar to those for the sign analysis segment.

Table 37. Correlations and parameter estimates for sign arrow-per-lane indicator: Ramp segments.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, unfamiliar, no GPS, right, day	ΔV-*σ* (km/h)	−0.456	Negative
Older, unfamiliar, no GPS, right, day	j_{lat}-*Max* (g/s)	−0.097	Negative
Older, unfamiliar, no GPS, right, day	j_{lat}-*Min* (g/s)	0.097	Positive
Younger, familiar, right, day	a_{long}-*σ* (g)	−0.006	Negative
Younger, unfamiliar, no GPS, right, day	j_{long}-*σ* (g/s)	0.015	Positive

Subject Sign Diagrammatic Indicator

Similarly, the diagrammatic sign indicator had significant correlations, with only 4 of the 56 models. All four correlations, however, were positive correlations indicating increased driver acceleration activity at ramp locations with diagrammatic signs (table 38).

Table 38. Correlations and parameter estimates for diagrammatic sign indicator: Ramp segments.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Younger, familiar, right, day	j_{lat}-*μ* (g/s)	0.013	Positive
Younger, unfamiliar, no GPS, right, day	a_{long}-*σ* (g)	0.010	Positive
Younger, unfamiliar, no GPS, right, day	a_{long}-*absσ* (g)	0.009	Positive
Younger, unfamiliar, no GPS, right, day	a_{long}-*absMax* (g)	0.032	Positive

Sign Lighted Indicator

This variable appeared as a significant independent variable in 13 of the 56 driver behavior models, which were overwhelmingly for daytime, unfamiliar drivers. The observation indicates that the significance of sign lighting was not due to improved sign visibility when lighted, but mostly because sign lighting was a surrogate for complex urban interchange areas in which sign lighting is most commonly used. Again, all significant correlations for this variable were negative, indicating reduced driver acceleration activity (table 39).

Table 39. Correlations and parameter estimates for sign lighting presence: Ramp segments.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Older, unfamiliar, no GPS, right, day	ΔV-*μ* (km/h)	−3.201	Negative
Older, unfamiliar, no GPS, right, day	ΔV-*Max* (km/h)	−3.427	Negative
Older, unfamiliar, no GPS, right, day	ΔV-*Min* (km/h)	−3.100	Negative
Older, unfamiliar, no GPS, right, day	a_{lat}-*absMax* (g)	−0.017	Negative
Younger, familiar, right, day	j_{lat}-*μ* (g/s)	−0.006	Negative

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Younger, unfamiliar, no GPS, right, day	a_{lat}-σ (g)	−0.007	Negative
Younger, unfamiliar, no GPS, right, day	ΔV-μ (km/h)	−4.262	Negative
Younger, unfamiliar, no GPS, right, day	ΔV-Min (km/h)	−3.582	Negative
Younger, unfamiliar, no GPS, right, day	ΔV-σ (km/h)	−0.527	Negative
Younger, unfamiliar, no GPS, right, day	a_{long}-$abs\mu$ (g)	−0.004	Negative
Younger, unfamiliar, no GPS, right, day	a_{long}-$absMax$ (g)	−0.008	Negative
Younger, unfamiliar, no GPS, right, day	a_{lat}-$abs\mu$ (g)	−0.010	Negative
Younger, unfamiliar, no GPS, right, day	a_{lat}-$absMax$ (g)	−0.024	Negative

Sign Visual Background Complexity

Sign visual background complexity (figure 9 to figure 13) appeared in 7 of the 56 driver behavior models as a significant independent variable. All correlations were for longitudinal acceleration variables except for one, which was for the maximum speed amount (table 40). The directions of the correlation are mixed in nature.

Table 40. Correlations and parameter estimates for visual background complexity: Ramp segments.

Scenario (Driver Age, Route Familiarity, GPS Usage, Ramp Side, Trip Time)	Driver Behavior Variable	Parameter Estimate	Correlation
Unfamiliar, no GPS, left, day	ΔV-Max (km/h)	−3.298	Negative
Older, familiar, right, day	a_{long}-$abs\mu$ (g)	0.004	Positive
Older, familiar, right, day	a_{long}-$absMax$ (g)	0.008	Positive
Younger, familiar, right, day	a_{long}-$abs\mu$ (g)	0.002	Positive
Younger, familiar, right, Night	a_{long}-Min (g)	−0.007	Negative
Younger, unfamiliar, no GPS, right, day	a_{long}-σ (g)	0.001	Positive
Younger, unfamiliar, no GPS, right, day	j_{long}-μ (g/s)	−0.001	Negative

Summary and Discussion of Sign Complexity Effects on Driver Behaviors

During this analysis, the project team fitted mixed-effect models to learn the correlations between sign-related variables and driver behaviors. The analysis considered 10 scenarios for each of the two segments (i.e., segment at sign and segment at ramp junction). This modeling effort used only variables most relevant to sign complexity as independent variables. Overall, the effort resulted in 56 significant models (out of 260 models developed) for each of the analysis segments. The following section summarizes and discusses the findings.

Correlations Between Sign Complexity and Driver Behaviors

This project used the variable called "Number of Words on Subject Sign" as the primary measurement of sign complexity. During SHRP2 driver behavior data analysis, that variable significantly correlated with a large number of driver behavior variables for both the sign analysis segment and the ramp analysis segment. The results showed that:

- The sign complexity measure more frequently correlated with the behaviors of drivers who were unfamiliar with the routes than with the behaviors of drivers who were presumably familiar with the routes based on number of significant correlations. This phenomenon was particularly evident among younger drivers during daytime at the sign analysis segment and among all unfamiliar drivers during daytime at the ramp analysis segment.

- Overall, increased sign complexity correlated with higher speeds and reduced acceleration activity. Positive correlations with speed-related variables tended to be more evident for daytime trips than nighttime trips, which was particularly evident for the ramp analysis segment. Higher speeds in approaches to signs and ramps are, possibly, indicators of unfamiliar drivers' not being well aware of and/or well prepared for the approaching ramps. The combination of reduced longitudinal deceleration activity with reduced lateral acceleration activity—particularly at the sign segment—seems to indicate that drivers were overly cautious and taking time to digest the information without making the necessary maneuvers.

- For older, unfamiliar drivers, the sign analysis segment had a number of significant correlations for nighttime models. The ramp analysis segment, however, had limited correlations for unfamiliar drivers during nighttime. Comparison of daytime and nighttime nonpeak hours for which SHRP2 data were used showed that daytime generally had more traffic compared with nighttime. Fewer vehicular conflicts during nighttime potentially enabled unfamiliar drivers to navigate more easily at the ramp locations, thereby reducing the impacts of sign complexity on driver behaviors.

- Comparison of sign–driver behavior correlations at the two analysis segments showed that the sign segment had considerably more correlations for nighttime trips and for lateral acceleration variables. The values of the elasticities for the correlations, however, were generally comparable between the two analysis segments. Most correlation elasticities are relatively small. The impacts of signs on driver behaviors are expected to be subtle—especially when such signs, along with lane configuration and other traffic control methods, are designed to meet applicable standards such as those of the AASHTO Green Book and MUTCD, although the fact that a large number of significant correlations were found should outweigh the values of the elasticities.[79,1]

Effects of Other Sign Variables on Driver Behaviors

The results for other sign variables showed the following:

- Subject sign arrow-per-lane indicator: The project team found that an arrow-per-lane sign had many significant correlations with driver behaviors—particularly for unfamiliar drivers at the sign analysis segment. The correlations were found to be overwhelmingly positive (i.e., an arrow-per-lane sign correlated with increased deceleration and lateral acceleration activity). The correlation pattern was largely opposite that for number of words on subject sign. Assuming arrow-per-lane signs provide better lane choice information for unfamiliar drivers compared with other signs, such a correlation pattern should therefore be considered the desired driver behavior. The pattern further supports a conclusion that unfamiliar drivers were cautious and/or nervous when approaching signs with more words and were not making the appropriate navigation maneuvers. While this variable had many correlations for the sign analysis segment, it had limited correlations at the ramp analysis segment, possibly indicating that drivers were better prepared to exit at ramp junction points when arrow-per-lane signs were there.

- Guide on pavement indicator: The presence of routing directions on pavement correlated in general with decreased longitudinal acceleration—or increased deceleration—activity and increased lateral acceleration activity. This correlation pattern suggested that the provision of guidance on pavement correlated with more vehicle activity at both the sign and ramp analysis segments, which likely indicates that drivers were making the necessary maneuvers to prepare for taking the route options they desired.

- Sign diagrammatic indicator: A diagrammatic guide sign also correlated with increased acceleration activity at both the sign and ramp analysis segments. At the sign segment, all correlations were for lateral acceleration, while at the ramp segment, more correlations were for longitudinal acceleration.

- Number of words on other applicable signs: The number of words on other applicable signs at sign gantry locations correlated with several driver behaviors at both the sign and ramp analysis segments. In general, the presence of other applicable signs correlated with more lateral acceleration, more deceleration activity, and lower speeds for both analysis segments. In addition, this variable had a relatively high number of correlations at both analysis segments. Typical other applicable signs in this study were speed limit signs, HOV lane regulation signs, and, in a few cases, additional destination signs mounted on the side of the sign gantry. This variable, however, is discrete, with limited variance; and a majority of sign gantries did not have other applicable signs present. Ramp speed limit signs represented the most common other applicable signs among the limited cases.

- Number of words on other signs at the same gantry: This variable in general had limited correlations with driver behavior variables for both analysis segments. Based on the limited correlations, most of the correlations were negative. In addition, most correlations were for lateral acceleration variables at the sign segment but for longitudinal acceleration variables at the ramp segment.

- Sign lighted indicator: The presence of sign lighting had overwhelmingly negative correlations with driver behaviors, indicating lower speeds and more deceleration activity. Interestingly, the variable in most cases correlated with driver behaviors during daytime, indicating that sign lighting was likely a surrogate for urban interchange locations with higher traffic and lower speed limits.

- Sign visual background complexity: This variable also had a relatively small number of significant correlations. The limited correlations seem to suggest that more complex visual background for signs correlated with higher speed and more acceleration activity. A complex visual background in many cases indicates that drivers were approaching an urban environment with significant commercial developments in the vicinity.

Implications of Sign Impacts on Driver Behaviors

Overall, the sign complexity models show that sign complexity affected unfamiliar drivers much more than it did familiar drivers. A combination of the analysis results shows that correlations for more complex signs point to increased cautious and/or nervous driving behavior and less preparedness for routes, which can potentially lead to crashes. Although the research team analyzed a relatively large number of naturalistic trips, it did not capture a significant number of trips by unfamiliar drivers that involved sudden lane changing or deceleration activity as a result of misunderstandings of signs. That observation, however, indicates that most drivers were able to understand the guide signs and choose the route they were supposed to take, which proves that the studied signs were understandable to most drivers regardless of the amount of information on them. However, some drivers might have chosen to proceed even after realizing they were taking an exit by mistake, which further reduces sudden, risky driver behaviors at such locations.

CORRELATIONS WITH DRIVER, ROADWAY, AND TRAFFIC CONDITIONS

In addition to the mixed-effect models the project team developed for sign-related variables, the team developed a separate set of mixed-effect models for all variables, including detailed driver, roadway, and traffic variables. The primary purpose of the models was to identify candidates among the detailed roadway and traffic variables that agencies consider during sign design in conjunction with sign complexity to mitigate safety impacts and improve efficiency.

Overview of Modeling Results With All Variables

An analysis involving all independent variables resulted in 109 significant mixed-effect models for the sign analysis segment and 98 significant models for the ramp analysis segment (out of the 260 models developed for each analysis segment). Among the significant models for the sign analysis segment, the number of words on subject sign variable was a significant independent variable for 31 models (table 41). In addition, number of words was a significant variable in 21 models for the ramp analysis segment (table 42).

Due to the inclusion of a much larger set of variables depicting roadway, traffic, and driver conditions, the multivariate modeling effort resulted in a smaller number of models, with the sign complexity measure being significant. The significance is inevitable because the additional variables would have competing or conflicting effects on driver behaviors. Some, including, particularly, roadway variables, could understandably have greater effects on driver behaviors than sign complexity could. At the sign analysis segments, the correlation pattern was mostly consistent with that identified during the sign variable modeling effort (table 41). The limited correlations in general indicated higher speeds and lower acceleration activity as the number of words on the subject sign increased. A few more positive correlations emerged for cases that were insignificant during the sign variable modeling. For the ramp analysis segment, the correlations were much more limited (table 42). Based on the correlations, however, positive correlations dominated the lateral acceleration variables for younger, unfamiliar drivers. Most of the correlations, however, were previously not significant during sign variable modeling. Among positive correlations, two were previously negative in separate analysis of sign variables, indicating the stronger influence of the nonsign variables on driver behaviors.

Table 41. Parameter estimates for number of words on subject sign: Sign analysis segments.

Variable	Older Drivers, Ramps on Right				Younger Drivers, Ramps on Right				All Drivers, Left Ramps	
	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night
ΔV-μ (km/h)	—	—	6.4E-01	—	—	—	—	3.2E-01	—	—
ΔV-σ (km/h)	—	−6.4E-02	—	—	—	—	—	—	—	−1.6E-01
ΔV-Max (km/h)	—	—	3.6E-01	—	—	—	—	2.8E-01	—	—
ΔV-Min (km/h)	—	—	4.9E-01	—	—	—	—	3.3E-01	—	—
a_{long}-μ (g)	—	—	—	—	—	—	—	—	2.3E-03	—
a_{long}-σ (g)	—	—	—	—	—	—	—	—	—	−1.4E-03
a_{long}-Min (g)	—	—	—	—	—	—	—	—	2.7E-03	—
a_{long}-$abs\sigma$ (g)	—	—	—	—	—	—	—	—	—	−1.0E-03
a_{long}-$absMax$ (g)	−2.5E-03	—	—	−1.9E-03	—	—	—	—	—	—
j_{long}-σ (g/s)	—	—	—	—	—	—	−3.9E-03	—	—	—
j_{long}-Max (g/s)	—	—	—	—	—	—	−1.7E-02	—	—	—
j_{long}-Min (g/s)	—	—	—	—	—	—	1.5E-02	—	—	—
a_{lat}-μ (g)	—	—	—	—	—	—	—	8.5E-04	—	—
a_{lat}-σ (g)	—	—	—	—	—	−9.0E-04	—	—	—	—
a_{lat}-Max (g)	—	—	—	—	—	—	—	—	2.3E-03	—
a_{lat}-Min (g)	—	—	—	—	—	1.6E-03	—	1.2E-03	—	—
a_{lat}-$abs\mu$ (g)	−1.1E-03	−8.6E-04	−6.7E-04	—	—	—	—	−4.8E-04	—	—
a_{lat}-$abs\sigma$ (g)	—	—	—	—	—	−6.8E-04	—	—	—	—
a_{lat}-$absMax$ (g)	—	—	—	—	—	−2.6E-03	—	—	—	—
j_{lat}-Min (g/s)	—	—	—	—	—	—	—	—	—	2.9E-02
j_{lat}-σ (g/s)	—	—	—	−3.1E-03	—	—	—	—	—	−5.6E-03

— = No data.

Table 42. Parameter estimates for number of words on subject sign: Ramp analysis segments.

Variable	Older Drivers, Ramps on Right				Younger Drivers, Ramps on Right				All Drivers, Left Ramps	
	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Familiar, Day	Familiar, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night	Unfamiliar, No GPS, Day	Unfamiliar, No GPS, Night
ΔV-σ (km/h)	—	—	—	—	—	—	—	—	—	−2.9E-01
ΔV-Max (km/h)	—	—	—	—	—	—	5.0E-01	—	—	—
a_{long}-σ (g)	—	—	—	—	—	−7.9E-04	—	—	—	—
a_{long}-Max (g)	—	—	—	—	—	—	—	—	—	−5.5E-03
a_{long}-$abs\mu$ (g)	−1.5E-03	—	—	—	—	—	—	—	—	—
a_{long}-$absMax$ (g)	−2.9E-03	—	—	—	—	—	—	—	—	—
j_{long}-μ (g/s)	—	—	—	—	—	—	3.5E-04	2.6E-04	—	—
j_{long}-σ (g/s)	—	—	—	—	—	—	—	—	−8.0E-03	—
j_{long}-Max (g/s)	—	—	—	−1.4E-02	—	—	—	—	—	−4.2E-02
a_{lat}-σ (g)	—	—	—	—	—	—	6.8E-04	1.2E-03	—	—
a_{lat}-Max (g)	—	—	—	—	—	—	—	3.8E-03	—	—
a_{lat}-Min (g)	—	—	—	—	—	2.2E-03	1.6E-03	1.3E-03	—	—
a_{lat}-$abs\mu$ (g)	—	—	—	—	—	—	7.0E-04	—	—	—
a_{lat}-$absMax$ (g)	—	—	—	—	—	—	4.8E-04	—	—	—

— = No data.

Table 43 and table 44 list the variables that appeared as significant in at least 10 multivariate mixed-effect models in the overall modeling results. As illustrated in the tables, roadway-related variables dominated the tops of both lists. In both lists, distance from last interchange was the most common significant variable in the driver behavior models. The following section discusses in more detail the nonsign variables and their effects.

Table 43. Variables appeared as significant in 10 or more multivariate models: Sign analysis segments.

No.	Variable	No. of Models
1	Distance from previous interchange	65
2	Distance from previous off-ramp	55
3	Distance to route ramp	55
4	Distance from previous on-ramp	46
5	Mainline speed limit	38
6	Road curve indicator	38
7	Number of words on subject sign	31
8	Distance from previous advance sign	26
9	Number of words on other applicable signs	25
10	Complex ramp indicator	21
11	Number of signs	16
12	Sign lighting indicator	16
13	Traffic LOS C indicator	16
14	Visual complexity rating	16
15	Number of route options on sign	15
16	Number of route options on sign structure	13
17	Subject sign arrow-per-lane indicator	11
18	Maximum number of lane changes required	10
19	Number of advance signs per mile	10
20	Number of lanes for route option	10
21	Number of words on other signs	10

Note: A total of 260 models were developed for the variables listed.

Table 44. Variables appeared as significant in 10 or more multivariate models: ramp analysis segments.

No.	Variable	No. of Models
1	Distance from previous interchange	50
2	Mainline speed limit	48
3	Speed reduction at ramp	47
4	Distance from previous off-ramp	41
5	Distance from previous on-ramp	35
6	Distance from previous advance sign	25
7	Number of words on subject sign	21
8	Total number of lanes	21
9	Driver crash history	17
10	Number of words on other applicable signs	17
11	Traffic LOS C indicator	16
12	Minimum number of lane changes required	14
13	Sign lighting indicator	14
14	Sign visual complexity rating	14
15	Distance to route ramp	13
16	Driver nearsightedness indicator	11
17	Road curve indicator	11

Note: A total of 260 models were developed for the variables listed.

Roadway and Traffic Variables With Significant Effects on Driver Behaviors

As discussed in a preceding section, a large number of roadway, traffic, and driver variables affected driver behaviors at the analysis segments. To better understand the effects, this section discusses the variables that appeared in at least 20 significant driver behavior models out of 260 total models developed.

Distance From Previous Interchange

Longer distances from the previous interchange—particularly system interchanges—overwhelmingly correlated with more uniform and decisive acceleration behavior (i.e., lower standard deviation and maximum longitudinal and lateral acceleration rates but higher mean and minimum acceleration rates using one scenario as an example) (table 45). Interchanges allow a large volume of traffic to enter a freeway from another roadway that may have different roadway and traffic conditions. The aftereffects of navigating through a sometimes complex interchange onto a new freeway, coupled with new roadway and traffic conditions, could affect driver behavior—particularly when it comes to the capability of reacting to additional navigational demands. Therefore, relevant design guidelines recommend that interchanges be spaced at least 1 mi apart.[80]

Table 45. Correlations for distance to previous interchange: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-μ (g)	8.7E-07	Positive
a_{long}-σ (g)	−2.4E-07	Negative
a_{long}-Min (g)	9.4E-09	Positive
a_{lat}-μ (g)	8.4E-09	Positive
a_{lat}-σ (g)	−2.7E-07	Negative
a_{lat}-Max (g)	−2.0E-07	Negative
j_{long}-σ (g/s)	3.9E-07	Positive
a_{long}-$abs\mu$ (g)	2.1E-09	Positive
a_{long}-$abs\sigma$ (g)	−2.3E-07	Negative
a_{lat}-$abs\sigma$ (g)	−3.1E-07	Negative
a_{lat}-$absMax$ (g)	−6.6E-07	Negative

Distance From Previous Exit Ramp

The distance from the previous exit ramp was a significant variable for a large number of models. With correlations for the sign analysis segment and the scenario for younger, unfamiliar drivers, daytime, and right ramps as an example (table 46 using one scenario as an example), results found that longer distance to the previous exit ramp correlated with higher mean deceleration and lateral acceleration rates and lower acceleration standard deviations. AASHTO recommends a minimum distance of 1,000 ft between two successive exit ramps (table 47).[5]

Table 46. Correlations for distance from previous exit ramp: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-μ (g)	−2.7E-07	Negative
a_{long}-σ (g)	−3.7E-07	Negative
a_{lat}-μ (g)	6.1E-07	Positive
a_{lat}-σ (g)	−2.3E-07	Negative
a_{lat}-Max (g)	−2.1E-07	Negative
a_{long}-$abs\mu$ (g)	−1.5E-07	Negative
a_{long}-$abs\sigma$ (g)	−1.2E-07	Negative
a_{lat}-$abs\sigma$ (g)	−2.8E-07	Negative
a_{lat}-$absMax$ (g)	−1.9E-06	Negative

Table 47. Minimum ramp terminal spacing recommended by AASHTO.[5]

Successive Ramp Category	Interchange Type	Roadway Type	Minimum (ft)
EN-EN or EX-EX	N/A	Full freeway	1,000
EN-EN or EX-EX	N/A	Collector–distributor road	800
EX-EN	N/A	Full freeway	500
EX-EN	N/A	Collector–distributor road	400
Turning roadways	System	N/A	800
Turning roadways	Service	N/A	600
EN-EX (weaving)	System to service	Full freeway	2,000
EN-EX (weaving)	System to service	Collector–distributor road	1,600
EN-EX (weaving)	Service to service	Full freeway	1,600
EN-EX (weaving)	Service to service	Collector–distributor road	1,000

EN = entrance; EX = exit; N/A = not applicable.

Distance to Route Ramp

Distance to route ramp correlates directly with amount of space and time drivers have for reacting to prepare for exiting. As such, correlations for this variable (table 48 for a sample scenario) show that longer distances between sign and ramp terminal correlated with lower deceleration activity, higher speeds, and lower lateral acceleration activity.

Table 48. Correlations for distance to route ramp: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-μ (g)	7.6E-06	Positive
a_{long}-σ (g)	−1.9E-06	Negative
a_{long}-Min (g)	9.4E-06	Positive
a_{lat}-σ (g)	−2.5E-06	Negative
a_{lat}-Max (g)	−5.3E-06	Negative
ΔV-μ (km/h)	0.002	Positive
ΔV-Max (km/h)	0.001	Positive
ΔV-Min (km/h)	0.002	Positive
ΔV-σ (km/h)	−1.3E-04	Negative
a_{long}-$abs\mu$ (g)	−2.1E-06	Negative
a_{long}-$abs\sigma$ (g)	−1.6E-06	Negative
a_{long}-$absMax$ (g)	−3.7E-06	Negative
a_{lat}-$abs\sigma$ (g)	−2.1E-06	Negative
a_{lat}-$absMax$ (g)	−1.0E-05	Negative

Distance From Previous Entrance Ramp

Entrance ramps immediately followed by exit ramps are frequently design issues that negatively affect safety and efficiency if not addressed properly. Entrance ramps allow traffic to merge onto a freeway, but they create disruptions to the mainline traffic flow—particularly the flow of traffic preparing to exit. Longer distances from an entrance ramp—prior to sign location—correlated with more deceleration activity, higher speeds, and higher but smoother (higher mean but lower jerk and variance) lateral acceleration. Table 49 shows a sample scenario.

Table 49. Correlations for distance from previous entrance ramp: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-μ (g)	−7.0E-07	Negative
a_{long}-σ (g)	4.4E-07	Positive
a_{lat}-μ (g)	7.8E-07	Positive
a_{lat}-σ (g)	−2.4E-07	Negative
ΔV-μ (km/h)	4.3E-04	Positive
ΔV-*Max* (km/h)	3.9E-04	Positive
ΔV-*Min* (km/h)	4.1E-04	Positive
j_{lat}-σ (g/s)	−4.4E-06	Negative
a_{long}-*abs*μ (g)	1.5E-07	Positive
a_{long}-*abs*σ (g)	4.5E-07	Positive
a_{lat}-*abs*σ (g)	1.1E-07	Positive

Mainline Speed Limit

Higher speed limits on a freeway correlated with less speeding but also with lower deceleration activity, as shown by correlations for an example scenario in table 50. Less busy freeways generally have higher speed limits, and therefore, higher mainline speed limits highly correlate with less complex roadway and traffic conditions.

Table 50. Correlations for mainline speed limit: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-σ (g)	−2.5E-04	Negative
a_{long}-*Min* (g)	0.001	Positive
ΔV-μ (km/h)	−1.162	Negative
ΔV-*Max* (km/h)	−1.216	Negative
ΔV-*Min* (km/h)	−1.108	Negative
ΔV-σ (km/h)	−0.027	Negative
a_{long}-*abs*μ (g)	−2.9E-04	Negative
a_{long}-*abs*σ (g)	−2.2E-04	Negative
a_{long}-*absMax* (g)	−0.001	Negative

Speed Limit Reduction on Ramp (i.e., Difference Between Mainline Speed Limit and Ramp Speed Limit).

This variable was among the most common significant variables in mixed-effect models for the ramp analysis segment but not the sign analysis segment. This significant variable is understandable because drivers might not know the speed reduction required by a ramp at the sign location. Further, as correlations in table 51 for a sample analysis scenario at the ramp analysis segment show, higher ramp speed reduction overwhelmingly correlated with more deceleration activity (e.g., lower mean acceleration rates but higher acceleration variance) and lower speeds.

Table 51. Correlations for speed limit reduction on ramp: Younger, unfamiliar drivers, daytime, right ramps, and ramp analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-μ (g)	−0.001	Negative
a_{long}-σ (g)	3.6E-04	Positive
a_{long}-Min (g)	−0.002	Negative
a_{lat}-σ (g)	0.001	Positive
ΔV-μ (km/h)	−0.176	Negative
ΔV-Min (km/h)	−0.279	Negative
ΔV-σ (km/h)	0.070	Positive
j_{long}-Min (g/s)	−0.003	Negative
a_{long}-$abs\mu$ (g)	0.001	Positive
a_{long}-$abs\sigma$ (g)	3.7E-04	Positive
a_{long}-$absMax$ (g)	0.001	Positive
a_{lat}-$abs\mu$ (g)	3.2E-04	Positive
a_{lat}-$absMax$ (g)	0.001	Positive

Curved Alignment Indicator

Curved mainline alignment understandably correlated with the lateral acceleration activity of drivers at the analysis segments. With the analysis scenario for younger, unfamiliar drivers during daytime at the sign analysis segment as an example (table 52), curved alignments overwhelmingly correlated positively with lateral acceleration variables, indicating more lateral acceleration activity on curves. Note that curved alignment also correlated with increased longitudinal acceleration variance, indicating that the additional lateral accelerating activity required by the roadway alignments on the mainline freeway complicated drivers' behavior prior to drivers' exiting of the freeway.

Table 52. Correlations for curved alignment: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-σ (g)	0.003	Positive
a_{lat}-μ (g)	0.011	Positive
a_{lat}-σ (g)	0.012	Positive
a_{lat}-Max (g)	0.034	Positive
j_{lat}-σ (g/s)	0.069	Positive
j_{lat}-Min (g/s)	−0.224	Negative
a_{lat}-$abs\mu$ (g)	0.004	Positive
a_{lat}-$abs\sigma$ (g)	0.011	Positive
a_{lat}-$absMax$ (g)	0.054	Positive

Distance From Previous Advance Sign

The results show that longer distance between a previous advance sign and a current subject sign correlated with more deceleration and higher acceleration variance (table 53). That observation suggests that an advance guide sign located a shorter distance from the sign at the ramp would result in smoother deceleration and smoother lane-changing behavior (e.g., lower longitudinal and lateral acceleration variances).

Table 53. Correlations for distance from previous advance sign: Younger, unfamiliar drivers, daytime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{long}-μ (g)	−2.8E-06	Negative
a_{long}-σ (g)	1.5E-06	Positive
a_{long}-Min (g)	−5.3E-06	Negative
a_{lat}-σ (g)	9.6E-07	Positive
a_{long}-$abs\mu$ (g)	1.5E-06	Positive
a_{long}-$abs\sigma$ (g)	1.3E-06	Positive
a_{lat}-$abs\sigma$ (g)	2.9E-07	Positive

Complex Ramp Indicator

During this analysis, ramp types such as diamond, parclo (partial cloverleaf) loop, and free-flow loop were classified as complex ramps based on their requirements for relatively considerable speed reductions. This variable, therefore, had effects on driver behavior that were similar to those of the ramp speed reduction variable. The mixed-effect modeling effort showed that complex ramps correlated with reduced speed and improved lateral acceleration variances. Table 54 shows correlations for a sample scenario.

Table 54. Correlations for complex ramp indicator: Younger, unfamiliar drivers, nighttime, right ramps, and sign analysis segment.

Variable	Parameter Estimate	Correlation
a_{lat}-σ (g)	0.003	Positive
a_{lat}-Min (g)	−0.014	Negative
ΔV-Max (km/h)	−2.502	Negative
ΔV-Min (km/h)	−2.508	Negative
a_{lat}-$abs\sigma$ (g)	0.002	Positive

Total Number of Lanes

The total number of lanes at a freeway sign location significantly affected driver lateral acceleration activity—particularly at the ramp segment. With correlations for younger, unfamiliar drivers during nighttime at the ramp analysis segment as an example (table 55), more lanes at a sign structure location and therefore at the ramp location interestingly correlated with reduced lateral acceleration, seemingly indicating that drivers prepared earlier for exiting at locations with more lanes.

Table 55. Correlations for complex ramp indicator: Younger, unfamiliar drivers, nighttime, right ramps, and ramp analysis segment.

Variable	Parameter Estimate	Correlation
a_{lat}-μ (g)	−0.007	Negative
a_{lat}-σ (g)	−0.007	Negative
a_{lat}-Max (g)	−0.014	Negative
j_{long}-Min (g/s)	0.052	Positive
a_{lat}-$abs\mu$ (g)	−0.005	Negative
a_{lat}-$abs\sigma$ (g)	−0.006	Negative

SIGN COMPLEXITY THRESHOLDS BASED ON DRIVER BEHAVIORS

Considering the sample sizes and frequency of significant correlations with sign variables, the project team selected the following analysis scenarios and driver behavior variables (table 56) for further univariate regression analysis for the purpose of identifying sign complexity thresholds. The team initially attempted to include the scenario for all drivers not using GPS for left ramps in the threshold development. However, due to the limited sample size, the analysis did not result in any meaningful results.

Table 56. Scenarios and driver behavior variables selected for identifying sign complexity thresholds.

Analysis Segment	Ramp Side	Driver Group	Time	Variable
Sign	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{long}-μ (g)
Sign	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{long}-σ (g)
Sign	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{lat}-μ (g)
Sign	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{lat}-σ (g)
Sign	Right	Older, unfamiliar drivers not using GPS	Nighttime	a_{long}-$abs\mu$ (g)
Sign	Right	Older, unfamiliar drivers not using GPS	Daytime	a_{lat}-Max (g)
Ramp	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{long}-$abs\mu$ (g)
Ramp	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{long}-μ (g)
Ramp	Right	Younger, unfamiliar drivers not using GPS	Daytime	a_{long}-σ (g)

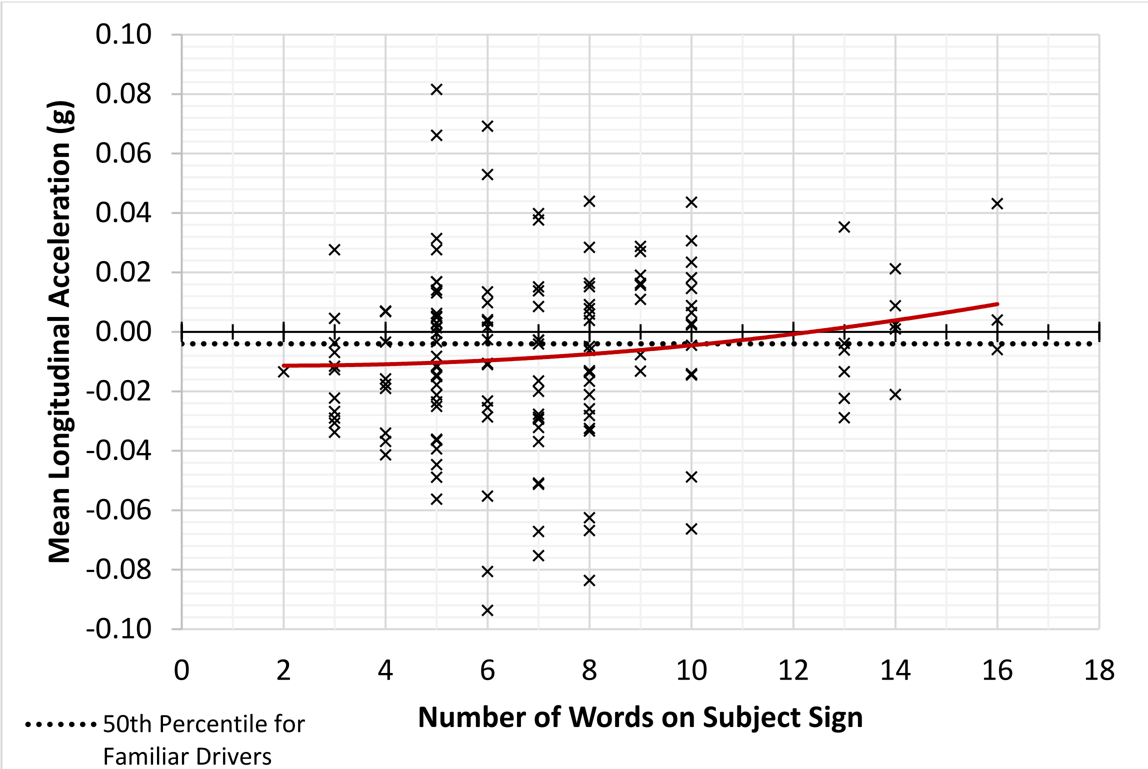
To identify potential thresholds for sign complexity, the project team developed univariate regression models for the selected driver behavior variable-scenario combinations by using number of words on subject sign as the independent variable. The team identified a potential threshold by determining the number of words that corresponds to the 50th percentile of the same driver behavior variable for familiar drivers during the same scenario conditions based on the regression model.

Table 57 lists the univariate regression models developed for the selected variable-scenario combinations, followed by charts showing the results graphically for each analysis (figure 23 through figure 42). For this analysis, the project team developed sign complexity thresholds for two roadway configurations: minimum lane change = 1 (i.e., the driver would have to switch one lane at a minimum to be in the exit lane) and minimum lane change = 0 (i.e., traffic in the rightmost lane at the sign location does not need to switch lanes to exit). Unavailable thresholds in the table indicate that the driver behavior of unfamiliar drivers based on the regression curve would not reach the 50th-percentile value of the familiar drivers for the same scenarios regardless of how simple the sign was.

Table 57. Univariate regression models for selected driver behavior variable-scenario combinations and the identified thresholds.

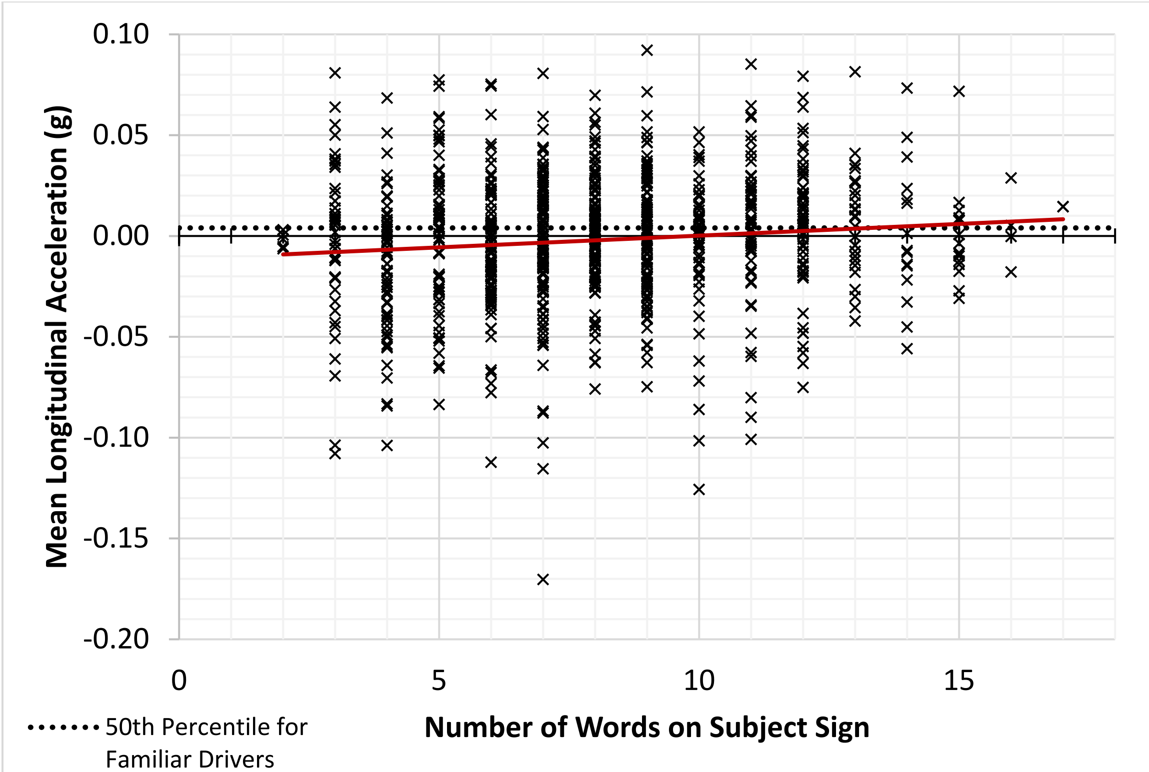
No.	Driver Category*	Driver Behavior Variable	Minimum Lane Change (No.)	Regression Equation**	R^2	50th Percentile for Familiar Drivers	Threshold for No. of Words	Figure Illustration
1	1	a_{long}-μ (g)	1	$y = 0.0001x^2 - 0.0004x - 0.011$	0.022	−0.005	9.7	Figure 23
2	1	a_{long}-σ (g)	1	$y = -0.0002x^2 + 0.0023x + 0.0182$	0.019	0.026	—	Figure 24
3	1	a_{long}-Min (g)	1	$y = 0.0012x^2 - 0.017x - 0.0165$	0.012	−0.060	10.8	Figure 25
4	1	a_{lat}-μ (g)	1	$y = -0.0001x^3 + 0.003x^2 - 0.0253x + 0.0747$	0.030	0.014	8.3	Figure 26
5	1	a_{lat}-σ (g)	1	$y = -0.0001x^2 + 0.0012x + 0.0235$	0.040	0.026	8.9	Figure 27
6	1	a_{long}-μ (g)	0	$y = 0.0012x - 0.0115$	0.011	−0.002	8.0	Figure 28
7	1	a_{long}-σ (g)	0	$y = 0.0307x^{-0.209}$	0.015	0.020	7.8	Figure 29
8	1	a_{long}-Min (g)	0	$y = 0.0028x - 0.0769$	0.023	−0.05	9.6	Figure 30
9	1	a_{lat}-μ (g)	0	$y = -9\text{E-}05x^2 + 0.0009x + 0.006$	0.004	0.005	10.9	Figure 31
10	1	a_{lat}-σ (g)	0	$y = 0.027x^{-0.114}$	0.011	0.020	16.2	Figure 32
11	2	a_{long}-μ (g)	1	$y = 0.0002x^2 - 0.0024x - 0.0128$	0.005	−0.010	13.1	Figure 33
12	2	a_{long}-σ (g)	1	$y = -0.0002x^2 + 0.0024x + 0.0201$	0.014	0.025	9.5	Figure 34
13	2	a_{long}-$abs\mu$ (g)	1	$y = -0.0004x^2 + 0.006x + 0.0197$	0.034	0.035	11.7	Figure 35
14	2	a_{long}-μ (g)	0	$y = -0.0003x^2 + 0.006x - 0.0449$	0.013	−0.014	10.0	Figure 36
15	2	a_{long}-σ (g)	0	$y = 0.0003x^2 - 0.0051x + 0.0525$	0.033	0.024	—	Figure 37
16	2	a_{long}-$abs\mu$ (g)	0	$y = 0.0002x^2 - 0.0046x + 0.0611$	0.013	0.032	—	Figure 38
17	3	a_{lat}-Max (g)	1	$y = 0.0006x^2 - 0.0146x + 0.1333$	0.124	0.060	7.1	Figure 39
18	3	a_{lat}-Max (g)	0	$y = 0.0002x^2 - 0.0062x + 0.0914$	0.015	0.060	6.4	Figure 40
19	4	a_{long}-$abs\mu$ (g)	1	$y = -0.0001x^2 + 0.0008x + 0.0297$	0.073	0.032	—	Figure 41
20	4	a_{long}-$abs\mu$ (g)	0	$y = -0.0009x + 0.0338$	0.022	0.024	10.6	Figure 42

*Driver category no. 1 contains younger drivers (eyesight 20/20 or better), daytime, ramps on right, and sign segment. Driver category no. 2 contains younger drivers (eyesight 20/20 or better), daytime, ramps on right, and ramp segment. Driver category no. 3 contains older drivers, daytime, ramps on right, and sign segment. Driver category no. 4 contains older drivers, nighttime, ramps on right, and sign segment.
**In the univariate equations, y is the driver behavior variable, and x is the number of words on subject sign.
— = No data.



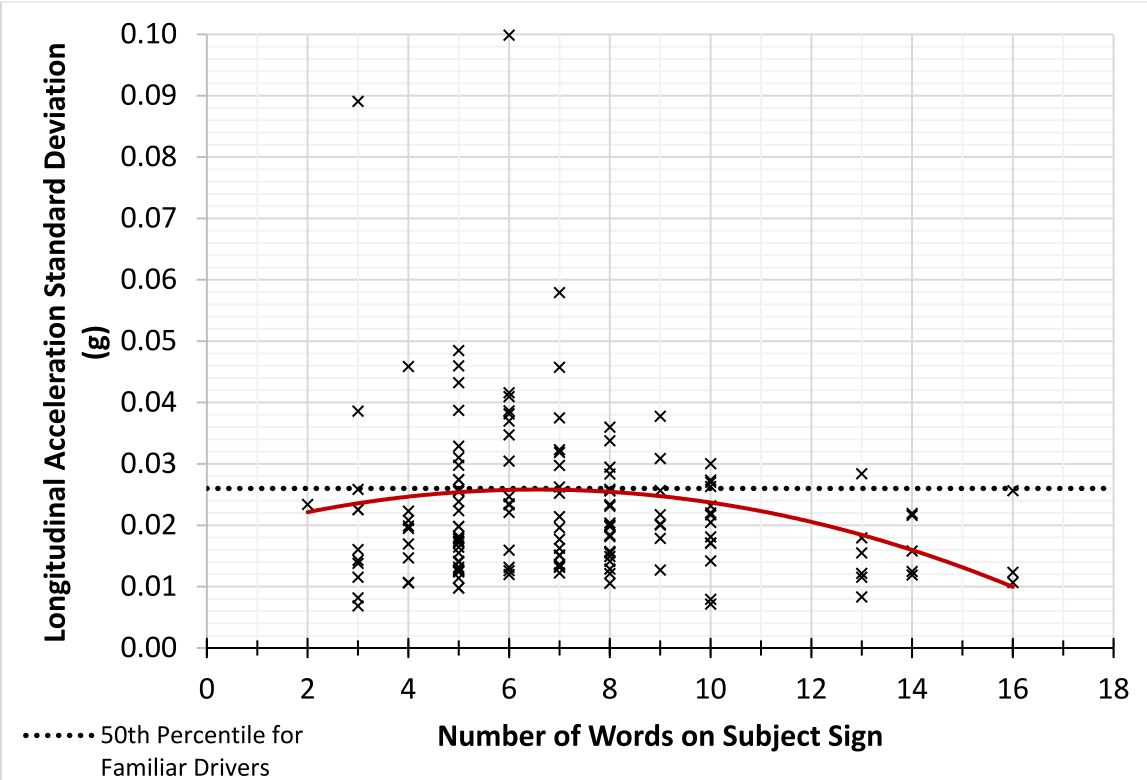
Note: Mean longitudinal acceleration, younger drivers, sign segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 23. Graph. Complexity threshold identification for mean longitudinal acceleration, driver category 1 with a minimum lane change of 1.



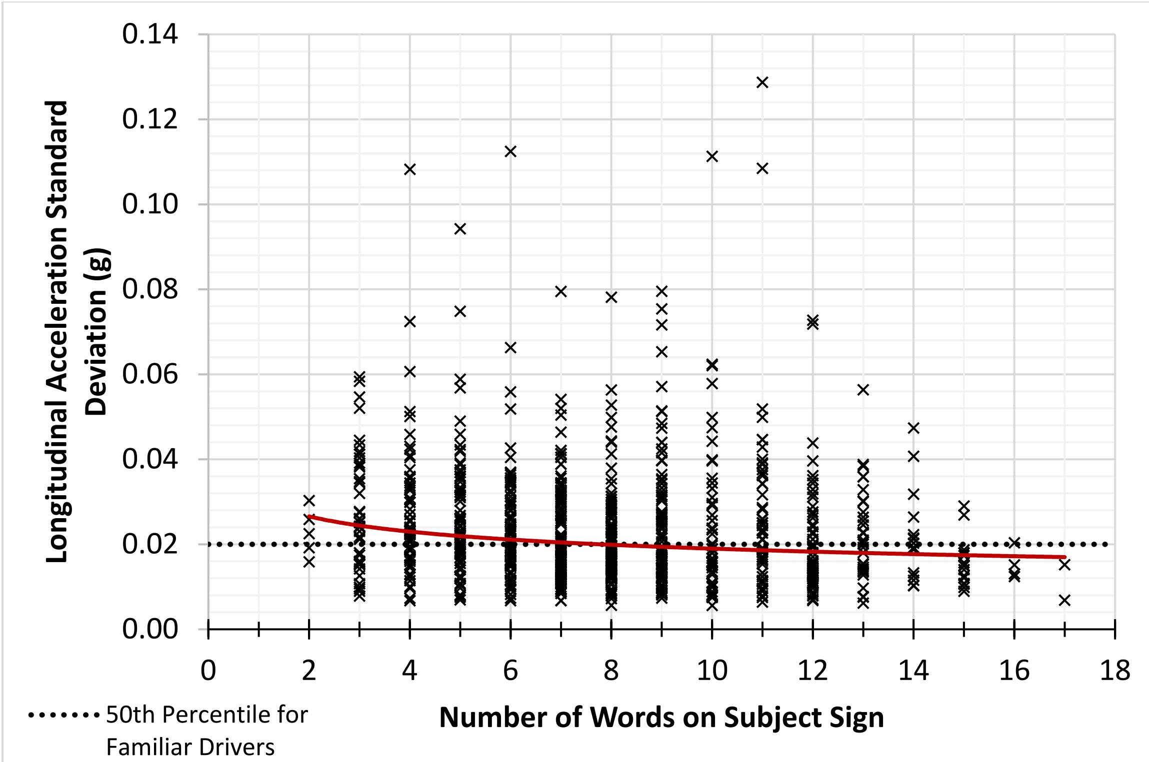
Note: Mean longitudinal acceleration, younger drivers, sign segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 24. Graph. Complexity threshold identification for mean longitudinal acceleration, driver category 1 with a minimum lane change of 0.



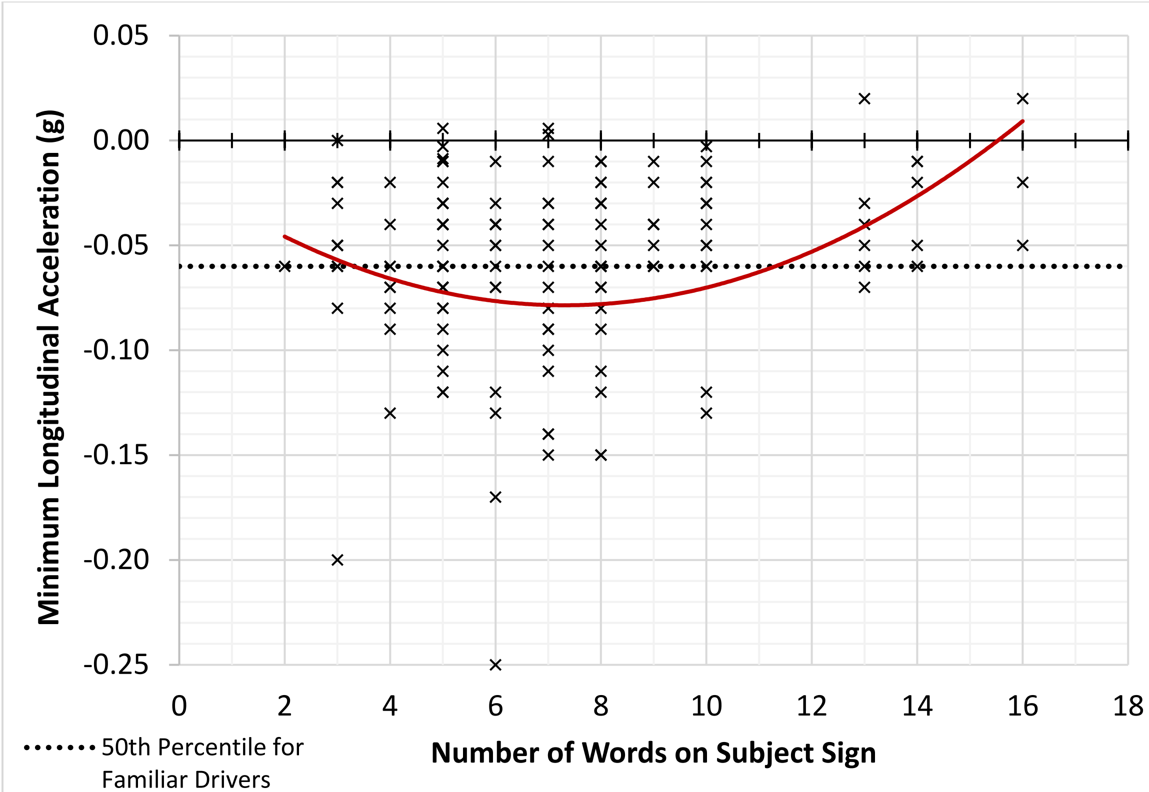
Note: Longitudinal acceleration standard deviation, younger drivers, sign segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 25. Graph. Complexity threshold identification for longitudinal acceleration standard deviation, driver category 1 with a minimum lane change of 1.



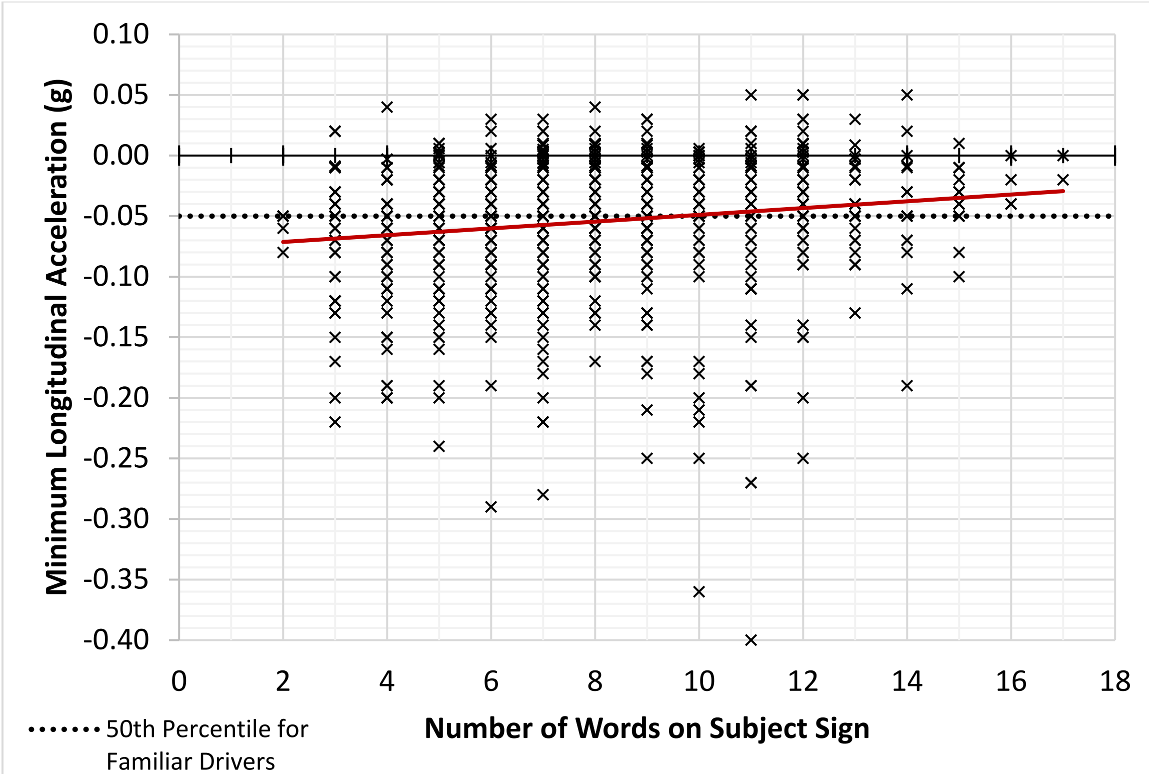
Note: Longitudinal acceleration standard deviation, younger drivers, sign segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 26. Graph. Complexity threshold identification for mean longitudinal acceleration, driver category 1 with a minimum lane change of 0.



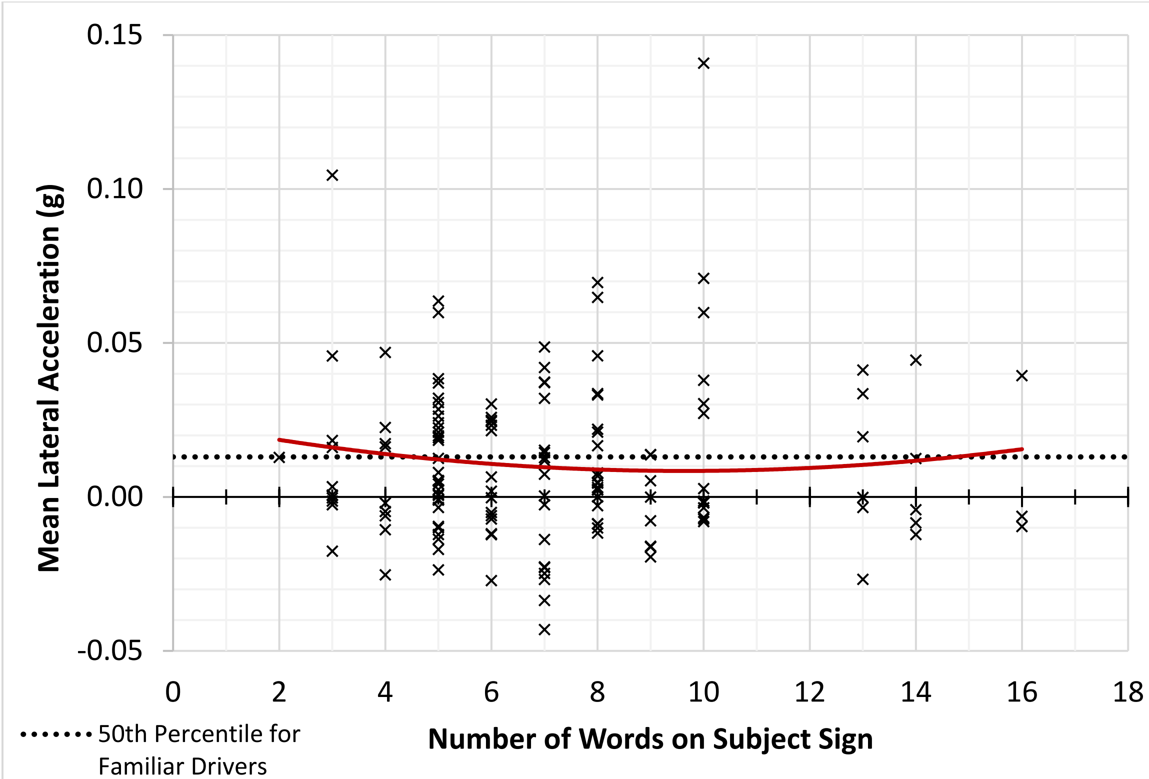
Note: Minimum longitudinal acceleration, younger drivers, sign segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 27. Graph. Complexity threshold identification for minimum longitudinal acceleration, driver category 1 with a minimum lane change of 1.



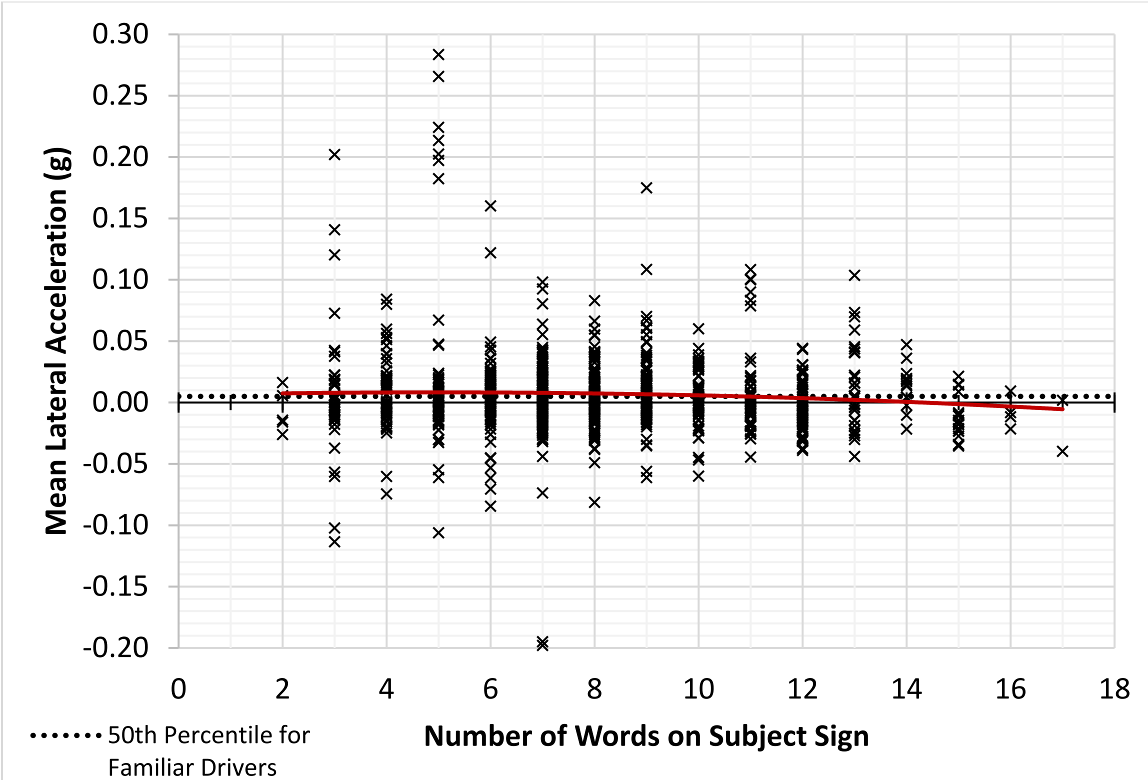
Note: Minimum longitudinal acceleration, younger drivers, sign segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 28. Graph. Complexity threshold identification for minimum longitudinal acceleration, driver category 1 with a minimum lane change of 0.



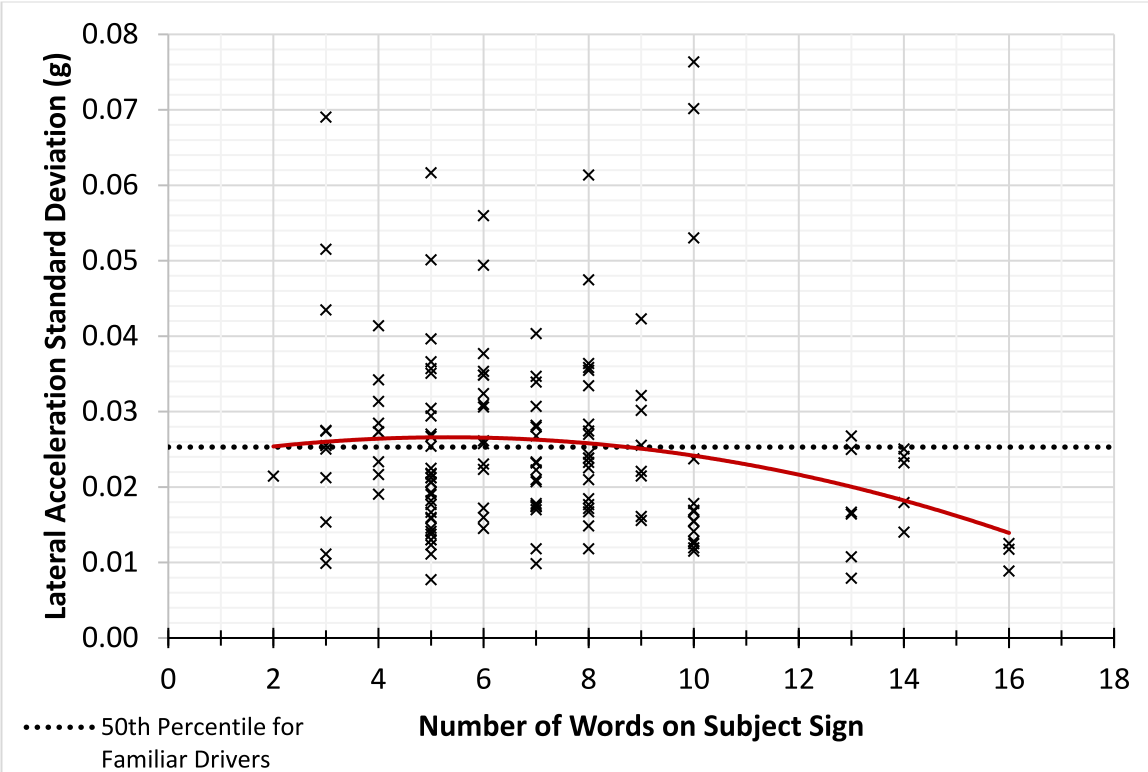
Note: Mean lateral acceleration, younger drivers, sign segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 29. Graph. Complexity threshold identification for mean lateral acceleration, driver category 1 with a minimum lane change of 1.



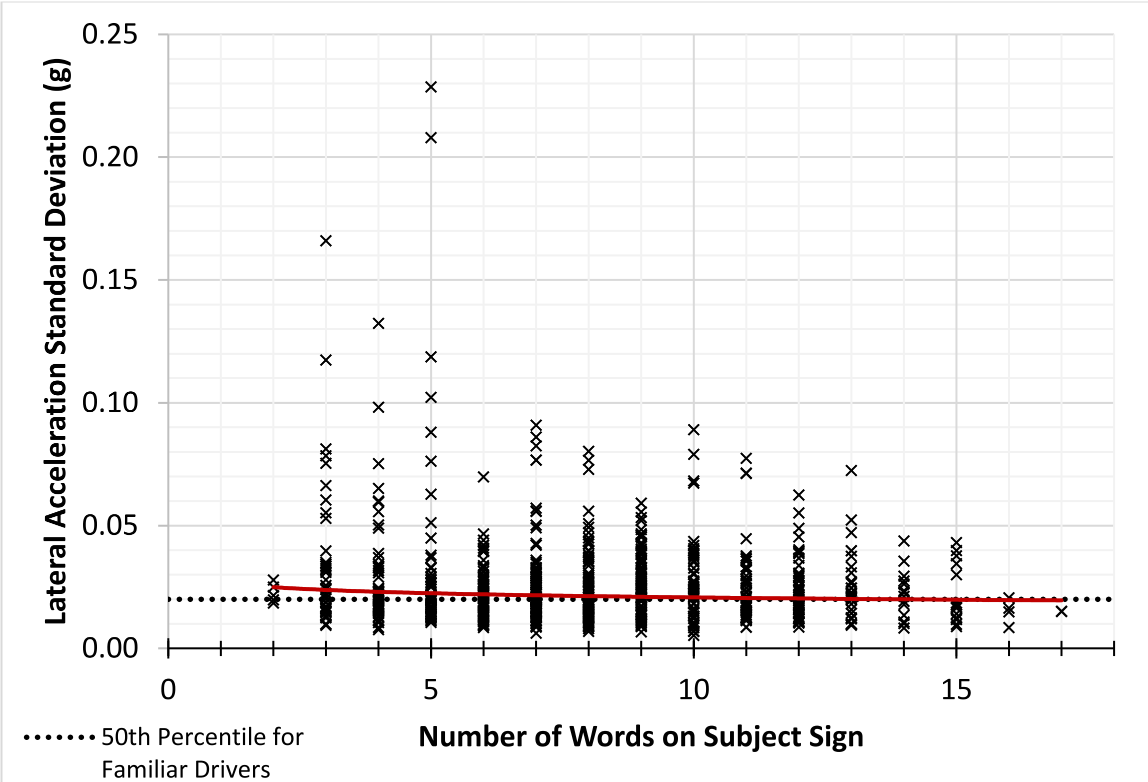
Note: Mean lateral acceleration, younger drivers, sign segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 30. Graph. Complexity threshold identification for mean lateral acceleration, driver category 1 with a minimum lane change of 0.



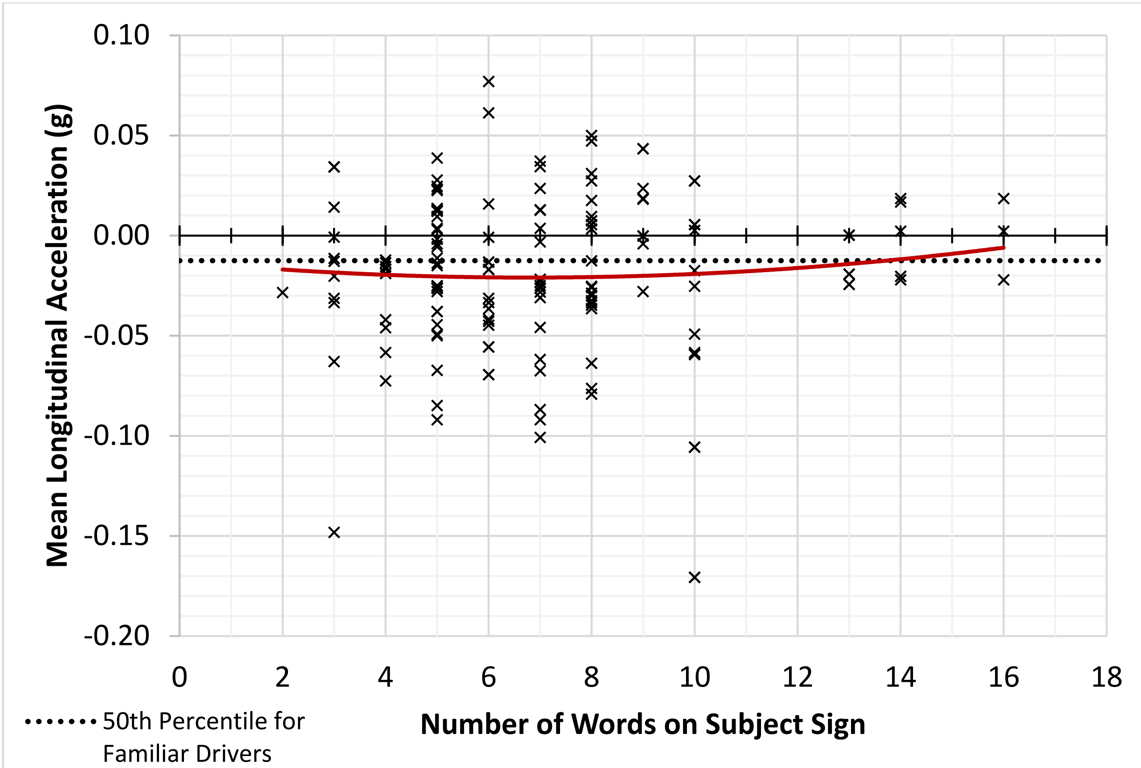
Note: Lateral acceleration standard deviation, younger drivers, sign segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 31. Graph. Complexity threshold identification for lateral acceleration standard deviation, driver category 1 with a minimum lane change of 1.



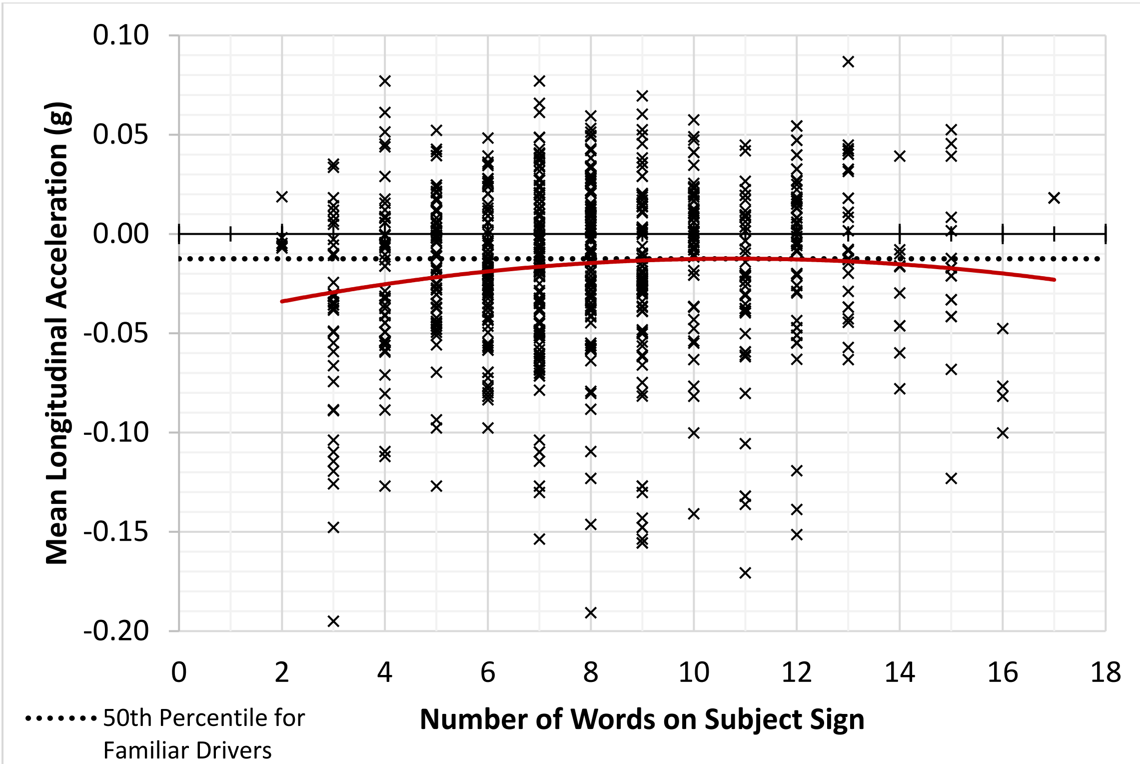
Note: Lateral acceleration standard deviation, younger drivers, sign segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 32. Graph. Complexity threshold identification for lateral acceleration standard deviation, driver category 1 with a minimum lane change of 0.



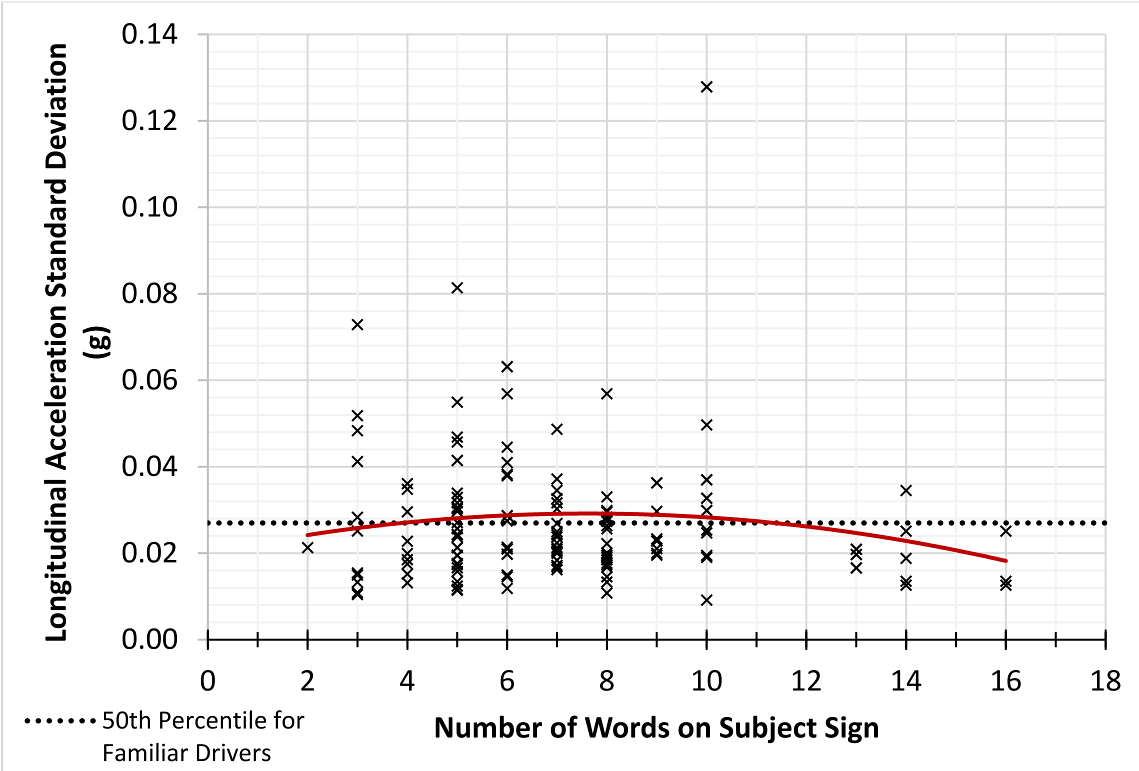
Note: Mean longitudinal acceleration, younger drivers, ramp segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 33. Graph. Complexity threshold identification for mean longitudinal acceleration, driver category 2 with a minimum lane change of 1.



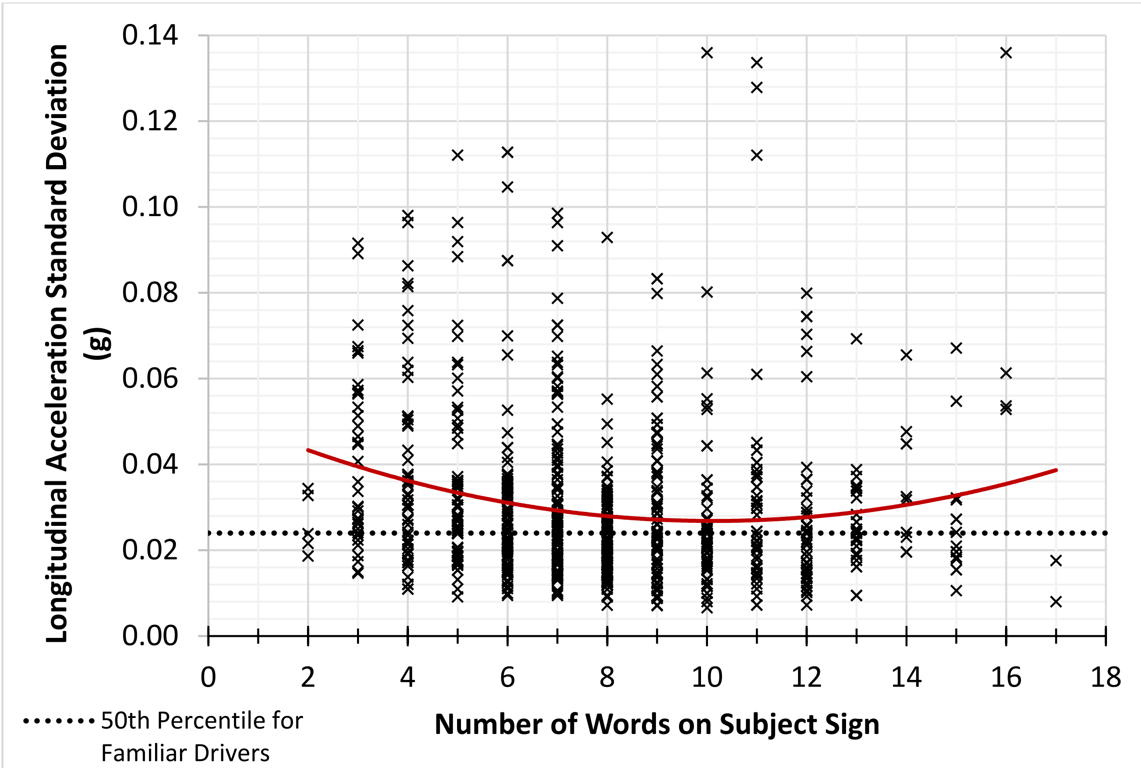
Note: Mean longitudinal acceleration, younger drivers, ramp segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 34. Graph. Complexity threshold identification for mean longitudinal acceleration, driver category 2 with a minimum lane change of 0.



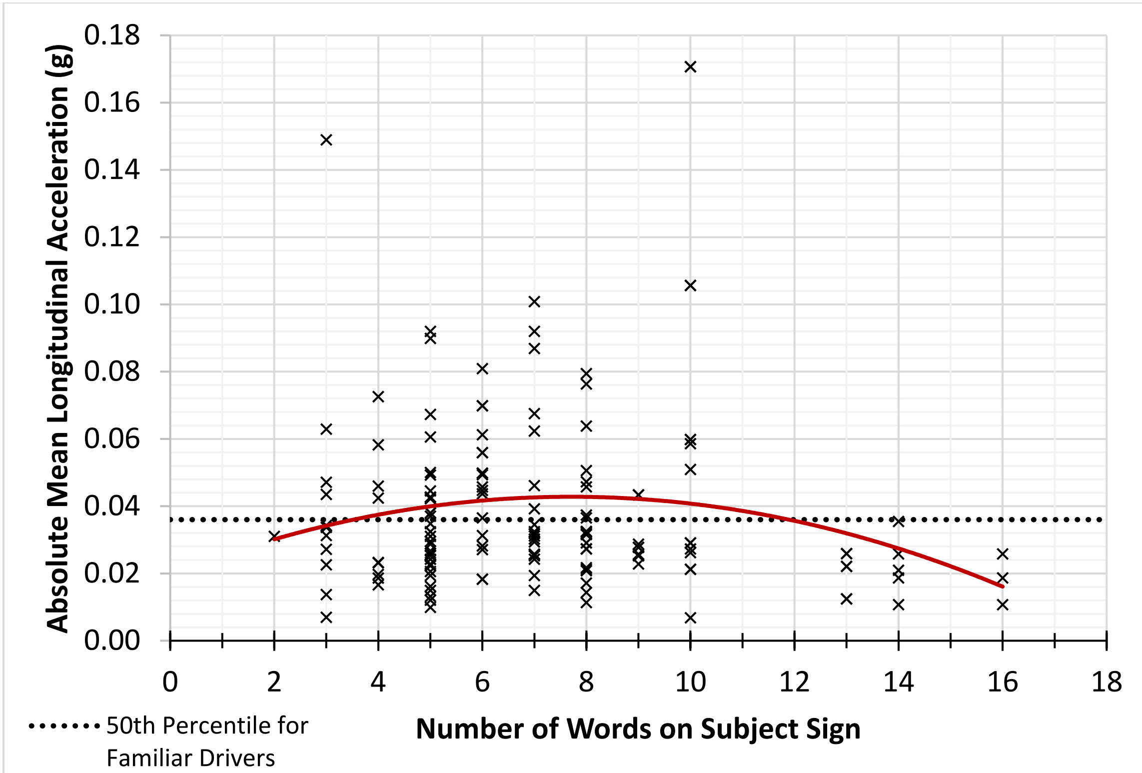
Note: Longitudinal acceleration standard deviation, younger drivers, ramp segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 35. Graph. Complexity threshold identification for longitudinal acceleration standard deviation, driver category 2 with a minimum lane change of 1.



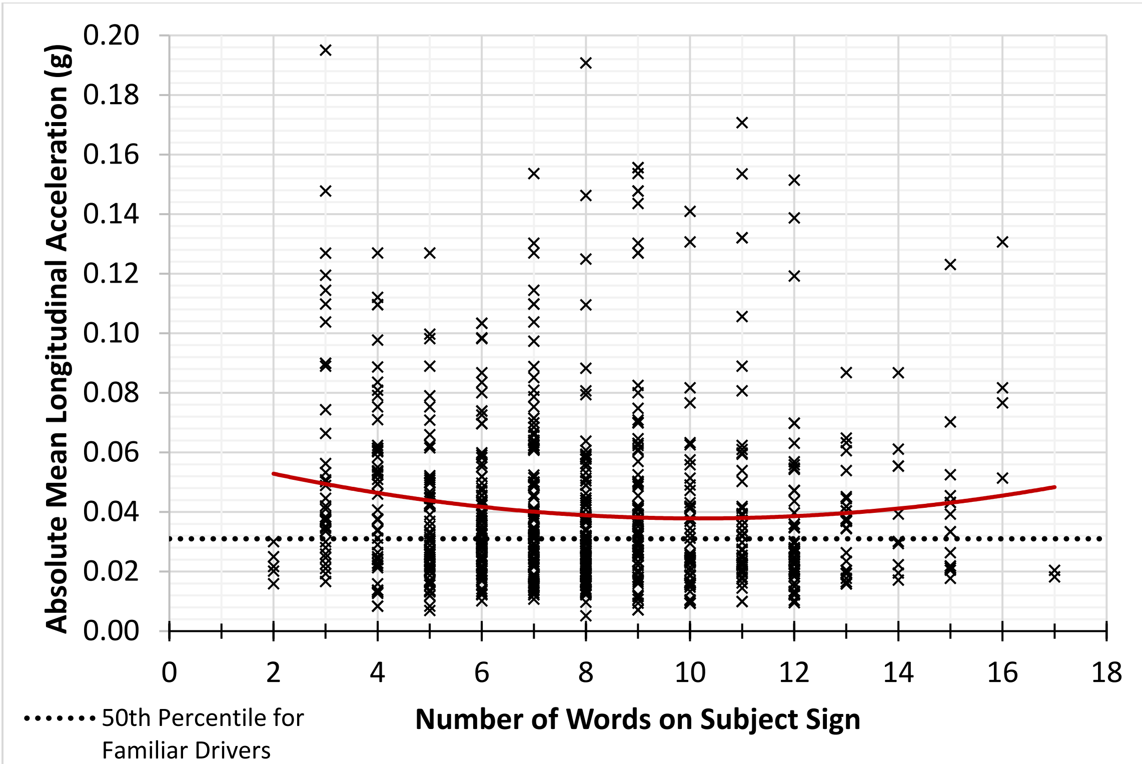
Note: Longitudinal acceleration standard deviation, younger drivers, ramp segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 36. Graph. Complexity threshold identification for longitudinal acceleration standard deviation, driver category 2 with a minimum lane change of 0.



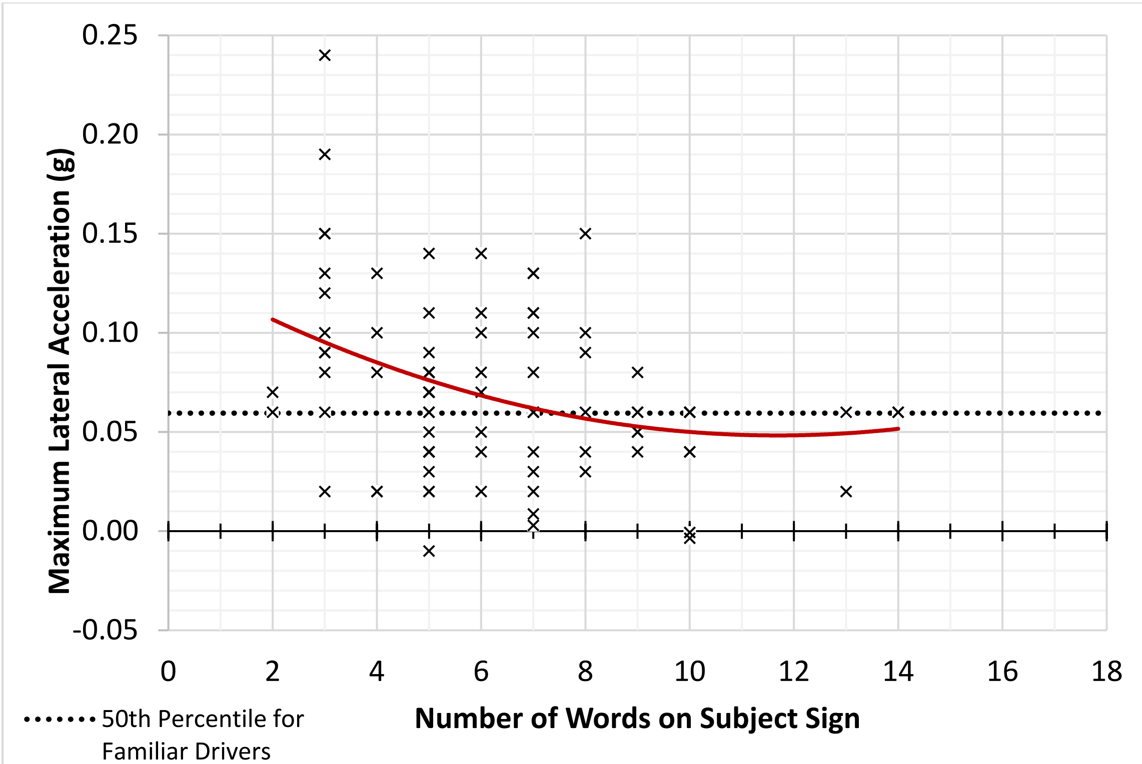
Note: Absolute mean longitudinal acceleration, younger drivers, ramp segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 37. Graph. Complexity threshold identification for mean absolute longitudinal acceleration, driver category 2 with a minimum lane change of 1.



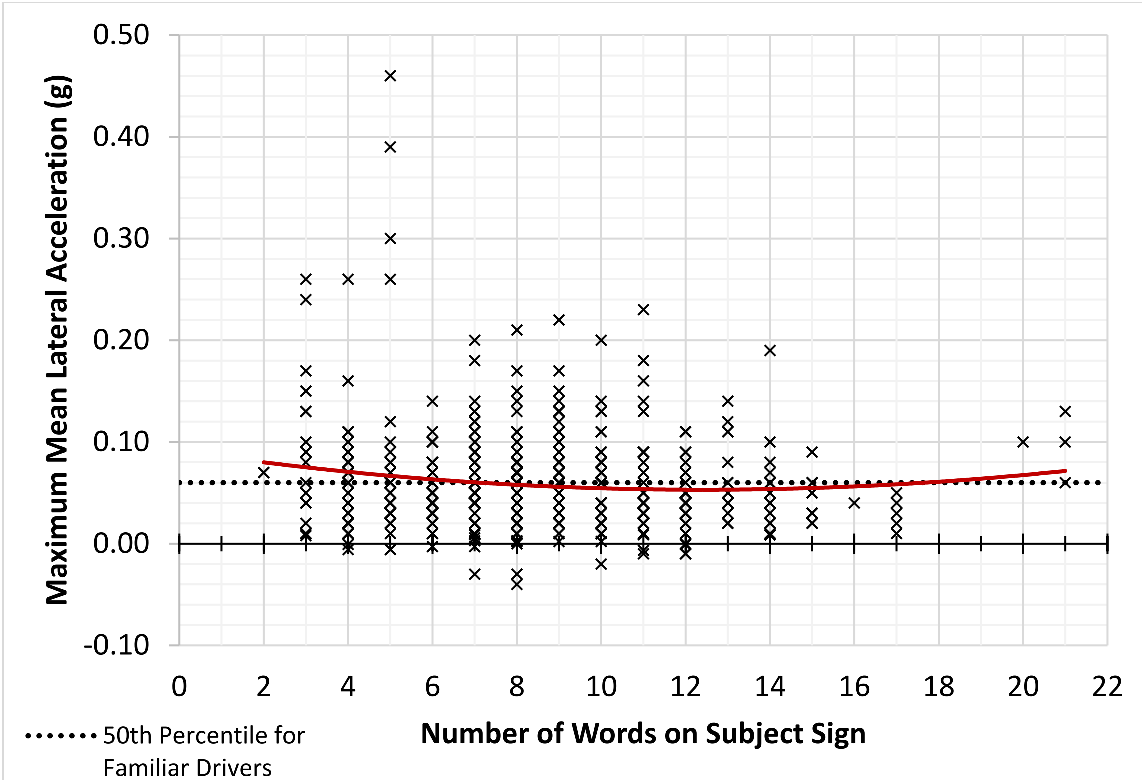
Note: Absolute mean longitudinal acceleration, younger drivers, ramp segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 38. Graph. Complexity threshold identification for mean absolute longitudinal acceleration, driver category 2 with a minimum lane change of 0.



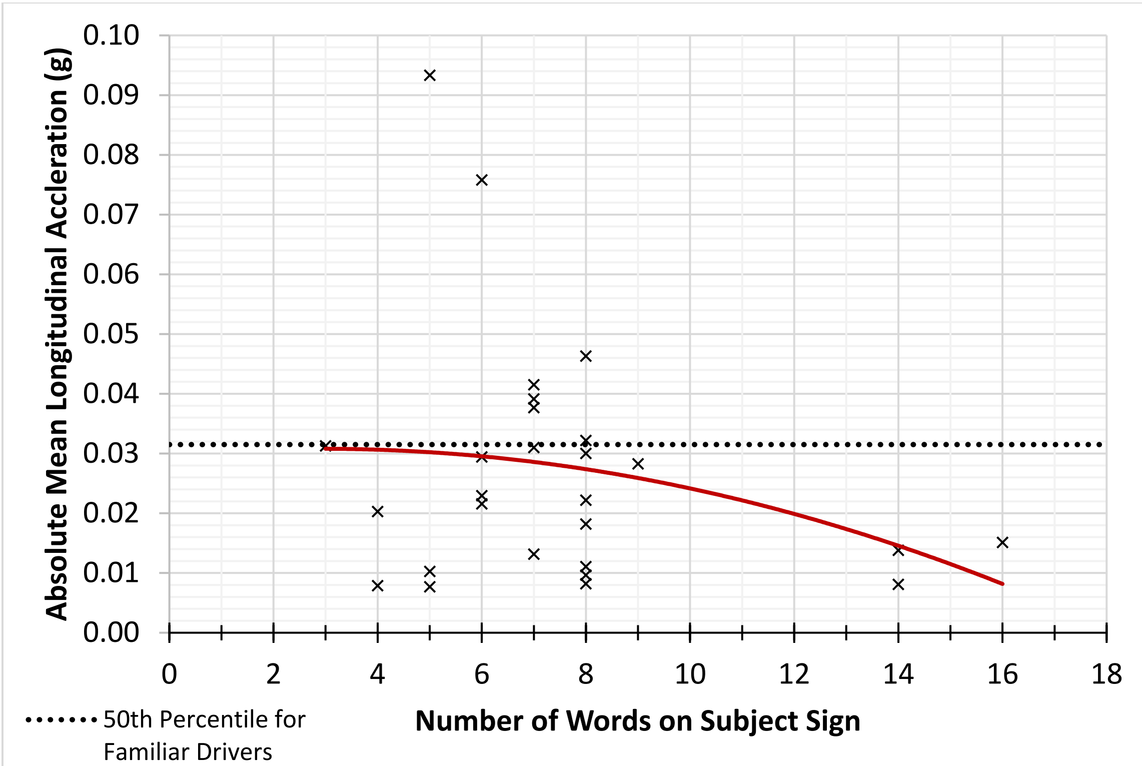
Note: Maximum lateral acceleration, older drivers, sign segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 39. Graph. Complexity threshold identification for maximum lateral acceleration, driver category 3 with a minimum lane change of 1.



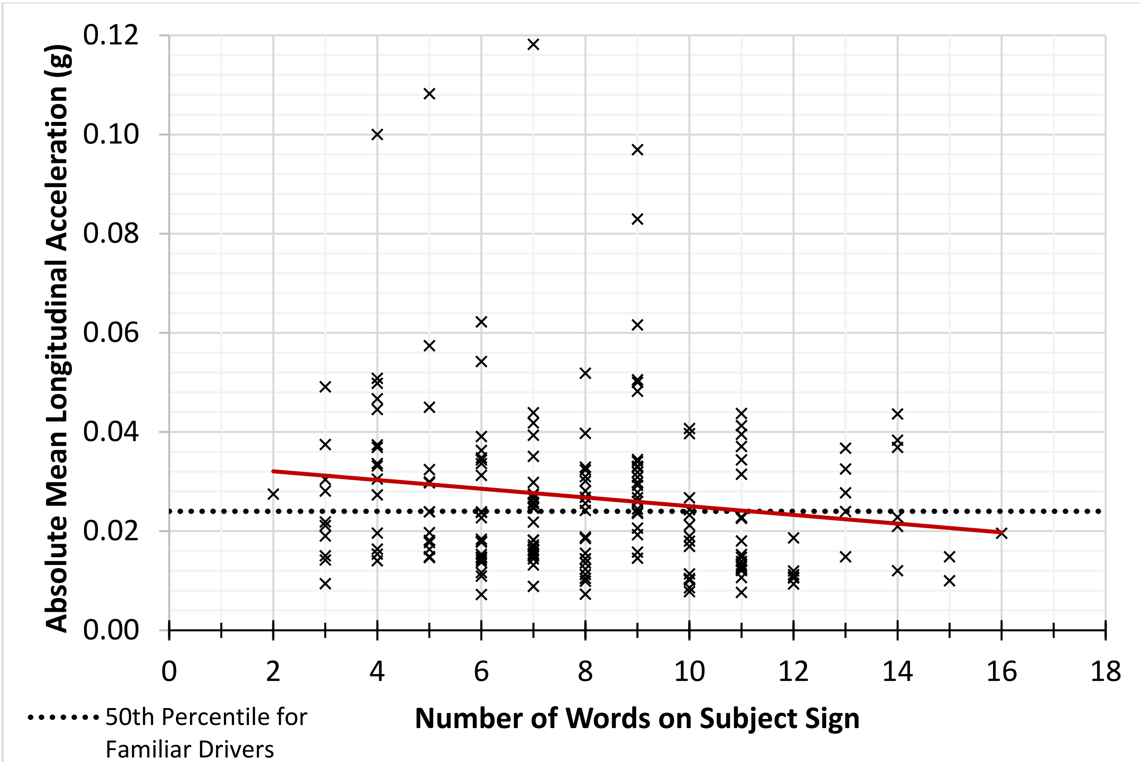
Note: Maximum lateral acceleration, older drivers, sign segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 40. Graph. Complexity threshold identification for maximum lateral acceleration, driver category 3 with a minimum lane change of 0.



Note: Absolute mean longitudinal acceleration, older drivers, ramp segment, minimum lane change = 1, eye acuity = 20/20, daytime.

Figure 41. Graph. Complexity threshold identification for mean absolute longitudinal acceleration, driver category 4 with a minimum lane change of 1.



Note: Absolute mean longitudinal acceleration, older drivers, ramp segment, minimum lane change = 0, eye acuity = 20/20, daytime.

Figure 42. Graph. Complexity threshold identification for mean absolute longitudinal acceleration, driver category 4 with a minimum lane change of 0.

Based on the foregoing results, the project team developed the following thresholds:

- Right ramps requiring at least one lane change for exiting traffic to be in the correct exit lane: Maximum sign complexity in this setting was identified at nine words, which is the median value of calculations 1–5 in table 57. The team determined the threshold based on driver behavior variables for younger drivers, daytime trips, and the sign segment.

- Right ramps requiring no lane changes for exiting traffic already in the rightmost lane to be in the correct exit lane: Maximum sign complexity in this setting was identified at 10 words, which is the median value of calculations 6–10 in table 57. The team determined the threshold based on driver variables for younger drivers, daytime trips, and the sign segment.

When determining the previous thresholds, researchers should note the following:

- The team based the previously suggested thresholds on safety-related behaviors of younger drivers (i.e., drivers younger than 65 yr of age): The decision was made primarily due to two reasons. Although this project used a large number of NDS trips, the sample sizes of trips for older drivers were limited when further divided by analysis scenarios. In addition, based on the values generated using the older driver group (e.g., calculations 17 and 18 in table 57), the values determined based on the driver behaviors of older drivers would be impractically stringent, resulting in potential challenges for sign design.

- The team based the previously suggested thresholds on daytime driver behaviors: The analysis results as shown in table 57 and the driver behavior modeling results previously discussed suggest that driver behaviors are less significantly correlated with sign complexity during nighttime—particularly for younger, unfamiliar drivers and for all drivers at the ramp segment. In addition, during nighttime, traffic levels tend to be extremely low, thereby giving drivers more flexibility to maneuver without causing safety concerns. This study analyzed only nonpeak hours for nighttime, and it verified traffic conditions based on trip videos to ensure traffic was not a significant factor in driver behaviors. In this project, nighttime scenarios overall also had smaller sample sizes compared with daytime scenarios.

- The team based the thresholds suggested previously on the sign analysis segment instead of the ramp analysis segment: As discussed in a preceding section, the sign analysis segment had considerably more significant correlations—especially for nighttime scenarios. In addition, the multivariate modeling results did not particularly suggest higher elasticity values for the correlations at the ramp analysis segment. Based on the threshold analysis results in table 57, however, the univariate models for the ramp analysis segment did not result in sufficient values leading to suggestions. The available values for calculations 11 and 12 seem to suggest a more relaxed sign complexity requirement and therefore were not used.

- The thresholds previously suggested were only for signs applicable to ramps on the right side; the team did not obtain sufficient data that could lead to reliable suggestions for left ramps.

CHAPTER 5. SHRP2 EVENT DATA ANALYSIS RESULTS

During the SHRP2 event data analysis, the project team analyzed video files for 1,475 safety events, consisting of 83 crashes and 1,392 near crashes that had occurred on entrance and exit ramps or in interchange areas. On receiving the requested event data, the project team first analyzed the forward-facing video files along with the event narratives of all events to identify those that could be potentially interesting based on the scope of this project. In the process, the team also excluded events that did not occur at freeway locations near ramps and that showed guide signs and excluded events that involved non-driving-related contributing factors such as severe adverse weather conditions, driver distraction, and glare affecting driver visibility.

After identifying a much smaller number of interesting events, the project team carefully analyzed all video files (i.e., face view, cabin view, forward facing, and rearview) in an effort to identify the potential roles guide signs might have played in leading to the occurrences of the safety events.

Although the SHRP2 NDS database contains a relatively large number of safety events, the sample sizes become limited when an analysis focuses on a specific type of safety event such as the sign-related events that this project focused on.(46) For that reason, conducting any meaningful statistical analyses based on safety events during this task was not practical. When analyzing events identified as potentially relevant to signs, the project team quickly recognized a number of challenges when it tried to identify the primary contributing factor in the events:

- Many involved low-visibility, traffic, and/or roadway factors. Without interviewing the subject drivers, the team found it difficult to know the dominant factor that led to the actions causing the events.
- Based solely on event video data, the team could not determine whether the sign involved was too complex, misleading, or nonvisible to the subject driver even if the driver appeared to have difficulty in maneuvering according to the guide sign.
- In many cases, face videos would not provide sufficient information on whether the driver was looking exactly at the overhead sign in question. Researchers could in many cases determine when a driver was looking attentively in a sign's direction. However, sign direction is typically travel direction, and many roadway-related objects are found in that direction.
- In cases in which events appeared related to guide signage, determinations of whether subject drivers misunderstood a sign, could not understand a sign in time, or changed their minds during the course of navigation were difficult.

The event data analysis, albeit with the limitations stated in the preceding list, gave the project team an opportunity to learn how different signs, roadways, and traffic conditions could negatively affect driver behaviors at freeway interchanges that could lead to safety risks. Overall, the event analysis showed that most of the events that had occurred were likely caused by a combination of factors such as signing, lane configuration, traffic conditions, and weather and visibility conditions. In particular, some events provided specific examples relevant to potential sign design issues that helped the project team draw a number of lessons:

- Traffic conditions frequently combine with sign issues to cause increased safety risks:
    - Subject driver is reading signs attentively while traffic ahead slows down, leading to increased rear-end collision risk.
    - Subject driver spends too much time reading signs, with limited time to switch lanes when lane change is required, thereby increasing crash risk when merging.
    - Subject driver is reading signs attentively while other vehicles merge into the travel path quickly in front, causing increased rear-end collision risk.
- Roadway-related factors may amplify sign-related issues that increase safety risks. Examples of such scenarios are:
    - Insufficient merging and weaving distances combined with complex and/or misleading guide sign designs: That scenario was particularly common on urban freeways with densely located ramps and frequent lane drops, additions, and/or shifts.
    - Limited sight distance for ramp junctions, causing unfamiliar drivers to be unsure of how far a ramp junction is located from the sign location: That scenario could increase safety risks—particularly when a significant speed reduction is required for entering the ramp.
    - Guide sign installed right at the ramp junction or after the painted gore nose: Signs located at or close to the ramp junction without advance signs can challenge drivers who are not familiar with the route—particularly when the signs are complex to understand. In such cases, drivers have limited time to take action while reading a sign and after reading it.
    - Signing challenges for closely located exit ramps: Based on some of the event videos, the project team identified a unique situation that caused signing confusion when closely located exit ramps were present—particularly when an exit-only lane was involved. For example, one event illustrated a scenario in which an exit ramp was shortly followed by an exit-only ramp. Both signs for the two exits were collocated on the same sign structure along with another sign directed at through traffic. In that case, the sign for the exit-only ramp appeared to be in the second right lane, although it was actually the rightmost lane, which caused driver confusion and therefore unsafe lane change behaviors.
- Sign design issues got identified during the event analysis:
    - Arrow-per-lane signs not aligned with corresponding lanes: Due to sign design or manufacturing or installation issues, some arrow-per-lane signs did not align with the corresponding lanes, which was evident based on the videos of a number of events.

- Wrong signing and/or inconsistent signing or lane configuration practices: Some events showed incorrect and/or inconsistent signing and lane-marking practices that could have contributed to events. Examples of such issues are signs for exit-only lanes without a yellow-highlighted EXIT ONLY legend and the left-lane marking of an exit-only lane, which was painted as a regular lane line instead of a wider, dotted lane line that indicates a lane drop.

- Other relevant roadway and lane configuration issues arose. The event analysis also showed a number of roadway and lane configuration issues that would raise signing challenges or lead to safety risks without proper signing. Examples of such scenarios are:

  - Lane reduction prior to an entrance ramp: A lane reduction closely followed by an entrance ramp would cause difficulties for the entering traffic while that entering traffic was merging. The causes were the increased traffic and, therefore, reduced gap availability in the right lane after combining the traffic from the two right lanes prior to the entrance ramp.

  - Multilane ramp merging with the mainline from right with left ramp lane dropped: In some cases—particularly at system interchanges when a multilane ramp merges with the mainline from the right—some States allow a drop of the left ramp lane, thereby forcing the right-lane traffic on the mainline and the left-lane traffic on the ramp to merge into the same lane. This design practice is problematic because of the common perception that lane drops typically occur to the rightmost lane and because traffic in left lanes typically maintains higher speeds.

- Driver errors caused crashes and near crashes at interchange locations. Several events included a scenario wherein a subject driver initially entered an exit ramp lane but decided to switch back into the mainline lanes. Such an action could be due to a number of reasons, such as misunderstanding of a sign, a change of mind, and/or lack of awareness of the lane configuration.

CHAPTER 6. SUMMARY, DISCUSSION, AND SUGGESTIONS

SUMMARY OF RESULTS

Complex freeway interchanges are difficult to navigate in many cases. Poorly designed signs and information overload at such locations, along with contributing roadway and traffic factors, frequently lead to increased crash risks. A sign design issue frequently seen on urban freeways is the use of complex guide signs. The 2009 MUTCD includes general provisions for the design and installation of freeway guide signs.[(1)] Though the manual identifies the issue of information overload on signs and the need to spread out information, it lacks detailed provisions for how to design signs and how to space signage to avoid the issue. Neither does the manual include a way to identify the maximum amount of information that should be allowed on freeway guide signs at any one location.

During this project, the research team analyzed a large set of SHRP2 NDS data in an effort to learn the correlations between driver behaviors relevant to safety and freeway guide signs at interchange areas.[(46)] The project involved a variety of NDS datasets, including primarily vehicle kinematic data, trip video recordings, driver data (i.e., demographic data, driving history data, and visual performance data), roadway data, and event data.[(4,45)] The data were collected and processed for a large number of freeway interchanges in six regions: Buffalo, NY; Durham-Raleigh, NC; Indianapolis, IN; Seattle-Tacoma, WA; State College, PA; and the Tampa, FL, region. The main data analysis effort focused on driver behavior analysis, supplemented with qualitative analysis results based on SHRP2 crashes and near crashes in freeway interchange areas. For each sign structure, the project team analyzed a number of data scenarios and two analysis segments: at the sign and at the ramp. Based on significant correlations, the team identified safety thresholds for the maximum amount of information to provide on freeway signs for different roadway settings.

The following summarizes the major findings of this research effort.

Sign Complexity Effects on Driver Behaviors

Correlations Between Sign Complexity and Driver Behaviors

The primary sign complexity variable, called "Number of Words on Subject Sign," was found to correlate significantly with a large number of driver behavior variables for both the sign analysis segment and the ramp analysis segment (figure 5). Overall, sign complexity models showed that sign complexity affected drivers unfamiliar with routes much more than it did drivers familiar with routes. Combining the analysis results showed that correlations for more complex signs point to increased cautious and/or nervous driving behaviors and less preparedness for ramps, which can potentially lead to higher risks of vehicle collisions.

During the driver behavior analysis, although the research team analyzed a relatively large number of naturalistic trips, the data did not capture a significant number of trips by unfamiliar drivers that involved sudden lane changes or deceleration as a result of misunderstandings of signs. That observation, however, indicates that most drivers were able to understand the guide signs and choose the route they were supposed to take, which proves that the studied signs were generally understandable regardless of the amount of information provided on them. However, there is a possibility that some drivers might have chosen to proceed despite realizing they had taken the exit by mistake. The choice to proceed despite taking the wrong exit further reduces the presence of sudden, risky driver behaviors.

The following summarizes the more detailed findings of the correlation analysis:

- The sign complexity measure more frequently correlated with the behaviors of drivers who were unfamiliar with the routes—particularly the behaviors of younger drivers during daytime at the sign analysis segment and of all unfamiliar drivers during daytime at the ramp analysis segment.

- Overall, increased sign complexity correlated with higher speeds and reduced acceleration activity. Higher speeds during approaches to signs and ramps are, possibly, indicators of unfamiliar drivers' not being well aware of and/or well prepared for the approaching ramps. Less longitudinal deceleration combined with less lateral acceleration—particularly at the sign segment—seems to indicate that drivers were overly cautious and taking time to digest the information without making the necessary maneuvers.

- For older, unfamiliar drivers, there were a number of significant correlations for nighttime models at the sign analysis segment. For the ramp analysis segment, however, there were limited correlations for unfamiliar drivers during nighttime. Comparing daytime and nighttime nonpeak hours for which SHRP2 data were used, daytime generally had more traffic compared with nighttime. Fewer vehicular conflicts at night due to less traffic potentially eased navigation for drivers unfamiliar with ramp locations, therefore reducing the impacts of sign complexity on driver behavior.

- In a comparison of sign–driver behavior correlations at the two analysis segments, the sign segment had considerably more correlations for nighttime trips and for lateral acceleration variables. The values of the elasticities for the correlations, however, were generally comparable between the two analysis segments. Most correlation elasticities are relatively small. The impacts of signs on driver behaviors are expected to be subtle—particularly when such signs, along with lane configuration and other traffic control methods, are designed to meet applicable standards (e.g., AASHTO Green Book and MUTCD).[79,1] Therefore, the fact that a large number of significant correlations were found should outweigh the values of the elasticities.

Effects of Other Sign Variables on Driver Behaviors

Following are findings relevant to other critical sign-related variables based on the driver behavior data analysis:

- Subject sign arrow-per-lane indicator: The team found that an arrow-per-lane sign had many significant correlations with driver behavior variables—particularly for unfamiliar drivers at the sign analysis segment. The team found the correlations were overwhelmingly positive (i.e., an arrow-per-lane sign correlated with increased deceleration and lateral acceleration activity), and the correlation pattern was largely opposite that for the number of words on subject sign variable, which was dominated by negative correlations—particularly for acceleration-related variables. Assuming, compared with other sign types, arrow-per-lane signs provide better lane choice information for unfamiliar drivers, such a correlation pattern therefore should be considered the desired driver behavior. The pattern further supports the previous conclusion that unfamiliar drivers were cautious and/or nervous when approaching signs with more words and were not making the appropriate navigation maneuvers. While this variable had many correlations for the sign analysis segment, it had limited correlations for the ramp analysis segment, possibly indicating that drivers were better prepared to exit at ramp junction points when arrow-per-lane signs were present.

- Guide on pavement: The presence of routing direction markings on pavement correlated in general with decreased longitudinal acceleration or increased deceleration activity and increased lateral acceleration activity. That correlation pattern suggests that the provision of guidance on pavement correlated with more vehicle activity at both the sign and the ramp analysis segments, which likely indicates that drivers were making the necessary maneuvers to prepare for taking their desired routes.

- Sign diagrammatic indicator: A diagrammatic sign correlated with increased acceleration activity at both the sign and the ramp analysis segments. At the sign segment, all correlations were for lateral acceleration, while at the ramp segment, more correlations were for longitudinal acceleration.

- Number of words on other applicable signs: The number of words on other applicable signs at sign gantry locations correlated with several driver behaviors at both the sign and the ramp analysis segments. In general, the presence of other applicable signs correlated with more lateral acceleration and deceleration activity and lower speeds for both analysis segments. In addition, this variable had a relatively high number of correlations at both analysis segments. The typical other applicable signs included speed limit signs, HOV-lane regulation signs, and, in a few cases, additional destination signs mounted on the side of the sign gantry. That last sign variable, however, is discrete and has limited variance (a majority of sign gantries did not have other applicable signs present). Ramp speed limit signs represented the most common other applicable signs among the limited cases.

- Number of words on other signs at the same gantry: This variable in general had limited correlations with the driver behavior variables for both analysis segments. Based on the limited correlations, most correlations were negative. In addition, most correlations were for lateral acceleration variables at the sign segment but for longitudinal acceleration variables at the ramp segment. The limited correlations seem to suggest that drivers were able to quickly identify the sign applicable to them and therefore not pay attention to other signs collocated on the same gantry. The drivers' quick identifications do not necessarily mean more signs can be collocated on a sign structure compared with the 2009 MUTCD recommendations.(1) Rather, the quick identification is most likely an indication that the 2009 MUTCD guidelines on the number of collocated signs are sufficient.

- Sign lighted indicator: The presence of sign lighting had overwhelmingly negative correlations with driver behaviors, indicating lower speeds and increased deceleration activity. Interestingly, the variable in most cases correlated with driver behaviors during daytime, indicating that sign lighting was likely a surrogate for urban interchange locations with higher traffic and lower speed limits.

- Sign visual background complexity: This variable also had a relatively small number of significant correlations. The limited correlations suggest that more complex visual background for signs correlated with higher speeds and increased acceleration activity, consistent with the correlation pattern for the sign complexity measure. Note that complex visual background in many cases indicates that the drivers were approaching urban environments with significant commercial developments.

Driver Behavior Correlations With Roadway, Driver, Trip, and Traffic Variables

Through a multivariate modeling process, the team analyzed a large number of roadway, driver, trip, and traffic variables that could have affected driver behaviors at freeway interchange areas. The purpose was to understand how these variables might have played roles jointly with the sign-related variables to negatively affect driver behavior and safety.

Following are the major significant variables along with their correlations with driver behaviors:

- Distance to previous interchange: Longer distances from the previous interchange—particularly system interchanges—overwhelmingly correlated with more uniform and decisive acceleration behavior (i.e., lower standard deviation and maximum longitudinal and lateral acceleration rates but higher mean and minimum acceleration rates).

- Distance from previous exit ramp: The distance from the previous exit ramp was a significant variable in a large number of the models. With correlations for the sign analysis segment and the scenario for younger, unfamiliar drivers, daytime, and right ramps as an example, longer distance to the previous exit ramp correlated with higher mean deceleration and lateral acceleration rates and lower acceleration standard deviations.

- Distance to route ramp: Distance to route ramp correlates directly with amount of space and time drivers have for reacting to prepare for exiting. As such, correlations for this variable show that longer distances between a sign and a ramp terminal correlated with lower deceleration activity, higher speeds, and lower lateral acceleration activity.

- Distance from previous entrance ramp: Entrance ramps immediately followed by exit ramps are frequently roadway design challenges affecting safety and efficiency if not addressed properly. Entrance ramps allow traffic to merge onto a freeway, but they can disrupt the mainline traffic flow—particularly the flow of traffic preparing to exit. Longer distances from an entrance ramp prior to sign location correlated with more deceleration activity, higher speeds, and higher but smoother (higher mean but lower jerk and variance) lateral acceleration. Those correlations provide evidence for expected driver behaviors at locations with closely related ramps.

- Mainline speed limit: Higher speed limits on freeway mainlines correlated with less speeding but also lower deceleration activity. Higher speed limits are more likely on less busy freeways, and therefore higher mainline speed limits highly correlate with less complex roadway and traffic conditions.

- Speed limit reduction on ramp (i.e., difference between mainline speed limit and ramp speed limit): This variable was among the most common significant variables in the mixed-effect models for the ramp analysis segment but not the sign analysis segment. The significance is understandable because drivers might not know the speed reduction required by a ramp at the sign location. Further, higher ramp speed reduction overwhelmingly correlated with more deceleration activity (e.g., lower mean acceleration rates but higher acceleration variance) and lower speeds.

- Curved alignment indicator: Curved mainline alignment understandably correlated with the lateral acceleration activity of drivers at the analysis segments. Curved alignments overwhelmingly correlated positively with lateral acceleration variables, indicating more lateral acceleration activity on curves. Curved alignments also correlated with increased longitudinal acceleration variance, indicating that the additional lateral acceleration activity required by roadway alignment on the mainline freeway complicated drivers' behavior prior to drivers' exiting the freeway.

- Distance from previous advance sign: Longer distance between a previous advance sign and a current subject sign correlated with more deceleration and higher acceleration variance. That observation suggests that an advance guide sign located a shorter distance from the sign at the ramp would result in smoother deceleration and smoother lane-changing behaviors.

- Complex ramp indicator: During this analysis, ramp types such as diamond, parclo loop, and free-flow loop were classified as complex ramps based on their requirements for relatively considerable speed reductions. The mixed-effect modeling showed that complex ramps correlated with reduced speed and improved lateral acceleration variances.

- Total number of lanes: Total number of lanes at a freeway sign location was found to significantly affect driver lateral acceleration activity, particularly at the ramp segment. More lanes at the sign structure location—and therefore at the ramp location, however—tended to correlate with reduced lateral acceleration activity, seemingly indicating that drivers prepared earlier for exiting at locations with more lanes.

Determination of Sign Complexity Thresholds

The research team developed univariate regression models for the sign complexity measure and a number of selected driver behavior variables. The team selected driver variables and scenarios based on the previous correlation analysis results such that it used the most significant driver behavior variable-analysis scenario combinations for determining sign complexity thresholds. As part of that task, the team developed linear or nonlinear regression models for 20 driver behavior variable-analysis scenario combinations. Based on each regression model, the team developed a maximum sign complexity level by comparing the behaviors of drivers who were unfamiliar with the routes with the behaviors of familiar drivers.

Based on the results, the project team developed the following thresholds:

- Right ramps requiring at least one lane change for exiting traffic to be in the correct exit lane: The maximum sign complexity in this setting was identified at nine words, excluding symbols but including numerals. The threshold was determined based on driver behavior variables for younger drivers, daytime trips, and the sign segment.

- Right ramps requiring no lane changes for exiting traffic already in the rightmost lane to be in the correct exit lane: The maximum sign complexity in this setting was identified as 10 words. The threshold was determined based on driver behavior variables for younger drivers, daytime trips, and the sign segment.

Note that the foregoing thresholds as determined were based on younger drivers (i.e., drivers younger than 65 yr of age) and daytime driver behaviors. The younger driver scenarios had larger sample sizes, which increased the reliability of the thresholds. In addition, the thresholds generated based on older driver behaviors could be impractically stringent. The analysis results also show that driver behaviors correlate less significantly with sign complexity during nighttime—particularly for younger, unfamiliar drivers, which is most likely due to lower traffic levels, which give drivers more flexibility to maneuver without causing safety concerns. This study used only nonpeak hour, nighttime trips.

The thresholds suggested previously were only for signs applicable to ramps on the right side. The team did not obtain sufficient data that could lead to reliable suggestions for left-side ramps during this project.

Safety Event Analysis Results

The researchers qualitatively analyzed the detailed data, including video recordings, of 1,475 events (i.e., crashes and near crashes) that had occurred in freeway interchange areas and/or on entrance and exit ramps. The team performed the analysis via an iterative process, with most relevant events first identified through a preliminary screening process and later analyzed in a more detailed manner.

During the analysis of safety events, the project team quickly recognized a number of challenges. A majority of the events, if not all, were the results of multiple factors such as those related to roadway, traffic, signing, weather, visibility, and/or drivers. The interaction between multiple factors made it difficult to attribute an event to a single factor such as sign complexity without a narrative directly from the subject driver. In cases in which events appeared to be most likely attributable to sign-related issues, the research team had difficulty in determining whether subject drivers misunderstood a sign, could not understand a sign in time, or changed their minds during the course of navigation.

The challenges encountered during the event analysis by no means invalidate the effort or the importance of guide signs with regard to safety. The challenges in fact emphasize the realities that signing-related issues jointly affect safety together with other factors mentioned earlier and that it may be important to view and interpret driver behavior data analysis results in this context. Regardless of the challenges, though, the researchers observed and summarized a number of scenarios wherein problematic guide sign design issues could increase safety risks. The scenarios helped in interpretation of the driver behavior data analysis results and, later, formulation of the suggestions.

SUGGESTIONS

Suggested Maximum Sign Complexity

After combining the findings of the different analyses, the researchers suggest the following:

- When used for exits on the right side that require at least one lane change to the right from the rightmost lane at the sign location, a guide sign should not contain more than nine words, excluding symbols (e.g., arrows) but including numerals (and symbols containing letters and/or numerals such as route number included in a shield).

- When used for exits on the right side when the minimum number of lane changes required from the traffic in the rightmost lane at the sign location is zero, a guide sign should not contain more than 10 words, excluding symbols but including numerals.

The researchers developed the aforementioned criteria based both on behavior data about drivers younger than 65 yr of age and on daytime driver behavior.

With regard to use of the aforementioned maximum sign complexity criteria, it may be important to consider other information or regulatory signs installed at the same sign location—for example, separate signs about managed lanes, expressways, load or vehicle type requirements, speed limit, general information signs, and tourist-oriented directional signs. The addition of such signs at the same location as a complex guide sign increases overall sign reading time—thereby increasing safety risks—and/or competes for a driver's attention, thereby reducing the effectiveness of some or all applicable signs. For those reasons, the research team suggests that at a location with a complex guide sign, agencies avoid the installation of other signs applicable to the guide sign's targeted traffic. A complex guide sign in this case is defined as a sign containing eight or more words, which is the lowest threshold identified in table 57 based on the safety-related driving behaviors of younger drivers.

This research was unable to develop sign complexity criteria for ramps on the left side due to low sample sizes for left ramps. Practitioners should adjust—and most likely lower—the criteria accordingly to reflect field roadway and traffic conditions.

Factors and Strategies Mitigating Sign Complexity Impacts

Based on this project, the research team identified the following factors and impact mitigation strategies to improve sign effectiveness and safety:

- This project showed that arrow-per-lane signs and, to a lesser degree, diagrammatic signs reduce the effects of increased numbers of words on guide signs and therefore help drivers better understand guide sign instructions. Therefore, the research team suggests that whenever possible, the choice be arrow-per-lane signs for guide signs at freeway interchanges. Diagrammatic signs may be used in place of arrow-per-lane signs if the latter cannot be used due to installation restrictions.

- The researchers found that on-pavement guide markings had effects that countered the effects of increased numbers of words on guide signs. Therefore, the research team suggests that when possible and appropriate, the choice be guidance markings on pavement to improve sign effectiveness and alleviate potential confusion caused by complex guide signs. Such on-pavement guidance markings may include route numbers, lane control arrows, and other lane restriction markings.

- The driver behavior data analysis showed that the use of advance signs—particularly advance signs at shorter distances from current signs—improve driver behavior by reducing acceleration variances. The research team suggests that when possible and appropriate, the choice be advance guide signs—particularly if subject guide signs are considered complex with regard to the amount of information included.

In addition to the foregoing factors, eliminating or mitigating the factors or scenarios discussed in the following section can help mitigate the impacts of sign complexity on driver behavior and safety.

Factors and Scenarios Warranting Further-Simplified Signs

Based on this project, the research team identified the following factors and scenarios that would warrant further-simplified signs to improve sign effectiveness and safety:

- Distance from previous interchange: When a major upstream interchange is located close to the subject exit ramp (e.g., less than 1 mi away), it is suggested to either apply more stringent sign complexity criteria or take actions to alleviate the adverse effects of sign complexity.

- Distance from previous exit ramp: From a guide sign design point of view, closely located exit ramps add additional demands for the number of signs and amounts of information to be provided, thereby increasing sign complexity. When possible, agencies should space consecutive exit ramps appropriately so as to enable adequate and safe signing. When such a requirement cannot be met, agencies would do well to develop proper strategies to ensure that guide signs can stay within the maximum complexity thresholds.

- Distance to route ramp: The distance between a guide sign and the subject ramp correlated significantly with several driver behavior variables. Agencies should avoid complex guide signs if only a relatively short distance is available between the guide sign location and the subject ramp junction. When possible, agencies should not install a complex guide sign right at the ramp junction.

- Distance from previous entrance ramp: Closely located entrance–exit ramp pairs raise merging or weaving challenges for traffic and therefore increase safety risks and decrease operational efficiency. When an exit ramp closely follows an entrance ramp, complex guide signs are to be avoided. If an agency must use such signs, agencies would do well to improve navigation by taking the mitigation measures discussed in a preceding section.

- Mainline speed limit: Mainline speed limit correlated significantly with a number of driver behavior variables at the analysis segments. Accordingly, agencies should not use complex guide signs on freeways with high speed limits. If they cannot avoid the use of such signs, the research team suggests taking additional measures to help with driver navigation and reduce the negative impacts of sign complexity.

- Speed limit reduction on ramp: Speed limit reduction on ramps is a significant factor correlated to driver behavior variables—particularly at the ramp analysis segment. At ramp locations requiring considerable speed reduction, agencies would do well to avoid complex guide signs or to take remedial measures so that drivers have sufficient time to read complex ramp speed limit signs and reduce speed safely.

Other Relevant Suggestions

Having combined all the research findings, the research team suggests that the following additional measures could potentially improve guide sign design practices for safer and more efficient freeway operations:

- Conduct sign design reviews and field sign inspections: Transportation agencies would do well to routinely conduct guide sign review at the roadway design stage so as to identify and resolve guide sign design issues early on. During and after sign installation, agencies would do well to conduct periodic sign inspections to ensure that signs have been installed according to design and that the installed signs do not have issues. Potential sign-related issues are problematic sign structure location, limited sight distance, inconsistent or incorrect design, incorrect or inconsistent lane marking, misalignment with corresponding lanes, unnecessarily complicated legend design, and misleading information, such as a scenario in which a sign becomes misleading due to a specific roadway configuration at or near the sign's location.

- Have sign designers review roadway design: The project team found that roadway features can negatively affect driver behavior and safety in conjunction with sign design issues. In addition, some roadway design features may limit better designs of guide signs. That is why it may be important that sign designers conduct reviews of freeway design schematics and that roadway designers conduct reviews for the purpose of sign design during the design stage of a freeway project. Such reviews would provide opportunities for coordination between interchange design and sign design. In addition, such reviews would help identify potential signing challenges early on.

- Provide space before the physical gore nose: Based on the event analysis, some near crashes involved vehicles that were driving through the painted gore area at ramp junctions. Painted gore areas may provide space for a driver to avoid a crash outcome when exiting a ramp lane late after having passed a painted gore nose. While not encouraged, such driver actions do take place, and therefore providing a forgiving space such as a painted, traversable gore area to help avoid a severe outcome should a driver decide to change lanes at the gore location may be important.

- Reduce merging and lanes: During the event analysis, the research team identified safety events that involved reduction of the left lane of a multilane ramp that merges with a freeway from the right side of the mainline. Such a lane configuration forces traffic in the right lane of the mainline to merge with that in the left lane of the ramp within a limited distance, thereby significantly increasing navigation and signing challenges. The research team suggests that at entrance ramp junctions, ramp lanes be dropped only from the rightmost lane of a multilane ramp. Multilane ramps are used most frequently for system interchanges and therefore frequently carry large volumes of traffic traveling at higher speeds.

- Avoid lane reductions immediately prior to ramps: Lane reductions immediately prior to ramps result in increased traffic in the rightmost lane and therefore increase challenges to merging and lane changing. Such challenges inevitably make it more difficult to read guide signs and navigate safely.

In interpretation of the findings of this research, the NDS trips reflected roadway and signing conditions that are mostly consistent with current policies and guidelines (e.g., the AASHTO roadway design guide and MUTCD).(5,1) Therefore, the suggestions should not be considered as conflicting with sign-related guidelines in the 2009 MUTCD but supplemental to them.

LIMITATIONS AND FUTURE RESEARCH

During this project, the research team analyzed a large number of NDS trips in efforts to understand the impacts of sign complexity on driver behavior and to identify sign complexity thresholds based on the identified impacts. The team was able to successfully identify sign complexity thresholds for ramps on the right side but due to limited sample size, was unable to identify such thresholds for ramps on the left side.

The team noticed that although statistically significant, many of the parameter estimates (or elasticities) in the mixed models were relatively small. For example, an increase of one word on a subject sign correlated with a change of 0.001 g in longitudinal acceleration for the scenario defined as younger, unfamiliar drivers not using GPS, right-side ramps, daytime, and at the sign analysis segment (table 23). However, due to the following reasons, relatively small changes may not necessarily mean they are unmeaningful:

- The study sites are actual roadway locations designed by following MUTCD requirements: Adherence to MUTCD requirements with regard to lane configuration, ramp design, and sign spacing would address a large magnitude of correlation (i.e., large enough to be considered obviously unsafe) between signage and driver behaviors.(1) The statistically significant correlations identified in this project can therefore be considered the portion of correlations that MUTCD requirements cannot treat. Such correlations may still be meaningful in the sense that they contribute to safety risks that MUTCD requirements are not sufficient to address.

- The current correlation analysis results assumed a linear correlation between sign complexity levels and driver behaviors: That assumption is, potentially, not the case for many refined scenarios, as discussed in chapter 4. As illustrated by the plots used in identifying sign complexity thresholds (i.e., figure 23 through figure 42), the sign–driver behavior correlations for many scenarios were nonlinear. At certain ranges of sign complexity, changes in driver behavior variables are considerably larger than under assumption of a linear correlation.

This project included a driver behavior data analysis and a safety event analysis based on SHPR2 NDS data. While the SHRP2 safety events provided information on how sign-related issues could have contributed to increased safety risks at freeway interchange areas, the research team could not conduct meaningful statistical analysis due to the limited sample size of the safety events. A crash data analysis based on police-reported crashes, including high-severity crashes, may provide more information on safety performance information with regard to signs with different complexity levels. Such an analysis, however, was not included in the scope of the current study.

This study resulted in suggestions regarding maximum complexity thresholds for freeway guide signs at exit ramps on the right side of a mainline. For other ramp scenarios (e.g., left ramps), similar thresholds may be determined using the suggested thresholds as a baseline. In addition, controlled field tests and/or further laboratory- or simulation-based studies may verify the suggestions and extend them to additional freeway scenarios.

APPENDIX A. SHRP2 TRIP VIDEO DATA REDUCTION PROTOCOL

The freeway guide signs project is looking at specific approaches to freeway exit ramp design. The reduction task may provide information for the research team with regard to the environmental characteristics present and the driver tasks performed at the time of the selected approach.

The assessment window will be one of the following:

- The first 30 s of the event window (for event windows greater than or equal to 30 s long but less than 120 s).

- The length of the event window (for event windows that are less than 30 s long but greater than 5 s).

The start and end times of the assessment window will be provided in the reduction log. Due to the aforementioned logic, the assessment window will often not include the entire event window but assess only the duration of the assessment window indicated in the reduction log.

Reduction Tool Setup and Use

The following items are the steps for reduction tool setup and use:

1. This task is using events from the new SHRP2 collection.

2. The events are titled "Eric_FHWA_Interchange_10000," but reductionists should rely on the numerical "Event_ID" listed in the reduction log.

3. The following views and data graphs are required to be open:

    a. video (all – Forward, Rear, Face, Hands).
    b. vtti.speed network (or vtti.speed_gps if network speed unavailable).

4. The user should overlay the event onto the chart and zoom in to the assessment window (times provided in reduction log).

5. The question annotation is titled "Freeway Signs."

Reduction Log

The following items are the steps for filling out the reduction log:

1. The reduction log is titled "Freeway Signs Reduction."

2. The columns "Assess_Start" and "Assess End" indicate the time stamps within which the reduction is to be completed. (The time stamps will often not be the same as the event start and end.)

3. The reductionist should sign out an Event ID by entering a name in the “Name” column and then saving the log.

4. After the event has been reduced, the reductionist should enter the date in the “Date” column and save the log.

5. The reductionist should leave a note in the “Notes” column of the spreadsheet if unusual circumstances are present or if information needs communication to the QA or Coordinator.

6. At the start of every shift, the reductionist should look at previously reduced rows to find any QA feedback:

    a. All QA feedback should be addressed before starting new events.

    b. If the reductionist agrees with the suggested changes, the reductionist should update the annotation in Hawkeye and add a date to the “Date Changes Made” column.

    c. If the reductionist disagrees or does not fully understand the feedback, the reductionist should enter a note in the “Reductionist Response” column and leave blank the “Date Changes Made” column.

    d. The “Date Changes Made” column should not be filled out until the reductionist and the QA reductionist are in agreement about the event coding and all changes have been made to the annotation.

Validation Step

All validation questions must be answered regardless of their pass/fail status. Once all four questions have been answered, if one or more are indicative of “FAIL” conditions, reduction should stop, be saved, and go on to the next event. If all four indicate “PASS” conditions, the main reduction questions can continue:

1. Video: Is the front video good, and is it aligned with the time series data during the assessment window? Time stamp on video and time stamp in play controller are within about 200 milliseconds:

    - Yes, good (PASS).

    - No, bad video (FAIL, leave a note): Can include black videos, corrupted videos, cameras not showing proper field of view, etc.

    - No, bad time alignment (FAIL).

    - Unknown (FAIL, leave a note).

2. Construction: Is the subject vehicle in a construction zone or construction zone approach during any part of the assessment window?

    - No (PASS): No construction present.
    - Yes (FAIL): Construction present or in approach to construction.
    - Unknown (FAIL, leave a note).

3. Weather: What is the worst weather condition observed during the assessment window?

    - No adverse conditions (PASS) (clear or overcast only).

    - Adverse conditions, no or minor effect (PASS). (Light rain or drizzle, light snow, or other minor weather conditions with negligible effect on visibility. Windshield wipers are either not activated or activated at an appropriate interval longer than 3 s).

    - Adverse conditions, visibility affected (FAIL). (Includes fog, rain, snow, and other adverse conditions that affect visibility.)

    - Unknown (FAIL, leave a note). (Weather conditions are unknown and thus, effect on visibility unknown.)

4. Traffic density: What is the worst (heaviest) level of traffic density present during the assessment window?

    - LOS A1 (PASS): Free flow no lead traffic.

    - LOS A2 (PASS): Free flow leading traffic present.

    - LOS B (PASS): Flow with some restrictions.

    - LOS C (PASS): Stable flow maneuverability and speed more restricted.

    - LOS D, E, or F (FAIL): Includes:

        - Unstable flow: Temporary restrictions, substantially slow driver.
        - Flow unstable, vehicles unable to pass, temporary stoppages, etc.
        - Forced traffic flow condition with low speeds and traffic volumes that are below capacity.

    - Unknown (FAIL, leave a note).

Reduction Steps

If all validation questions yield "PASS" conditions, continue with the following reduction questions:

5. Lighting: What is the darkest lighting condition observed during the assessment window?

    - Day/dawn/dusk.
    - Darkness lighted (continuous or spot lighting).
    - Darkness not lighted.
    - Unknown (leave a note).

6. Surface condition: What is the worst roadway surface condition observed during the assessment window?

    - Dry.

    - Other (includes rain, snow, ice, gravel, dirt road, gravel over asphalt, mud/oil/other).

    - Unknown (leave a note).

7. Visual obstruction: Were any visual obstructions potentially affecting the subject's view of overhead roadway signs during the assessment window? Visual obstructions must be clearly present on the video and believed to be affecting sight distance, creating blind spots, etc., that are relevant to overhead signs:

    - No obstruction (No visual obstructions of present overhead signs were observed at any point during the assessment window, and no obstructions of potential overhead signs were observed for 5 or more consecutive seconds regardless of overhead sign presence).

    - Sunlight (Direct bright sunlight decreased the visibility of at least one present overhead sign at any point during the assessment window or for at least 5 consecutive seconds during the assessment window regardless of overhead sign presence).

    - Reflected glare (Reflected glare due primarily to light (sunlight, headlights, or other light) being reflected off the subject vehicle, off another vehicle, or off other exterior objects decreased the visibility of at least one present overhead sign at any point during the assessment window or for at least 5 consecutive seconds during the assessment window regardless of overhead sign presence).

    - Windshield impairment (The driver's side of the subject vehicle's windshield was broken or otherwise disfigured or was at least partially covered by some material such as dirt, rain, or snow in such a way as to potentially affect the driver's ability to properly view potential overhead signs).

- Large vehicle (A large vehicle, such as a heavy truck that the subject is following closely, obstructed the subject's view of at least one present overhead sign at any point during the assessment window or for at least 5 consecutive seconds during the assessment window regardless of overhead sign presence).

- Other obstruction (Leave a note. Another known type of visual obstruction not listed in previous categories decreased the visibility of at least one present overhead sign at any point during the assessment window or for at least 5 consecutive seconds during the assessment window regardless of overhead sign presence. May include tarp covering of an overhead sign, a tree overhanging in front of an overhead signs, etc.).

- Unknown (Leave a note. It is unknown whether an obstruction exists or not).

8. GPS indication: Is there any indication that any type of GPS navigation system may have been in use during the assessment window?

    - None observed.

    - Nomadic GPS device observed (A device that was likely a dedicated GPS device can be seen with a screen mounted on a dashboard or on or near the windshield inside a vehicle. May be identified by reflection on windshield as well, provided that the device is believed to be mounted and not integrated. Code this category only when the device appears to have been on or unable to determine).

    - Nomadic GPS cable observed (A cable that may have been connecting an unseen dedicated GPS. For example, a power cable potentially connecting an unseen GPS device to an in-vehicle power supply. If a cable is seen but is believed to have been connected to a device not used as a GPS device, do not code this category).

    - Smart phone navigation possible (A cell phone appears to have been mounted, placed, or held within driver's view for potential navigation assistance).

    - Integrated system in use (A system or screen that was integrated into the vehicle and may have included GPS functionality appears to have been in use through observation of visual or manual interaction or actual screen display. May be identified by reflection on windshield as well, provided that the device is believed to have been integrated and not nomadic or mounted).

    - Integrated system present (A system or screen that was integrated into the vehicle and may have included GPS functionality appears to have been present, but use is unknown).

    - Other (Leave a note).

    - Unknown (Leave a note).

9. Task engagement: What is the subject driver's most complex level of continuous secondary task engagement (5 s minimum) during the assessment window? Tasks are to be categorized by degree of driver engagement: simple, moderate, or complex. The categorization will be the highest degree of secondary task engaged in during the assessment second window that is continuous and lasts for a minimum of 5 consecutive seconds within that assessment window (table 58):

   - None.
   - Simple.
   - Moderate.
   - Complex.
   - Unable to determine.

10. Notes: Enter any notes relevant to the assessment window to describe any unique characteristics. Also define any "unknown" options selected in the previous variables as well as for any "other" responses to the visual obstruction or GPS navigation variables. "Other" responses to other listed variables do not require notes for this task.

Table 58. Basic grouping of secondary tasks.

Secondary Task Category*	Secondary Task Description
Simple	Talking or singing to self or passenger
Simple	Dancing
Simple	Holding object
Simple	Talking or listening on hands-free cell phone (no holding of phone)
Simple	Reaching for object not manufacturer installed (not having to search)
Simple	Adjusting steering wheel buttons
Simple	Adjusting or monitoring center stack (quick adjustments)
Simple	Adjusting or monitoring other devices integral to vehicle (quick adjustments)
Simple	Some personal hygiene (appendix B)
Moderate	Reaching for object not manufacturer installed (having to search)
Moderate	Adjusting or monitoring center stack (longer adjustments)
Moderate	Adjusting or monitoring other devices integral to vehicle (longer or more involved adjustments)
Moderate	Some personal hygiene (appendix B)
Moderate	Cognitive, other
Moderate	Talking or listening on handheld cell phone (talking and holding phone)
Moderate	Eating or drinking
Moderate	Looking at object or event external to vehicle (not driving related, repeated or long glances)
Moderate	Looking at object or event internal to vehicle (other than isolated, quick glances)
Moderate	Two simultaneous simple tasks
Complex	Reading
Complex	Writing
Complex	Manipulating object
Complex	More than three simultaneous simple tasks
Complex	More than two simultaneous moderate tasks.
Complex	One or more moderate tasks plus one or more simple tasks

*The Simple category includes secondary tasks that can generally be completed without hands and without looking at the task or with only a quick glance and hand movement or touch. The Moderate category includes secondary tasks that generally require one-hand involvement with repeated or extended action and/or one to three brief (<2-s) eye glances. The Complex category includes secondary tasks that generally involve both hands and/or repeated or extended (>2-s) eye glances or that require cognitive multitasking.

APPENDIX B. DETAILED DESCRIPTION OF DATA USED FOR DRIVER BEHAVIOR ANALYSIS

Table 59 and table 60 show summary statistics about the study locations and drivers represented in the final driver behavior data. Table 61 lists the summary statistics of the processed data points (i.e., trip segments by analysis areas) by selected variables. As the table shows, the majority of data was collected in Florida, New York, North Carolina, and Washington.

Table 59. Numbers of interchanges and drivers for which SHRP2 trips were analyzed.

Location	Interchange Count	Driver Count
Seattle-Tacoma, WA	24	577
Tampa, FL, region	22	397
Durham-Raleigh, NC	24	394
Buffalo, NY	15	370
Indianapolis, IN	13	126
State College, PA	1	61
Total	99	1,925

Table 60. Summary statistics of NDS drivers with trips analyzed.

Driver Variable	Variable Value	Driver Count
Age (yr)	64 yr or younger	1,407
Age (yr)	65 yr or older	518
Number of crashes past 3 yr	0 or no data	1,541
Number of crashes past 3 yr	1 or more	384
Number of moving or traffic violations past 3 yr	0 or no data	1,335
Number of moving or traffic violations past 3 yr	1 or more	590
Years driving	<5 yr or no data	405
Years driving	5 yr or more but <10 yr	358
Years driving	10 yr or more	1,162
Miles of driving per year	<5,000 mi or no data	207
Miles of driving per year	5,000 mi or more	1,718
Day far acuity both eyes	20/20 or better or not reported	1,484
Day far acuity both eyes	Lower than 20/20	441
Ishihara test for color blindness	Correct for 2nd–6th plates	484
Ishihara test for color blindness	Correct for at least three plates	1,490
Ishihara test for color blindness	Correct for at least two plates	1,682
Ishihara test for color blindness	Incorrect for four or more plates	243
Total	**Cumulative driver count**	**1,925**

Table 61. Summary statistics of analyzed trip segments.

Trip Variable	Variable Value	Count
Data collection site	FL	1,554
Data collection site	IN	757
Data collection site	NC	1,556
Data collection Site	NY	1,057
Data collection Site	PA	160
Data collection Site	WA	2,787
Driver age-group	64 yr or younger	5,397
Driver age-group	65 yr or older	2,474
Time	Daytime nonpeak	4,859

Trip Variable	Variable Value	Count
Time	Nighttime nonpeak	3,012
Familiarity	Familiar trips	1,945
Familiarity	Unfamiliar trips	5,926
GPS usage	None observed	5,509
GPS usage	Smart phone navigation possible	2,349
GPS usage	Unknown	13
Traffic density	LOS A1	245
Traffic density	LOS A2	1,721
Traffic density	LOS B	4,635
Traffic density	LOS C	1,270
Roadway alignment	Curve	1,178
Roadway alignment	Straight	6,693
Sign visual complexity	Minimal objects and light sources. Low traffic	2,143
Sign visual complexity	Low commercial activity, some nearby light sources and signs. Low traffic	2,735
Sign visual complexity	Illuminated commercial signs, moderate number of other signs and light sources. Low to moderate traffic	2,134
Sign visual complexity	Moderate commercial activity with illuminated signs and businesses. Moderate to high traffic volume	594
Sign visual complexity	Heavy commercial activity with illuminated signs and businesses. High opposing traffic volume and glare	265
Speed limit	50 mph or below	1,064
Speed limit	55 mph	2,176
Speed limit	60 mph	2,871
Speed limit	65 mph	1,297
Speed limit	70 mph	437
Speed limit	No data*	26
ADT	<10,000	492
ADT	10,000–19,999	559
ADT	20,000–29,999	664
ADT	30,000–39,999	573
ADT	40,000–49,999	318
ADT	50,000–99,999	1,207
ADT	100,000–149,999	1,550
ADT	150,000–199,999	655
ADT	200,000–250,000	189
ADT	No data*	1,664

*Both SHRP2 RID and State HPMS data did not include information for collector–distributor roads. These data are currently re-collected manually.

Figure 43 through figure 46 graphically illustrate the distribution of trip segments for the driver behavior analysis by sign complexity variables.

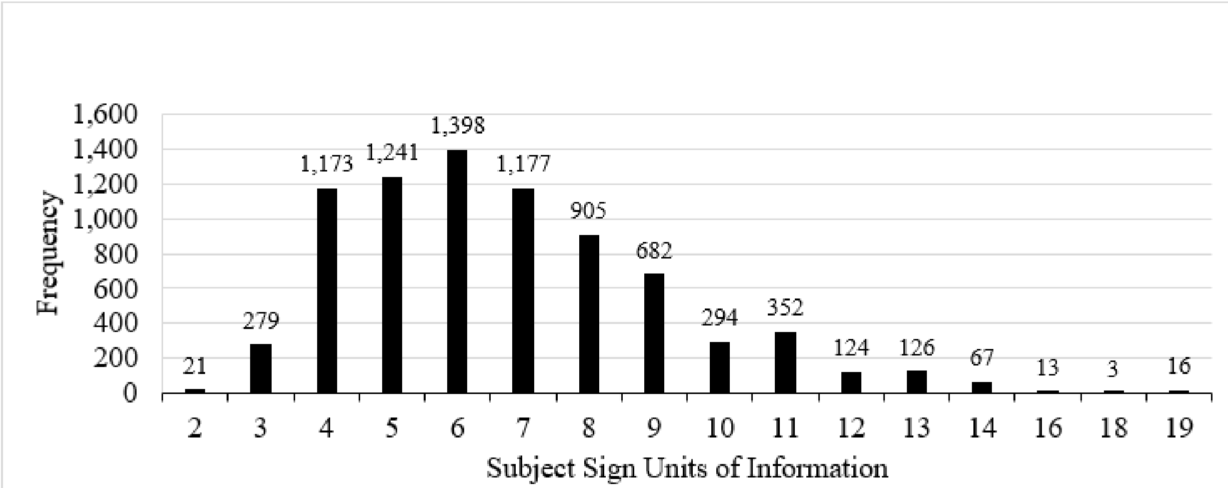


Figure 43. Graph. Distribution of trip segments by subject sign units of information.

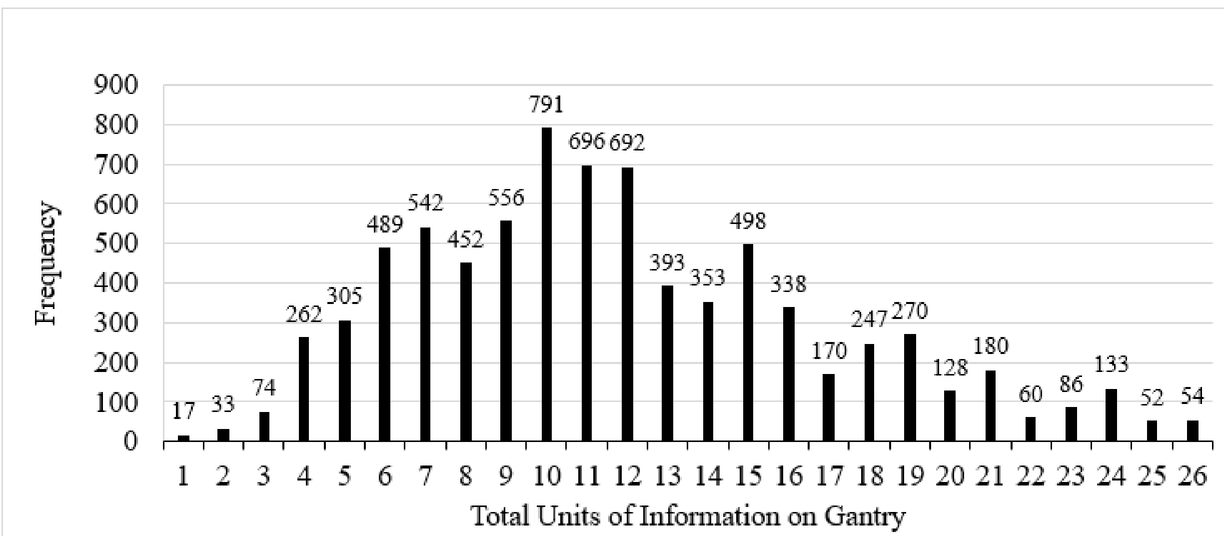


Figure 44. Graph. Distribution of trip segments by total units of information on sign gantry.

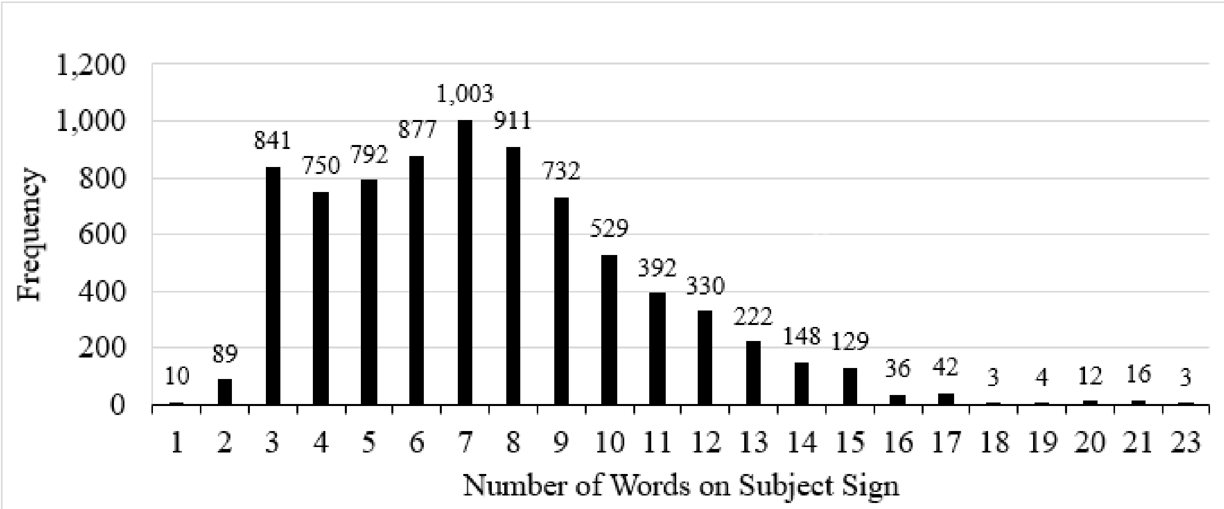


Figure 45. Graph. Distribution of trip segments by subject sign number of words.

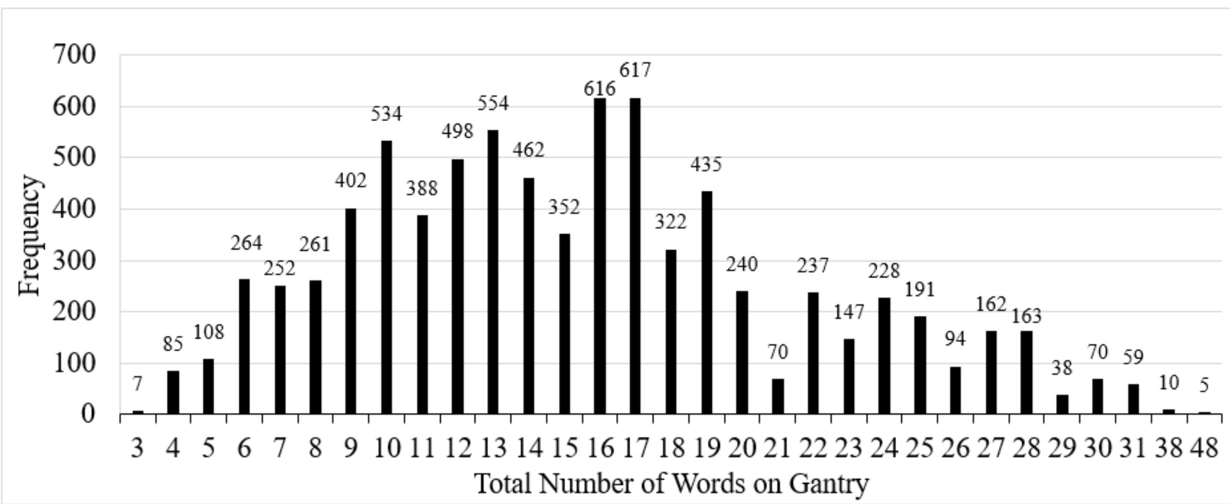


Figure 46. Graph. Distribution of trip segments by total number of words on sign gantry.

Table 62 lists the minimum, maximum, mean, and standard deviation values for all preliminary driver behavior variables.

Table 62. Summary statistics for driver behavior variables.

Variable	Analysis Segment at Sign				Analysis Segment at Ramp			
	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation
a_{long}-μ	−0.444	0.186	−0.006	0.032	−0.444	0.142	−0.009	0.037
a_{long}-σ	<0.001	0.264	0.023	0.015	<0.001	0.248	0.025	0.017
a_{long}-Max	−0.380	1.790	0.044	0.050	−0.380	1.760	0.042	0.052
a_{long}-Min	−1.800	0.090	−0.059	0.063	−1.920	0.120	−0.065	0.067
a_{lat}-μ	−0.260	0.392	0.007	0.036	−0.311	0.382	0.015	0.052
a_{lat}-σ	<0.001	0.292	0.025	0.016	<0.001	0.219	0.030	0.022
a_{lat}-Max	−0.190	1.830	0.063	0.063	−0.230	1.830	0.078	0.081
a_{lat}-Min	−1.770	0.330	−0.047	0.054	−1.810	0.230	−0.046	0.059
ΔV-σ	0	18.8	1.5	1.5	0	18.3	1.6	1.7
j_{long}-μ	−0.081	0.129	−0.001	0.011	−0.001	0.001	<0.001	<0.001
j_{long}-σ	0	3.776	0.216	0.125	0	0.004	<0.001	<0.001
j_{long}-Max	0	18.200	0.546	0.551	−0.001	0.018	0.001	0.001
j_{long}-Min	−18.400	0.000	−0.558	0.560	−0.019	0.001	−0.001	0.001
j_{lat}-μ	−0.090	0.059	0.001	0.011	−0.001	0.001	<0.001	<0.001
j_{lat}-σ	0	3.990	0.195	0.120	0	0.003	0.000	<0.001
j_{lat}-Max	0	18.100	0.504	0.547	−0.001	0.018	0.001	<0.001
j_{lat}-Min	−18.100	0.000	−0.506	0.545	−0.018	0.001	−0.001	<0.001
a_{long}-$abs\mu$	0.003	0.444	0.030	0.021	0	0.444	0.032	0.026
a_{long}-$abs\sigma$	<0.001	0.258	0.018	0.013	0	0.241	0.020	0.015
a_{long}-$absMax$	0.010	1.800	0.079	0.066	0	1.920	0.084	0.068
a_{lat}-$abs\mu$	0.003	0.392	0.029	0.027	0	0.382	0.040	0.041
a_{lat}-$abs\sigma$	<0.001	0.244	0.019	0.014	0	0.212	0.025	0.020
a_{lat}-$absMax$	0.003	1.830	0.083	0.068	0	1.830	0.100	0.080

APPENDIX C. PRELIMINARY DRIVER BEHAVIOR–SIGN COMPLEXITY CORRELATION SCREENING RESULTS

Table 63 through table 65 list the number of significant correlations between the four primary sign complexity and driver behavior variables for Hoeffding's measure of dependence, Kendall's tau-b coefficient, and Spearman's rank-order correlation.(72, 73,75) The Pearson correlation test results are discussed in chapter 4.(74) The tests were conducted for four sign performance metrics: subject sign units of information, log-transformed subject sign units of information, subject sign number of words, and log-transformed subject sign number of words.

Table 63. Count of significant correlations: Hoeffding's measure of dependence.(72)

Variable	Action				Sign			
	No. Words	Log No. Words	Units Action Info.	Log Units Info.	No. Words	Log No. Words	Units Info.	Log Units Info.
a_{long}-μ (g)	6	6	1	1	6	6	2	2
a_{long}-σ (g)	5	5	4	4	6	6	5	5
a_{long}-Max (g)	3	3	5	5	1	1	2	2
a_{long}-Min (g)	9	9	6	6	7	7	3	3
a_{lat}-μ (g)	1	1	3	3	5	5	2	2
a_{lat}-σ (g)	1	1	1	1	3	3	2	2
a_{lat}-Max (g)	3	3	2	2	4	4	1	1
a_{lat}-Min (g)	3	3	4	4	2	2	1	1
ΔV-μ (km/h)	4	4	3	3	5	5	1	1
ΔV-Max (km/h)	5	5	3	3	6	6	1	1
ΔV-Min (km/h)	5	5	4	4	5	5	2	2
ΔV-σ (km/h)	3	3	3	3	4	4	1	1
j_{long}-μ (g/s)	4	4	4	4	0	0	0	0
j_{long}-σ (g/s)	3	3	4	4	2	2	3	3
j_{long}-Max (g/s)	4	4	3	3	4	4	5	5
j_{long}-Min (g/s)	3	3	5	5	1	1	3	3
j_{lat}-μ (g/s)	3	3	2	2	0	0	0	0
j_{lat}-σ (g/s)	3	3	3	3	3	3	2	2
j_{lat}-Max (g/s)	4	4	4	4	2	2	2	2
j_{lat}-Min (g/s)	4	4	5	5	3	3	2	2
a_{long}-$abs\mu$ (g)	5	5	4	4	6	6	3	3
a_{long}-$abs\sigma$ (g)	6	6	6	6	7	7	5	5
a_{long}-$absMax$ (g)	8	8	7	7	6	6	6	6
a_{lat}-$abs\mu$ (g)	1	1	1	1	1	1	2	2
a_{lat}-$abs\sigma$ (g)	2	2	2	2	3	3	1	1
a_{lat}-$absMax$ (g)	4	4	4	4	6	6	1	1
Total	**102**	**102**	**93**	**93**	**98**	**98**	**58**	**58**

Table 64. Count of significant correlations: Kendall's tau-b coefficient.[73]

Variable	Action				Sign			
	No. Words	Log No. Words	Units Info.	Log Units Info.	No. Words	Log No. Words	Units Info.	Log Units Info.
a_{long}-μ (g)	4	4	0	0	6	6	3	3
a_{long}-σ (g)	5	5	4	4	7	7	6	6
a_{long}-Max (g)	2	2	2	2	1	1	2	2
a_{long}-Min (g)	8	8	5	5	8	8	5	5
a_{lat}-μ (g)	1	1	3	3	2	2	2	2
a_{lat}-σ (g)	1	1	1	1	4	4	2	2
a_{lat}-Max (g)	1	1	1	1	4	4	1	1
a_{lat}-Min (g)	2	2	4	4	1	1	1	1
ΔV-μ (km/h)	4	4	3	3	5	5	3	3
ΔV-Max (km/h)	5	5	1	1	6	6	3	3
ΔV-Min (km/h)	4	4	3	3	5	5	3	3
ΔV-σ (km/h)	5	5	3	3	6	6	2	2
j_{long}-μ (g/s)	3	3	4	4	0	0	0	0
j_{long}-σ (g/s)	3	3	4	4	2	2	3	3
j_{long}-Max (g/s)	4	4	5	5	4	4	6	6
j_{long}-Min (g/s)	3	3	5	5	3	3	3	3
j_{lat}-μ (g/s)	2	2	2	2	0	0	0	0
j_{lat}-σ (g/s)	3	3	3	3	5	5	3	3
j_{lat}-Max (g/s)	2	2	4	4	3	3	3	3
j_{lat}-Min (g/s)	4	4	6	6	4	4	4	4
a_{long}-$abs\mu$ (g)	5	5	4	4	6	6	3	3
a_{long}-$abs\sigma$ (g)	6	6	6	6	8	8	6	6
a_{long}-$absMax$ (g)	8	8	7	7	9	9	6	6
a_{lat}-$abs\mu$ (g)	1	1	1	1	3	3	2	2
a_{lat}-$abs\sigma$ (g)	1	1	1	1	5	5	1	1
a_{lat}-$absMax$ (g)	2	2	2	2	6	6	1	1
Total	**89**	**89**	**84**	**84**	**113**	**113**	**74**	**74**

Table 65. Count of significant correlations: Spearman's rank-order correlation.[75]

Variable	Action				Sign			
	No. Words	Log No. Words	Units Info.	Log Units Info.	No. Words	Log No. Words	Units Info.	Log Units Info.
a_{long}-μ (g)	4	4	0	0	6	6	3	3
a_{long}-σ (g)	5	5	4	4	7	7	5	5
a_{long}-Max (g)	1	1	2	2	1	1	2	2
a_{long}-Min (g)	8	8	5	5	8	8	5	5
a_{lat}-μ (g)	1	1	3	3	2	2	2	2
a_{lat}-σ (g)	1	1	1	1	4	4	2	2
a_{lat}-Max (g)	1	1	1	1	4	4	1	1
a_{lat}-Min (g)	2	2	4	4	1	1	1	1
ΔV-μ (km/h)	4	4	3	3	5	5	3	3
ΔV-Max (km/h)	5	5	1	1	6	6	2	2
ΔV-Min (km/h)	4	4	3	3	5	5	3	3
ΔV-σ (km/h)	5	5	3	3	6	6	3	3
j_{long}-μ (g/s)	3	3	4	4	0	0	0	0
j_{long}-σ (g/s)	3	3	4	4	2	2	3	3
j_{long}-Max (g/s)	4	4	5	5	4	4	6	6
j_{long}-Min (g/s)	3	3	5	5	3	3	3	3
j_{lat}-μ (g/s)	2	2	2	2	0	0	0	0
j_{lat}-σ (g/s)	3	3	5	5	5	5	3	3
j_{lat}-Max (g/s)	3	3	4	4	3	3	2	2
j_{lat}-Min (g/s)	4	4	6	6	4	4	5	5
a_{long}-$abs\mu$ (g)	5	5	4	4	6	6	3	3
a_{long}-$abs\sigma$ (g)	6	6	6	6	8	8	6	6
a_{long}-$absMax$ (g)	8	8	7	7	9	9	6	6
a_{lat}-$abs\mu$ (g)	0	0	1	1	3	3	2	2
a_{lat}-$abs\sigma$ (g)	1	1	1	1	5	5	1	1
a_{lat}-$absMax$ (g)	2	2	2	2	6	6	1	1
Total	**88**	**88**	**86**	**86**	**113**	**113**	**73**	**73**

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The original map in figure 4 is the copyrighted property of Esri and is accessible at https://www.arcgis.com/home/item.html?id=10df2279f9684e4a9f6a7f08febac2a9 (Reference number: 10df2279f9684e4a9f6a7f08febac2a9).[52] FHWA modified figure 4 to show an example of the sign structures and driver routes selected for analysis in this study.

The original diagram in figure 7 is © 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open-access article distributed under terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/). Figures from the original publication are available via license: Creative Commons Attribution NonCommercial-ShareAlike 4.0 International.[63]

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