

GDOT Research Project No. 12-27

Final Report

FACTORS INFLUENCING VISUAL SEARCH IN COMPLEX DRIVING ENVIRONMENTS

By

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Contents

List of Tables
List of Figuresi
Executive Summary x
Acknowledgementsxvi
1. Introduction
1.1 Study Objectives
1.2 Significance and Background
2. Driver-perceived Complexity of Static Roadway Environments
2.1 Experiment Methodology: Static Roadway Environments
2.2 Describing Driver-perceived Complexity of Static Roadway Environments 14
3. Predicting Driver-perceived Complexity of Static Roadway Environments
3.1 Classification of Characteristics Present in Static Roadway Environments 2
3.2 Factor Analysis of Roadway Characteristics in Roadway Environments
3.3 Predictive Model of Driver-perceived Complexity of Static Roadway Environments
3.4 Effects of Experience on Driver-perceived Complexity of Static Roadway Environments
3.5 Perceived Complexity of Simulated vs. On-road Environments
4. Driver-Perceived Complexity of Dynamic, Simulated Roadway Environments 5
4.1 Selected Roadway Factors

4.2	Experiment Method: Dynamic Roadway Environments	67
4.3	Results	69
4.4	Discussion of Findings	79
5. Co	nclusions and Recommendations	83
5.1	Static Roadway Environments Experiments	83
5.2	Dynamic, Simulated Roadway Environments Experiment	85
5.3	Applications of Findings	86
5.4	Future Directions	87
Referen	ices	89
Append	lix A: Roadway Characteristics Classification Analysis	1

List of Tables

Table 2-1: Summary of Participants: Static Roadway Environments Experiment
Table 2-2: Participant Age & Grade Ranges: Static Roadway Environments Experiment 10
Table 2-3: Probability Table of Perceived Complexity Ratings of RoadwayEnvironments by Participant Sample, Roadway Environment Type, and Taskversus Visual Complexity Questions
Table 3-1: Roadway Characteristics Classified across Roadway Environment Images
Table 3-2: Final Roadway Characteristics Used for Factor Analysis 26
Table 3-3: Retained Roadway Environment Factors from EFA
Table 3-4: Sample Low, Median, and High Roadway Images associated with Five Factors 28
Table 3-5: Model 1 – By-Image Linear Regression Coefficient Estimates for Significant Predictors with Main Factors Only
Table 3-6: Model 2 – By-Image Linear Regression Coefficient Estimates for Significant Predictors with Main Factors and Two-Way Interactions Allowed 30
Table 3-7: High School Participants' Time after Licensure (months)
Table 3-8: College-level and Festival Participants' Experience Levels (years)
Table 3-9: Linear Regression Predictive Model 3 and Model 4 with Time following Licensure as an Independent Variable
Table 3-10: Linear Regression Predictive Model 5, High School Only, and Model 6 College/Festival Only High School Participants versus College/Festival Participants 46
Table 3-11: Linear Regression Predictive Model 7, High School with 1–6 months following Licensure and Model 8, High School with 7–12 Months following Licensure High School Participants: 1–12 Months following Licensure

Table 4-1: Low and High Levels of Roadway Factors 6	50
Table 4-2: Ratings Distribution Comparisons for High/Low Roadway Factor Levels7	73
Table 4-3: Effects Table of Roadway Factors on Perceived Complexity	77
Table 4-4: Ratings Distribution Comparisons for Demographic Variables	79
Table A-1: Rotated Pattern Matrix: Maximum Likelihood Extraction with Promax Rotation	-1

List of Figures

Figure 2-1: Sample On-road Environment Images	12
Figure 2-2: Sample Driving Simulated Roadway Environment Images	12
Figure 2-3: Custom Keyboard Cover Used in Experiment	14
Figure 2-4: Ratings of Perceived Complexity for Participant Samples, Aggregated Across Image Type and Complexity Question	17
Figure 2-5: Ratings of Perceived Complexity for Task and Visual Complexity Questions, Aggregated Across Participant Groups and Image Type	17
Figure 2-6: Ratings of Perceived Complexity for On-road vs. Simulated Roadway Images, Aggregated Across Participant Groups and Complexity Question	18
Figure 2-7: Probability Density Functions of Beta-distributed Fits for Perceived Complexities of 100 Static Roadway Environments	19
Figure 2-8: Descriptive Power of Beta Distribution in Response Differentiation: (a) Image A with Ratings Mean of 2.0; and (b) Image B with Ratings Mean of 2.0	21
Figure 3-1: Ratings of Perceived Complexity Aggregated Across Complexity Question and Image Type for High School Participants with Varied Lengths of Elapsed Time following Licensure	38
Figure 3-2: Ratings of Perceived Complexity for College-level and Festival Participants with Varied Lengths of Driving Experience, Aggregated Across Complexity Question and Image Type	38
Figure 3-3: By-Image Median Differences in Perceived Complexity Between High School	41
Figure 3-4: By-Image Median Differences in Perceived Complexity Between 1–6 and 7–12 Month Participants in High School Samples, Aggregated Across Complexity Question and Image Type (7–12 month to 1–6 month participants)	41

Figure 3-5: By-Image Median Differences in Perceived Complexity Between <5 Years and >15 Years Participants in College and Festival Samples, Aggregated Across Complexity Question and Image Type
Figure 3-6: By-Image Mean Rating in Perceived Complexity Across Sampled Age Groups, (Aggregated Across Complexity Question and Image Type)
Figure 3-7: Distributions of (a) On-road and (b) Simulated Roadway Environment Complexity Ratings by Institution of Origin
Figure 3-8: Median Differences between Task and Visual Complexity Questions for (a) On-road and (b) Simulated Environments
Figure 3-9: Probability Density Functions of Beta-distributed Fits for Perceived Complexities of (a) On-road and (b) Simulated Roadway Environments
Figure 4-1: Roadway Objects Present in Work Zone
Figure 4-2: Left: High Level of Lane Configuration Factor for PCB; Right: High Level of Lane Configuration Factor for Work Drums
Figure 4-3: Ratings Distributions for Experiment Replications 1 and 2
Figure 4-4: Probability Density Functions of Beta- Distributed Fits for Perceived Complexities of 32 Roadway Videos
Figure 4-5: (a) Beta-distributed Fit for Roadway Video with Low Levels across All Factors ($R^2 = 0.98$); (b) Beta-distributed Fit for Roadway Video with High Levels across All Factors ($R^2 = 0.97$)
Figure 4-6: Ratings Distributions for Roadway Factors
Figure 4-7: Main Effects of Roadway Factors on Perceived Complexity

Executive Summary

Roadways are dynamic engineering systems, incorporating mixed modes of transportation with varying degrees of vehicle automation to form a complex and shared environment in which drivers must operate. This is compounded by a wide array of invehicle and personal technologies competing for the driver's limited attention, making it ever more important to understand driver perception of the roadway environment. Driver perception has long played a significant role in transportation engineering. For example, perception-reaction time, a parameter widely applied within roadway design and traffic engineering to calculate sight distances, horizontal and vertical curvature, signal timing parameters, etc., depends critically on driver perception.

The primary goal for this research project was to examine the effects of selected roadway conditions (i.e., environment factors) on driver perception with the intent of informing both roadway design guidance and future driver perception research. Ultimately, these efforts seek to create roadway environments conducive to safe driving.

Study Objectives

The objectives for this study were as follows:

- Review and summarize existing research that examines the impacts of roadway environments on both driver-perceived complexity and on performance or behavior.
- Identify characteristics of roadway environments contributing to driverperceived complexity.

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- Develop descriptive and predictive models of driver-perceived complexity of static and dynamic roadway environments.
- Extend research efforts to encompass multiple driver-demographic groups, including young drivers.
- Examine differences in drivers' ratings of perceived complexity of simulated versus on-road environments as a precursor to studying roadway complexity in driving simulators.
- Make recommendations that can be applied in the field and provide guidance for future research that will further examine the effect of specific roadway factors on driver perception, behavior, or performance.

Static Roadway Study

The objective for the static roadway study was to model the impacts of roadway characteristics on driver-perceived complexity using static photographs (i.e., 100 images with six repetitions) of a wide variety of existing roadways and comparable simulator images from the point of view of the driver. Using these static roadway images, study participants were given a brief interval to rate the "complexity" of each image. The study included participants from four sites: (1) a high school in Kennesaw, Georgia; (2) a rural public university in Morehead, Kentucky; (3) an urban public university in Atlanta, Georgia; and (4) a public festival in Atlanta, Georgia. Participants at the college and festival sites were required to have a valid driver's license and at least two years of driving experience. High school participants had no licensure or driving experience requirements to participate.

A primary finding of the static roadway experiments was that simulated images, for this data set, were more likely to have a lower rating than the on-road images. While the underlying cause for the lower complexities of the simulator images is uncertain, the findings indicate a potential bias in that simulator scenarios may be failing to capture sufficient complexity when used to evaluate real-world treatments.

Among the factors considered, *Environmental Conditions, Urban Arterial*, and *Roadside Restrictions* were all seen to affect perceived complexity. *Environmental Conditions* highlights the potential importance of the presence of heavy vehicles, inclement weather, and lighting conditions. Interestingly, the highest *Environmental Conditions* factor values were for the simulator inclement weather images, highlighting weather conditions as a possible means to increase complexity in a simulator scenario. The *Urban Arterial* factor indicates that as the urban characteristics of an image increased (or decreased) participants tended toward higher (or lower) complexity ratings. *Roadside Restrictions* (i.e., barrier separation, delineation devices, work zones, etc.) also contributed to higher complexity ratings, potentially indicating the impact of an increasingly constrained roadway image.

When considering driver experience, this study shows that drivers with varied lengths of time since licensure, particularly those with the least (i.e., under 12 months) versus those with the highest (i.e., over 15 years) have statistically significant differences in ratings of perceived complexity, but generally appear to perceive specific roadway factors similarly within roadway environments. More experienced drivers tended to rate images as more complex than novice drivers, demonstrating a possible impact of experience on driver perception and/or visual search patterns. However, confounded in this finding is that, for the given data, time elapsed following licensure is highly correlated with age; thus, it is not possible to distinguish between influence of age and the driving experience on perceived complexity.

Younger drivers' perceived complexity tended to be more influenced by the difference between urban and non-urban environments. A greater sense of openness in an image decreased the perceived complexity, with younger drivers being most sensitive to this factor. A potential correlate of this observation could be that younger drivers are failing to perceive the complexity (i.e., risks) of driving in non-urban environments, thus increasing their likelihood of an incident. This observation may highlight a need to place more emphasis on the challenges of rural and freeway conditions in driver education aimed at younger drivers, and it is worthy of additional research.

Dynamic Roadway Environments Study

In a separate study, researchers asked participants to rate the complexity of short driving simulator videos rather than static images. Results from the dynamic roadway environments study indicated that the *Traffic* factor had the greatest effect on perceived complexity ratings, followed by *Work Zone Treatment, Lane Configuration, Roadway Objects*, and the *Urban/Rural* factor. Also, the effect on perceived complexity of a change in lane configuration or addition of roadway objects is greater in a work zone with lower path guidance (i.e., drums) than one with higher path guidance (i.e., portable concrete barriers). This finding could foreshadow a possible reason for the reduction in driver performance in the vicinity of work zones delineated with work drums. This result also agrees well with the research team's previous studies on work zone delineation. It was also seen that many of the factors influencing perceived complexity are likely not

independent and their impact on perceived complexity is not the sum of each factor's individual impact. The co-existence of factors requires an adjustment of the overall perceived complexity of the environment (i.e., not additive effects).

Overall, these results provide a foundation for the design of simulator experiments that further examine the effects of traffic and work-zone configuration on driver behavior and performance. They also provide an understanding of some of the perceptual shifts that occur in the presence of specific roadway environment factors—shifts that may result in increased risk of likelihood of driver error and, ultimately, crashes.

Applications of Findings

The findings from this research project can be applied within several contexts to further the safety of multiple driver groups across varied roadway environments. First, the study of perceived complexity differences between simulated and on-road environments showed that while the same range of complexity can be achieved between simulated and on-road environments, simulator studies may need to adjust (e.g., overcomplicate) images to achieve equivalent levels of perceived complexity for the comparable factors in on-road environments. These findings also provide context for interpreting simulator study results, and applying these results to on-road environments.

Overall, the findings support existing driver performance literature and suggest that reduced driver performance observed in the presence of certain roadway factors/attributes may be due in part to an increased risk associated with perception of these factors that is separate from the exposure risk associated with the presence of these factors in the roadway environment. Additionally, the identification of roadway factors that most significantly influence perceived complexity for various driver demographic groups can be used to guide road safety audits executed for roadway system locations with high crash rates. Finally, this project has shown that integrating the discussion of complex driving environments into driver training for new drivers may benefit this vulnerable demographic of road users.

Future Directions

The work presented here provides a strong foundation for corollary human factors in transportation engineering research, safety, and operations initiatives. Results from the simulated and on-road environment studies provide a basis for future driving simulator studies to explore the most significant factors that were found to influence driver perception in greater detail, and particularly to make the connection between perception of complexity and driver performance measures such as lane deviations, speed adherence, and cognitive workload. A next step that would add significant insight to this work is the study of the roadway factors that impact crash rates using available crash data. This knowledge would allow for a deeper understanding of how shifts in transportation system users' psychological and perceptual assessments of their environment affect performance and safety on a larger scale.

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1. Introduction

Roadways are dynamic engineering systems, incorporating mixed modes of transportation with varying degrees of vehicle automation into a complex and shared environment in which drivers must operate. This is compounded by a wide array of invehicle and personal technologies competing for the driver's limited attention, making it ever more important to understand driver perception of the roadway environment. Driver perception has long played a significant role in transportation engineering. For example, perception-reaction time, a parameter widely applied within roadway design and traffic engineering to calculate sight distances, horizontal and vertical curvature, signal timing parameters, etc., is critically dependent on driver perception.

The primary goal for this research project was to examine the effects of selected roadway conditions (i.e., environment factors) on driver perception with the intent of informing both roadway design guidance and future driver perception research. Ultimately, these efforts seek to create roadway environments conducive to safe driving.

1.1 Study Objectives

The objectives for this study were the following:

- Review and summarize existing research examining the impacts of roadway environments on both driver-perceived complexity and its impact on performance or behavior.
- Identify characteristics of roadway environments contributing to driverperceived complexity.

- Develop descriptive and predictive models of driver-perceived complexity of static and dynamic roadway environments.
- Extend research efforts to encompass multiple driver-demographic groups, including young drivers.
- Examine differences in drivers' ratings of perceived complexity of simulated versus on-road environments as a precursor to studying roadway complexity in driving simulators.
- Make recommendations that can be applied in the field and provide guidance for future research that will further examine the effect of specific roadway factors on driver perception, behavior, or performance.

1.2 Significance and Background

A significant portion of crashes on the roadway is attributable to human error (Treat et al. 1979; *Highway Safety Manual* 2010), and identifying the capabilities and limitations of drivers is crucial for the design of safe and functional transportation systems. As stated in the *Highway Safety Manual*, "Understanding how drivers interact with the roadway allows highway agencies to plan and construct highways in a manner that minimizes human error and its resultant crashes" (2010). Given the importance of human factors in roadway safety and design, this research sought to examine roadway environment factors that could impact driver perception, attention, behavior, or performance across varied roadway environments. Detailed within the remainder of this chapter is an overview of driver perception and roadway complexity concepts. The researchers present additional literature later in this report.

1.2.1 Driver Perception and Attention

Perception and behavior are critical to the safety and functionality of transportation systems (Dewar, Olson, and Alexander 2002; Olson and Farber 2003). Perception is "a process that begins with sensation (i.e., input from the senses—vision, hearing, etc.) but involves a complex process of analysis, integration and interpretation" (Dewar, Olson, and Alexander 2002). Through preception, drivers determine what information is relevant to the operation of their vehicles within the roadway environment. Driver behavior is, in part, a response to perception.

Despite the centrality of driver perception to vehicle operations, the majority of traffic devices and roadway configurations today were not designed for optimal human perception and performance. The aspects of roadway design that influence perception and driver behavior are increasingly important as the system becomes more complex and the competition for the driver's attention from non-roadway environment sources increases. This is illustrated by a study recently sponsored by the Georgia Department of Transportation (RP 10-07, Improved Methods for Delineating Diverges in Work Zones), which found that the perceptual Gestalt principles of "continuity" and "closure" significantly impacted a driver's detection and accurate interpretation of work zone channelizing devices (Greenwood et al. 2016; Xu et al. 2015). Gestalt principles address how visual sensory inputs are organized into meaningful forms (Goldstein and Brockmole 2013). However, until recently the development of design standards and guidance has not widely considered driver perception. For example, many of the standards found in the *Manual on Uniform Traffic Control Devices* (MUTCD) for traffic

devices and configurations were recommended without significant consideration of driver awareness, perception, and performance (Pain, McGee, and Knapp 1981).

1.2.2 Roadway Complexity

Roadway complexity influences both the speed and accuracy at which a driver interprets a roadway scene. Various roadway characteristics, design features, and roadside objects have been reported in the literature to impact drivers' behavior and performance across a range of roadway environments (Young et al. 2009; Horberry et al. 2006; Brookhuis, de Vries, and de Waard 1991; Schiessl 2008; Teh et al. 2014; Zeitlin 1995; Edquist, Rudin-Brown, and Lenné 2012; Stinchcombe and Gagnon 2010; Paxion, Galy, and Berthelon 2014; Patten et al. 2006). Driving demands on attention may be a primary contributing factor to driver error, as humans have limited processing capacity per unit time (Paxion, Galy, and Berthelon 2014). Varied perceptual and cognitive conceptions of roadway environments may also contribute to driver error. As such, there is likely an optimal range of stimuli that drivers should be exposed to while undertaking the driving task. This may imply that the optimal roadway complexity is neither too complex-thereby overwhelming drivers' perceptual abilities-or overly simple (i.e., boring or monotonous)—resulting in driver inattention. The goal for this study was to examine the effects of specific roadway factors on driver-perceived complexity, with the goal of further understanding the range of roadway factors and interactions that would facilitate optimal driver behavior and performance.

To address this goal, Chapters 2 and 3 of this report present a static roadway study in which the researchers explored the impacts of roadway characteristics on driverperceived complexity using static photographs of a wide variety of existing roadways and simulator images from the point of view of the driver. Chapter 4 presents a subsequent dynamic roadway environments study in which researchers asked participants to rank the complexity of short driving-simulator videos rather than static images. Chapter 5 summarizes the findings and provides insights into their application.

2. Driver-perceived Complexity of Static Roadway Environments

The objective for the static roadway study was to model the impacts of roadway characteristics on driver-perceived complexity. The core images used to evaluate complexity were static photographs of a wide variety of existing roadways and "comparable" simulator images from the point of view of the driver. Using these static roadway images, study participants were given a brief interval to rate the complexity of each image. These ratings are considered a measure of drivers' perceptions regarding the complexity of the roadway environments. Throughout this report, the drivers' ratings are referred to as *perceived complexity*. These results provide an opportunity to evaluate the impact of roadway characteristics on perceived complexity. Additionally, the ratings resulting from the roadway photographs can be compared against the ratings resulting from the simulator, thus allowing for additional insight into a common method for researching driver behavior in a laboratory setting.

2.1 Experiment Methodology: Static Roadway Environments

This section details an overview of the experimental methodology, including a summary of the participants, experimental design, implementation, and data collection procedures. To obtain a wide cross section of drivers, the research team implemented the experiment at multiple sites. To comply with federal requirements, Institutional Review Boards and research offices of the respective institutions approved experimental procedures, participant recruitment and reimbursement, and data management procedures and protocols.

2.1.1 Overview of Participants

The data analyzed within this study include participants from four sites: (1) a high school in Kennesaw, Georgia; (2) a rural public university in Morehead, Kentucky; (3) an urban public university in Atlanta, Georgia; and (4) a public festival in Atlanta, Georgia. Table 2-1 gives relevant information involving data collection at each of these sites. Participants at the college and festival sites were required to have a valid driver's license and at least two years of driving experience. High school participants had no licensure or driving experience requirements to participate, although the analysis presented here excludes participants without a license or learner's permit. To reimburse participants for their time, college-level participants received extra credit toward an undergraduate psychology course in which they were enrolled at the time of the experiment. High school participants were recruited during two experiment phases that occurred in 2014 and 2015. Participants in the 2014 implementation received one hour of community service credit to be applied toward various service organizations at their school, while participants in the 2015 implementation received a ticket redeemable at a local chain restaurant. Festival participants received a \$10 coffee shop gift card for their time. Recruitment periods and reimbursements are summarized in Table 2-1, and age group demographics for each participant sample are presented in Table 2-2.

The research team obtained grade levels in lieu of ages for the high school participants. Five high school participants were removed from the data set for this analysis because they held neither a driver's license nor learner's permit, and one festival participant was removed from the data set due to failure to complete the experiment.

Participant Sample	Recruitment Period	Reimbursement	Male	Female	Choose Not To Answer	Total
High School Participants	Fall 2014; Fall 2015	Community service; Chicken sandwich ticket	47.7% (51)	50.5% (54)	1.9% (2)	37.2% (107)
College Participants (Urban Location)	Fall 2014	Extra credit for course	45.2% (19)	54.8% (23)	0% (0)	14.6% (42)
College Participants (Rural Location)	Fall 2014	Extra credit for course	31.6% (12)	68.4% (26)	0% (0)	13.2% (38)
Festival Participants	Fall 2015	\$10 Coffee gift card	43.6% (44)	56.4% (57)	0% (0)	35.1% 101
Total	N/A	N/A	43.8% (126)	55.6% (160)	0.7%	100% (288)

 Table 2-1: Summary of Participants: Static Roadway Environments Experiment

Age Range (years) or Grade Level	High School Participants	College Participants (Urban)	College Participants (Rural)	Festival Participants	Total
Grade 9	1.0% (1)	N/A	N/A	N/A	0.3% (1)
Grade 10	2.8% (3)	N/A	N/A	N/A	1.04% (3)
Grade 11	31.8% (34)	N/A	N/A	N/A	11.8% (34)
Grade 12	64.5% (69)	N/A	N/A	N/A	24.0% (69)
18–24	N/A	97.6% (41)	97.4% (37)	18.8% (19)	33.7% (97)
25–34	N/A	2.4% (1)	2.6% (1)	38.6% (39)	14.6% (41)
35–44	N/A	0% (0)	0% (0)	17.8% (18)	6.3% (18)
45–54	N/A	0% (0)	0% (0)	9.9% (10)	3.5% (10)
55-64	N/A	0% (0)	0% (0)	10.9% (11)	3.8% (11)
65+	N/A 0% 0% (0) (0)		3.0% (3)	1.04% (3)	
Choose Not	0%	0%	0%	1.0%	0.3%
to Answer	(0)	(0)	(0)	(1)	(1)
Participant	37.2%	14.6%	13.2%	35.1%	100%
Totals	(107)	(42)	(38)	(101)	(288)

 Table 2-2: Participant Age & Grade Ranges: Static Roadway Environments

 Experiment

2.1.2 Experimental Design

Over the course of this experiment, researchers obtained self-reported ratings of complexity and response times for a wide selection of roadway environments. They presented the roadway environments to participants as static images using Inquisit® 3 by Millisecond Software, a stimulus presentation and data acquisition platform. The high school and college experiments included 100 unique images. Each participant viewed six randomized repetitions of 100 unique images, for a total of 600 viewed images. For the

first part of the experiment, which consisted of three randomized repetitions of the 100 unique images, participants were asked to rate the images in accordance with how difficult it would be to drive through the scene. This question formulation is hereafter referred to as *task complexity*. Participants were then allowed a short self-timed break, followed by the remaining three image repetitions, for which participants were asked to rate how complex the roadway environments appeared. This question formulation is referred to as visual complexity over the remainder of this report. The variations in question formulation (i.e., task complexity versus visual complexity) enabled the examination of question responses related to how complex a scene appeared versus the perceived complexity of the driving task itself. Festival participants experienced an abbreviated version of the experiment, in which they saw two repetitions of the 100 unique images, with the first repetition being the task complexity question formulation, and the second repetition being the visual complexity question formulation. This reduced the number of replications and expedited the data collection process. The festival participants took part in the experiment at a temporary data collection site that the research team installed and operated at a public festival.

Of the 100 unique roadway images used in this experiment, 75 are of on-road environments (existing roadways), while 25 are simulated roadway environments. The 100 images were selected from an image bank of over 700 images using ratings from a panel of 11 researchers. These selected images were distributed across the complexity spectrum based on the aggregated ratings from the panel. The on-road environment images were taken from the perspective of a driver or front-seat passenger on roads located in California, Georgia, Kentucky, New York, Ohio, South Carolina, and Virginia. The simulated roadway environment images were created using the National Advanced Driving Simulator (NADS) MiniSim® software. Sample on-road and simulated roadway images used in this experiment are shown in Figure 2-1 and Figure 2-2, respectively. All images were sized to have the same aspect ratio (16:9) and a 1920 \times 1080 pixel resolution for consistent image quality. The computer monitors across all experiment iterations had consistent screen (i.e., 19.5–20 inch) and resolution specifications (i.e., 1600 \times 900), again to ensure consistent image quality across experiment implementations for the varied populations.



Figure 2-1: Sample On-road Environment Images



Figure 2-2: Sample Driving Simulated Roadway Environment Images

2.1.3 Experiment Implementation

During a typical data collection session, from one to ten participants were performing the task simultaneously at separate stations. High school and college participants signed informed consent or assent forms, and minors were required to obtain parental permission. Festival participants indicated consent via an electronic waiver-ofdocumentation of consent. All experiment iterations began with a brief instructional period, followed by a practice session. The experiment ended with a short demographic survey during which information regarding age/grade level, gender, location of licensure, driving experience, etc., was obtained from each participant. Finally, participants were debriefed regarding the purpose of this study. Additional details regarding differences in the high school implementation of this experiment, as well as further specifics pertaining to the experimental protocol, are included in the following sources (Shaw et al. 2015a; Shaw et al. 2016; Shaw et al. 2015b).

2.1.4 Data Collection Measures

Self-reported complexity ratings and response latencies were collected for each roadway environment, yielding six ratings and six response latencies per image per participant for the full experiment, or two ratings and two response latencies per image per participant for the abbreviated festival-based experiment. Ratings were made using a five-category integer scale, with 1 being the least complex and 5 being the most complex. Participants were asked to respond while the image was on the screen by striking the corresponding key on a custom keyboard outfitted with a special cover that had the numbers 1 through 5 located in the center of the keyboard (Figure 2-3). This cover was used to control for the participants' finger positions. For all ratings, participants were

instructed to use the index finger of their preferred hand. After the participants made a response or after 2.25 seconds had elapsed, whichever occurred first, a "pacing" screen was displayed and the participants could no longer respond to the image. The pacing screen instructed the participants to depress the spacebar to move to the next image. This procedure provided a mechanism for the participants to maintain control over the pace of the experiment. Response latencies represent the time taken for each participant to make a response, and were measured as the time between the depressed spacebar on the pacing screen and the rating of the following image. Non-responses, where the participant failed to respond while the image was on the screen, were removed from the data set used in the analysis in this report. Non-responses comprised 2.4% of the total data set.



Figure 2-3: Custom Keyboard Cover Used in Experiment

2.2 Describing Driver-perceived Complexity of Static Roadway

Environments

Aggregated results from this experiment, as well as an initial description of the predictive model, are presented here to provide a general overview of the data set. These results provide an initial familiarity with the analysis presented in the next several chapters.

2.2.1 Overall Ratings Distributions

The test results were aggregated using several factors, including participant ID (i.e., no personally identifiable information), type of roadway environment, and task versus visual complexity question formulations. The probabilities for each rating category (i.e., 1, 2, 3, 4, or 5) were calculated initially and arranged by each participant group, on-road versus simulated images, and whether it was a task versus visual complexity question. These results are summarized in Table 2-3.

Table 2-3: Probability Table of Perceived Complexity Ratings of Roadway Environments by Participant Sample, Roadway Environment Type, and Task versus Visual Complexity Questions

Sample	Image Type	Question	Ratings				
Sample			1	2	3	4	5
	On-road	Visual	0.40	0.21	0.20	0.11	0.08
College		Task	0.42	0.21	0.17	0.10	0.10
(Rural)		Visual	0.46	0.23	0.17	0.08	0.07
	Simulated	Task	0.51	0.19	0.15	0.09	0.07
	On road	Visual	0.28	0.28	0.23	0.14	0.08
College	Un-road	Task	0.34	0.28	0.19	0.13	0.05
(Urban)	Simulated	Visual	0.38	0.30	0.19	0.09	0.04
		Task	0.42	0.25	0.17	0.10	0.05
	On-road	Visual	0.35	0.26	0.20	0.12	0.08
High School		Task	0.40	0.26	0.18	0.10	0.05
ingii School	Simulated	Visual	0.43	0.27	0.17	0.09	0.04
		Task	0.47	0.23	0.15	0.10	0.05
Public Festival	On-road	Visual	0.36	0.20	0.18	0.16	0.10
		Task	0.35	0.23	0.18	0.15	0.09
	Simulated	Visual	0.41	0.21	0.16	0.12	0.09
		Task	0.43	0.20	0.15	0.14	0.09

Figure 2-4 illustrates the ratings distributions for the four participant samples, aggregated across image type and complexity question. Figure 2-5 shows the individual ratings distributions for both task and visual complexity formulations, aggregated by participant group and image type. Finally, Figure 2-6 provides the ratings distributions for simulated versus on-road environments, aggregated across participant groups and the complexity question. All image repetitions across participants were included in these ratings distributions. Statistical χ^2 (chi-squared) tests found statistically significant differences between the distributions shown in Figure 2-4 ($\chi 2 = 1325.7$, df = 12, p < 0.001***, $\alpha = 0.05$), Figure 2-5 ($\chi 2 = 250.2$, df = 4, p < 0.001***, $\alpha = 0.05$), and Figure 2-6 ($\chi 2 = 742.6$, df = 4, p < 0.001***, $\alpha = 0.05$), respectively. However, across each aggregation there is a consistent trend toward a greater concentration of complexity ratings of 1 and 2 (i.e., less complex) across all roadway environments. This trend is strongest when considering simulated images, where a significantly higher percentage of complexity ratings of 1 were recorded compared to that for the on-road images. However, significant caution must be exercised in extrapolating general conclusions from this imbalance. The research team chose the images using an internal selection process; and thus, it is possible that the team over-selected less complex roadways to compose the simulator image set, resulting in the disproportionate ratio of low ratings present in the data. This will be further discussed Section 3.5.











Figure 2-6: Ratings of Perceived Complexity for On-road vs. Simulated Roadway Images, Aggregated Across Participant Groups and Complexity Question

2.2.2 Beta-distributed Descriptive Model of Driver-perceived Complexity

In addition to the categorization as presented above, the variability in complexity rating for each image, across all participants and including both task and visual complexity responses, was also modeled using the beta distribution. The beta distribution was selected as a model for perceived complexity for several reasons; primarily, it is a bounded distribution that is defined over finite limits from 0 to 1. Additionally, the beta distribution is defined by two shape parameters (i.e., α , β), which allows for more nuanced descriptive measures of the data, particularly when compared to more easily biased descriptors such as mean and median (Hahn and Shapiro 1994). The beta distribution is a continuous distribution, while the five-category integer scale used for the ratings allowed for the collection of discrete data. As such, the ratings were transformed to comply with the constraints of the model. Each rating category (i.e., 1, 2, 3, 4, and 5) was allotted a bin width of 0.2, constituting a continuous distribution between 0 and 1.

The data were fit using the Statistics and Machine Learning Toolbox in Matlab® 2014, which provides functionality for beta parameter estimation using existing data. The coefficient of determination (\mathbb{R}^2) was used to measure goodness of fit for the roadway environments. The goodness of fit (\mathbb{R}^2) ranged from 0.81 to 0.995 across all images. One nighttime on-road image was not fit by the beta distribution, and was instead fit by a uniform distribution; the researchers believe that the beta fit algorithm in Matlab was unable to fit this particular image due to algorithmic insensitivity. After examining the beta-distributed fit for each image (Figure 2-7), it was found that the beta distribution was able to model perceived complexity ratings on a roadway environment basis with excellent goodness of fit. The overall variance of the beta-distributed fits across all roadway environments was found to be 0.034, with an adjusted mean of 2.26.



Figure 2-7: Probability Density Functions of Beta-distributed Fits for Perceived Complexities of 100 Static Roadway Environments
As discussed, the shape parameters of the beta distribution also allow for more nuanced descriptive measures of the shape of the distribution, which is particularly useful in cases where descriptors such as *mean* or *median* disguise important differences between response distributions across images. An example of such an instance is evident in Figure 2-8, where the roadway environments are shown above their respective distributions of complexity ratings. Both environments had aggregate means of 2.0, but the alpha and beta parameter differences indicate that Image B had responses that were more concentrated around 2, while Image A had more responses at the extremes, which caused the data to average out to approximately the same sample mean. Thus, the beta distribution is a potentially powerful tool to differentiate between the roadway environments.

In Chapter 3, the research team will use this static experiment data to develop models of perceived driver complexity for the given roadway images.





Figure 2-8: Descriptive Power of Beta Distribution in Response Differentiation: (a) Image A with Ratings Mean of 2.0; and (b) Image B with Ratings Mean of 2.0

3. Predicting Driver-perceived Complexity of Static Roadway Environments

This chapter details the development of predictive models for driver-perceived complexity, as influenced by roadway characteristics present in the static roadway environments. Included in this chapter are the steps executed to classify the roadway characteristics existing in each roadway environment, followed by the analytical approach applied to reduce these characteristics into a smaller set of roadway factors for use in the predictive models.

3.1 Classification of Characteristics Present in Static Roadway Environments

Roadway environment characteristics in each image were first classified using a binary scale, where 1 indicated presence and 0 indicated absence of the roadway characteristic being cataloged. Each of the 100 static roadway environments was classified with respect to the 70 characteristics listed in Table 3-1. The roadway characteristics in this comprehensive list were compiled from the transportation manuals and reports cited as sources in Table 3-1, as well as the research team's expertise. For grouping purposes during the initial stage of the classification process, this broad list of characteristics was initially organized into four sub-areas: *Geometric Design, Roadway Objects, Roadside Environment*, and *Operational*. Some of the characteristics included in the table are intended to be general descriptive indicators of the roadway environments being analyzed and, as such, not all of them are included in the complexity analysis, as further noted throughout the remainder of this report.

Table 3-1: Roadway Characteristics Classified across Roadway Environment Images

Sub-areas	Roadway Characteristics		
Geometric Design	Freeway/highway/uninterrupted flow facility, Arterial/collector facility, Residential streets, Rural/local roads, Vertical curves, Horizontal curves, Number of lanes, Narrow/constrained lanes, Two way left turn lane, Bike lanes, Bus only lane, Paved shoulders, Railroad-at-grade crossing		
Roadway Objects or Markings	Bridge infrastructure, Streetcar/light rail infrastructure, Streetcar/light rail vehicles, Tunnels, Bus turnouts, Buses/coaches, High occupancy vehicle facilities, Overhead signs, Medians, Decorated/vegetated medians, Crosswalks/pedestrian crossing zones, Grade-separated pedestrian crossing, Work zones, Trucks/heavy vehicles, Pedestrian refuge island, Centerline (no passing), Centerline (passing), Barrier separated, Scenic/artistic overhead bridge infrastructure		
Roadside Environment	Urban/rural, Mailboxes, Driveways, Roadside buildings, Parked cars, Emergency vehicles (side), Sidewalk, Guardrail, Roadside vegetation, Noise barriers/fencing, Retaining wall, Erosion control/silt fences, Pedestrians, Cyclists, Static signage, Dynamic signage, Billboards, Telephone wires/poles, Streetlights, Curb and gutter, Hydrants, Drainage channels/side slopes		
Operational	Time of day: low light versus daylight, Weather: snow/rain/fog versus clear conditions, Signalized intersections, Unsignalized intersections, Roundabouts, Entrance/exit ramps and interchanges, Ramp meters, Toll gates/bridge crossings, Heavy traffic, Emergency vehicles behind/front or passing, Work zone diverges/maneuvering, Pavement: potholes/road plates/poorly maintained pavement, Pavement markings: faded/unusual, Non–work zone delineation devices, Low traffic, No traffic		

Sources: Highway Safety Manual, NCHRP Report 600: Human Factors Guidelines for Road Systems, AASHTO: A Policy on Geometric Design of Highways and Streets, Highway Capacity Manual, Manual for Uniform Traffic Control Devices

3.2 Factor Analysis of Roadway Characteristics in Roadway Environments

Exploratory factor analysis (EFA) was applied within this study to reduce the 70 variables cataloged across the 100 static roadway environments. EFA is an established technique for reflecting common or underlying correlations (i.e., similarities and differences) within a set of observed variables. For example, roadside buildings, driveways, and mailboxes are intuitively related, meaning that the presence of one may increase the probability of the others being present in the environment.

3.2.1 Resolving Issues Using EFA

Highly correlated variables can affect regression models by confounding the estimated coefficients and increasing standard errors. Additionally, the 100 roadway environments and 70 variables are a large number of parameters to estimate relative to the number of observations; this occurrence often produces over-fitted models that are applicable only to the specific data set under study. Finally, interpretation of a model with 70 variables becomes highly cumbersome. EFA allows for a variable reduction, easing the ability to draw meaningful results from the model. A discussion of EFA procedures can be found in Rummel (1970).

3.2.2 Applying EFA to Roadway Environment Variables

Prior to executing EFA, the research team removed roadway environment variables with 5 or fewer occurrences across the 100 static roadway environments images, and consolidated several variables that were highly correlated with each other. Table 3-2 provides the final list of roadway environmental variables used in subsequent modeling.

Sub-areas	Roadway Characteristics
Geometric Design	Freeway/highway/uninterrupted flow facility, Arterial/collector facility, Rural/local roads, Vertical curves, Horizontal curves, Number of lanes, Narrow/constrained lanes, Paved shoulders
Roadway Objects or Markings	Bridge infrastructure, Overhead signs, Medians, Decorated/vegetated medians, Crosswalks/pedestrian crossing zones, Work zones, Trucks/heavy vehicles, Centerline (no passing), Centerline (passing), Barrier separated
Roadside Environment	Urban/rural, Driveways, Roadside buildings, Parked cars, Sidewalk, Guardrail, Roadside vegetation, Noise barriers/fencing, Pedestrians, Static signage, Telephone wires/poles, Streetlights, Curb and gutter, Hydrants, Drainage channels/side slopes
Operational	Time of day: low light versus daylight, Weather: snow/rain/fog versus clear conditions, Signalized intersections, Heavy traffic, Work zone diverges/maneuvering, Pavement markings: faded/unusual, Non–work zone delineation devices, Low traffic, No traffic

Table 3-2: Final Roadway Characteristics Used for Factor Analysis

Researchers used IBM SPSS Statistics 22[®] to analyze for factors among the remaining 42 variables. Optimization of the resulting factors was conducted using maximum likelihood extraction along with a promax oblique rotation to improve interpretability of the factors. After factor determination, Cattell's scree plot was used to determine the significant factors, and five factors were retained representing 31.2% of the variance present across the roadway environment test results. A limitation of EFA is that the resulting rotated factors require an independent examination to give them a common, or descriptive, meaning. Based on examination of the factor basis, these five factors were interpreted as: *Urban Arterial Environments, Roadside Restrictions, Environmental Conditions, Multilane and Median-Separated Facilities*, and *Moderate Vehicle Density*. The roadway characteristics that had strong correlations with these five factors are

detailed in Table 3-3. Table A-1 in the Appendix presents the rotated pattern coefficients for the five factors retained in the factor analysis solution. The factor scores from this factor analysis (which were calculated in SPSS using regression) were then used to develop predictive models of perceived complexity.

Retained Factors	Interpretation
Factor 1 : Urban Arterial Environments	This factor had high correlations with roadway characteristics such as curb and gutter, sidewalks, crosswalks, street lights, parked cars, roadside buildings, urban environments, pedestrians, signalized intersections, etc.
Factor 2 : Roadway Restrictions	This factor had high correlations with barrier-separated directions of travel and non–work zone delineation devices, and correlated somewhat with the presence of work zones.
Factor 3 : Environmental Conditions	This factor had high correlations with trucks/heavy vehicles, bad weather, poorly maintained or hard-to-see pavement markings, and dimly lit conditions. It had a negative correlation with the presence of street lights
Factor 4 : Multilane, Median- Separated Facility	This factor correlated strongly with the presence of medians or decorated medians on a facility with greater than three lanes in both directions of travel. It had negative correlations with double yellow centerlines, barrier-separated, and urban/rural facilities.
Factor 5 : <i>Moderate Vehicle Density</i>	This factor correlated strongly with the low traffic variable, with an equally strong negative correlation on the no traffic variable. Thus, this factor was interpreted to represent the presence of other vehicles in the roadway environment, but does not indicate at-capacity conditions.

Table 3-3: Retained Roadway Environment Factors from EFA

To aid in understanding and interpreting the factors, Table 3-4 provides an image with a high positive value, neutral value (i.e., the image is neither highly positive correlated nor negatively correlated with the factor), and negative value for each factor.

Retained Factors	Example Image with Low Ratings on Corresponding Factors	Example Image with Neutral Ratings on Corresponding Factors	Example Image with High Ratings on Corresponding Factors
Factor 1 : Urban Arterial Environment			
Factor 2: Roadway Restrictions			
Factor 3: Environmental Conditions			
Factor 4: Multilane, Median- Separated Facility			
Factor 5: Moderate Vehicle Density			

Table 3-4: Sample Low, Median, and High Roadway Images associated with Five Factors

3.3 Predictive Model of Driver-perceived Complexity of Static Roadway Environments

A linear modeling approach was implemented for this analysis by taking the mean rating across repetitions of each image for each participant, followed by a further aggregated mean across participants for each roadway environment image. As shown in Chapter 2, statistically significant differences do exist between the distributions of the participant groups, complexity question, and image type. However, the trends were similar across each of these groups. Thus, the first models (Model 1 and Model 2) explore the effects of the five factors across an aggregation of all data, with subsequent models exploring the various groupings. Although, given the strong trend in lower complexity levels across simulated images relative to on-road images, an additional binary *Image Type* variable is included where a simulated image is coded as 0 and on-road image is coded as 1. Table 3-5 presents Model 1, the linear regression coefficient estimates for significant predictors across all data with main factors only, and Table 3-6 presents Model 2, the linear regression coefficient estimates for significant predictors with main factors and two-way interactions allowed.

Significant Predictors	$\widehat{m{eta}}$ Estimates	Std. Error	t value	Pr (> t)
(Intercept)	2.03	0.13	15.62	< 0.001***
Image Type [†]	0.34	0.15	2.20	0.03*
Urban Arterial	0.27	0.07	4.10	< 0.001***
Roadside Restrictions	0.19	0.06	2.93	0.004**
Environmental Conditions	0.47	0.07	6.74	< 0.001***
Multiple R-Squared: 0.48 * p<0.05, ** p<0.01, *** p<0.001				

 Table 3-5: Model 1 – By-Image Linear Regression Coefficient Estimates for

 Significant Predictors with Main Factors Only

[†] Image Type variable binary value is 0 for Simulated and 1 for On-Road images

Table 3-6: Model 2 – By-Image Linear Regression Coefficient Estimates for
Significant Predictors with Main Factors and Two-Way Interactions Allowed

Significant Predictors	β Estimates	Std. Error	z value	Pr (> z)
(Intercept)	2.02	0.14	14.68	< 0.001***
Image Type [†]	0.60	0.16	3.78	<0.001***
Urban Arterial	0.24	0.07	3.62	<0.001***
Roadside Restrictions	0.22	0.07	3.06	0.003**
Environmental Conditions	0.40	0.07	5.89	<0.001***
Multilane Median-Separated Facility	-0.21	0.08	-2.77	0.007**
Roadside Restrictions: Multilane Median-Separated Facility	-0.32	0.15	-2.15	0.03*
Roadside Restrictions: Moderate Vehicle Density	-0.15	0.06	-2.60	0.01*
Environmental Conditions: Multilane Median-Separated Facility	-0.20	0.09	-2.27	0.02*
Multiple R-Squared: 0.55 * p<0.05, ** p<0.01, *** p<0.001				

^{\dagger} Image Type variable binary value is 0 for Simulated and 1 for On-Road images

For linear regression coefficient estimates with main factors only (see Model 1, Table 3-5) the *Image Type* (simulated vs. on-road) and three of the five factors (*Urban Arterial, Roadside Restrictions*, and *Environmental Conditions*) were retained.

A high coefficient, relative to the other variables, for the *Image Type* indicates that the simulated images were more likely to have a lower rating than the on-road images for the given image set. There are several possible contributors to these lower ratings. First, the characteristics found in the simulated images (e.g., the 70 characteristics outlined in Table 3-1) may differ from the on-road images, contributing to lower complexity levels. Second, lower ratings may be at least partially an artifact of the simulator image rendering (i.e., the simulated images are more "crisp" than the on-road). Third, an unknown factor(s) may be influencing the complexity ratings. While the underlying cause for the lower complexities of the simulator images is uncertain, the findings indicate a potential bias in that simulator scenarios may be failing to capture sufficient complexity when used to evaluate real-world treatments.

Of the retained factors, *Environmental Conditions* had the highest coefficient, indicating the importance of the presence of heavy vehicles, inclement weather, and lighting conditions. Interestingly, the highest *Environmental Conditions* factor values were for the simulator inclement weather images, highlighting weather conditions as a possible means to increase complexity in a simulator scenario. The *Urban Arterial* factor indicates that as the urban characteristics of an image increased (i.e., sidewalks, curb and gutter, roadside buildings, pedestrians, etc.) participants tended toward higher complexity ratings. Likewise, absence of these characteristics in an image resulted in a negative *Urban Arterial* factor value, contributing to a lower complexity rating. This trend was

most prominent for rural images and open-freeway images. Finally, *Roadside Restrictions* (i.e., barrier separation, delineation devices, work zones, etc.) also contribute to higher complexity rating, potentially indicating the impact of an increasingly constrained roadway image. These restrictions were most common in the freeway images. This will be further explored when considering two-way interactions.

Table 3-6 provides linear regression coefficient estimates when including main factors and two-way interactions (Model 2). Each of the factors in the initial main factors-only model remain: *Image Type*, *Urban Arterial*, *Roadside Restrictions*, and *Environmental Conditions*. Allowing two-way interactions in the model resulted in the addition of the *Multilane Median-Separated Facility* main factor and the following interactions: *Roadside Restrictions* with *Multilane Median-Separated Facility*, *Roadside Restrictions* with *Multilane Median-Separated Facility*, and *Environmental Conditions* with *Multilane Median-Separated Facility*.

In this model, the potential reduction in perceived complexity resulting from facilities with multiple lanes or a median (i.e., *Multilane Median-Separated Facility*) is seen. This potentially further indicates how a sense of openness in the image can reduce complexity. This concept is strengthened by the *Roadside Restrictions* with *Multilane Median-Separated Facility* interaction. This interaction has high positive values when both factors are negative, that is, rural conditions. Thus, this interaction term, having a negative model coefficient, acts to reflect a reduction in perceived complexity for the rural images.

The *Roadside Restrictions* with *Moderate Traffic Density* interaction indicates a reduction in complexity when moderate traffic exists on a facility with roadside

32

restrictions, relative to very low or congested traffic conditions. The potential likelihood is that the other vehicles on the roadway offer directional guidance. This interaction term has the highest influence on freeway images, while the interaction factor values tended to be small or negative in the more urban and rural environments. Finally, the *Environmental Conditions* with *Multilane Median-Separated Facilities* interaction again demonstrated that the presence of a more open space may partially negate the additional complexity of environmental conditions.

3.4 Effects of Experience on Driver-perceived Complexity of Static Roadway Environments

The National Highway Traffic Safety Administration (NHTSA) reported that in 2013 drivers between the ages of 15 and 20 represented approximately 13% of all drivers involved in police-reported crashes, and 9% of all drivers involved in fatal crashes; however, they comprised only 6% of the driving population (NHTSA 2015). Previous research has indicated that crash rates for young drivers decline rapidly as these drivers gain experience and skills, yet motor vehicle crashes remain the leading cause of death for this age group. Understanding the differences between these and more experienced drivers may lead to improvements in driver training that could have significant safety benefits. As a result, the research team made an intentional effort to expand data collection efforts to include young drivers (i.e., the high school sample) in the experiment. The young driver demographic obtained as part of these efforts is examined within this section to understand further the perceptual differences based on varied lengths of time elapsed following licensure.

3.4.1 Background and Motivation: Young Drivers

The acquisition of a driver's license for millions of teenagers around the United States and the world often represents a long-awaited achievement of independence and adulthood. Unfortunately, this rite of passage is accompanied by sobering statistics that have plagued the young-driver demographic for decades. It is well known that crash rates for teenage drivers are higher than for drivers in most other age groups (Massie, Campbell, and Williams 1995; Williams 2003; Underwood 2007; McCartt and Teoh 2015; Mayhew, Simpson, and Pak 2003), leading to a disproportionate representation of teenage drivers in motor vehicle injuries and fatalities (NHTSA 2015). Hundreds of research studies have examined causes for these statistics, many of them observing that crash rates decline rapidly over the first six months to one year after licensure, but still remain higher than crash rates for other age demographics (Williams 2003; McCartt and Teoh 2015; McCartt, Shabanova, and Leaf 2003; Mayhew, Simpson, and Pak 2003; Lee et al. 2011). Experience and maturation are believed to be largely responsible for this initial rapid reduction in crash rates in the months following licensure (Williams 2006; Underwood 2007; McCartt, Shabanova, and Leaf 2003; Mayhew, Simpson, and Pak 2003). However, it has also been found that as young drivers gain skills and confidence, they begin engaging in riskier behavior such as shorter headways and increased speeds (Chapman, Underwood, and Roberts 2002; Brown and Groeger 1988).

With the understanding that experience plays a significant role in the reduction of crash rates, this study examined potential differences in visual perception of complexity for roadway environments between young drivers with varying lengths of elapsed time following licensure. Several differences in visual search patterns between novice and experienced drivers have been documented in the literature, chief among those being that novice drivers have shorter eye fixations; smaller search areas; more vertical, as opposed to horizontal, search patterns; greater dependency and fixations on lane markers; and fewer fixations to their mirrors (Yang, Jaeger, and Mourant 2006; Mourant and Rockwell 1972; Mourant and Rockwell 1970; Crundall and Underwood 1998). Possible explanations for the decreased eye fixations of novice drivers revolve around greater cognitive workload for tasks such as lane-keeping behavior and speed adherence (Yang, Jaeger, and Mourant 2006; Mourant and Rockwell 1972). Additionally, novice drivers have been found to experience longer periods of peripheral narrowing, while more experienced drivers show shorter periods of more intense peripheral degradation during demanding stimulation in the foveal (i.e., front) field of view (Crundall, Underwood, and Chapman 2002; Crundall and Underwood 1998). Because visual search and visual demand have been shown to play causal roles in crash risks and fatalities under many different roadway conditions, differences in visual behavior between driver groups with varied experience levels are important to consider in the overall study of perception in roadway environments (Green 2002; Divekar et al. 2013).

3.4.2 Overview of Participants' Experience Levels

Table 3-7 and Table 3-8 summarize the experience levels for the four participant samples in the static roadway environments experiment. The high school participants were asked to report the length of time following licensure in months, while the college and festival participants reported length of their driving experience in years. All study participants were required to have at least two years of driving experience, with the exception of the high school participants. Both the high school and college-level samples in this study may be classified as young drivers; thus, this study examined perceptual differences between driver groups based on elapsed time following licensure, and does not extrapolate conclusions regarding impacts of age or maturation on driver perception.

License Type	Approximate Time following Licensure (months)	High School Participants
Learner's Permit	0	15% (16)
	1 – 6	28% (30)
	7 – 12	24.3% (26)
Driver's License	13 – 18	20.6% (22)
	19 – 24	10.3% (11)
	24+	1.9% (2)
Total		100% (107)

 Table 3-7: High School Participants' Time after

 Licensure (months)

 Table 3-8: College-level and Festival Participants' Experience Levels (years)

Approximate Time following Licensure (years)	College Participants (Urban)	College Participants (Rural)	Festival Participants	Experience Level Totals
< 5 years	69.0% (29)	84.2% (32)	10.3% (11)	39.8% (72)
5 – 10 years	28.6% (12)	10.5% (4)	15.9% (17)	18.2% (33)
11 – 15 years	2.4% (1)	2.6% (1)	22.4% (24)	14.4% (26)
> 15 years	0% (0)	2.6% (1)	45.8% (49)	27.6% (50)
Participant Totals	23.2% (42)	21.0% (38)	55.8% (101)	100% (181)

3.4.3 Analyzing Perceived Complexity Differences based on Experience

Figure 3-1 summarizes ratings distributions for the high school participants according to lengths of time following licensure in months, aggregated across complexity

question and image type. Figure 3-2 summarizes ratings distributions for the college-level and festival participants, who reported time following licensure in years, again aggregated across complexity question and image type. Chi-squared (χ^2) analyses indicated significant differences between the participant samples in these ratings distributions: $\chi^2 = 608.5$, df = 12, p < 0.001, $\alpha = 0.05$ for Figure 3-1; and $\chi^2 = 665.1$, df = 12, p < 0.001, $\alpha = 0.05$ for Figure 3-2, respectively. In both rating distributions, the participant demographic group with the least time following licensure had the greatest density of perceived complexity ratings of 1, and the participant demographic group with approximately the most time following licensure had the greatest density of perceived complexity ratings of 5 (on the complexity scale of 1 to 5).









In this section, median differences between corresponding images were compared across several of the groups with varied times following licensure (Figure 3-3, Figure 3-4, and Figure 3-5), again aggregated across complexity question and image type. To perform these analyses, median ratings for each participant in the respective group being examined were first calculated, followed by the median rating for each image across participants. Figure 3-3 presents a comparison between the median ratings of the 100 images for the high school sample relative to the college and festival participants. The high school participants can be considered novice drivers (i.e., less than two years of driving experience), while the college and festival participants were required to have at least two years of experience, and are considered more experienced drivers. The median differences were calculated by subtracting the median responses for each image for the novice sample

from the more experienced sample median responses. For example:

Median Difference for Image 1 =

College/Festival (Experienced) Drivers' Median Rating for Image 1 - High School (Novice) Drivers' Median Rating for Image 1

Thus, as shown in Figure 3-3, high school drivers rated 31% of the images as less complex relative to the more experienced college and festival participants. The sign test, a nonparametric test of paired median differences, resulted in significant differences in median ratings for the novice versus experienced driver comparison (n = 100 images, $p < 0.001^{***}$, $\alpha = 0.05$). This finding was similarly reflected in Figure 3-4, which shows that 28% of images were rated as less complex by drivers with 1–6 months of experience relative to drivers with 7–12 months of experience (n = 100 images, p = 0.04*, $\alpha = 0.05$).

In Figure 3-5, 53% of the images were rated as less complex by drivers with <5 years of experience relative to drivers with >15 years of experience; and the sign test once again reported significant differences between these participant demographic groups (n = 100 images, p < 0.001***, α = 0.05). Overall, these results suggest¹ that more experienced drivers tended to rate roadway images as more complex than novice drivers. However, as seen in Figure 3-6, these effects are most pronounced for the lowest and highest age ranges captured. When considering the middle ranges (i.e., from 1 to 15 years) there is no clear trend in perceived complexity.

¹ In the execution of the sign test, instances where median differences between questions were found to be 0 were randomly allocated as positive or negative signs. There is statistical debate over the best method to treat median differences of 0 in nonparametric statistics; this method of random allocation is currently accepted as a good choice for removing ties while reducing bias (Kvam and Vidakovic 2007).

















3.4.4 Exploring the Effects of Time following Licensure on Predictive Models

This section explores differences in predictive models of perceived complexity for participants with varied lengths of time following licensure. The models developed here are variants of the original predictive model presented in Section 3.3, extended to encompass different age demographics within the participant samples. Model 3 (Table 3-9) includes all participants (as in Section 3.3), with the addition of a non-interactive predictor (i.e., independent variable) that distinguishes between the high school participants and the other participants (i.e., college and festival). This new variable (called Experience Demographic Membership in the model) was found to be a significant predictor in Model 3 (see Table 3-9), indicating that participant membership in these groups influences perceived complexity ratings of the roadway environments. Similarly, a second model (Model 4) includes only the high school participants with 1 to 12 months following licensure, where the *Experience Demographic Membership* variable distinguishes between the 1 to 6 month and the 7 to 12 month group (see Table 3-9). The Experience Demographic Membership variable has a negative estimated coefficient in both Model 3 and Model 4, indicating that the overall perceived complexity ratings decrease in the lower experience groups, a finding consistent with those reported in Section 3.4.3.1.

In addition, the coefficients for Model 3 and Model 4 are similar, indicating both groups are influenced in a similar manner by the various factors. However, Model 4 (including high school students with 1 to 12 months of licensure) has a lower intercept, indicating the overall bias of this group to a lower complexity. Also, in Models 3 and 4

the main factor *Moderate Traffic Density* and the two-way interactions of *Urban Arterials* with *Roadside Restrictions*, *Environmental Conditions*, and *Moderate Traffic Density* are significant, which was not the case in Model 2 (i.e., main factors and twoway interactions across all participants). This implies that the younger drivers have a higher relative awareness of complexity in the urban environment, while not perceiving the complexity as the more experienced drivers do in the rural and freeway environments.

To explore these findings further, separate regression models were executed for high school participants only (Model 5), college/festival participants only (Model 6), 1-6 months following licensure participants (Model 7), and 7-12 months following licensure participants (Model 8). Significant predictors for these varied participant subsamples are summarized in Table 3-10 and Table 3-11. Table 3-10 shows that the significant predictors were generally the same in the separate regression models for the high school participants (Model 5) versus the college and festival participants (Model 6), with small variations in estimated coefficients for the predictors. The primary exception being that the impact of urban conditions was not significant for Moderate Traffic Density and the Urban Arterial with Environmental Conditions interaction, further indicating the lower perceived complexity of younger drivers in non-urban environments. The models detailed in Table 3-11 for high school participants in the 1-6 month time period following licensure (Model 7) relative to high school participants in the 7-12 month period following licensure (Model 8) again had factor coefficients similar to Model 2 (across all participants). However, the intercept values are again lower, supporting the observation of a bias to lower perceived complexity in the younger participants.

Significant Predictors	Model 3: w/ HS and College/Festival Experience Demographic Membership Variable (288 subjects, n = 100 images)	Model 4: w/ HS with 1–6 and 7–12 months licensure as Experience Demographic Membership Variable (56 subjects, n = 100 images)
	Estimate (significance)	Estimate (significance)
(Intercept)	2.11 (***)	1.96 (***)
Simulated (0) / On-Road (1)	0.58 (***)	0.56 (***)
Experience Demographic Membership Variable (younger drivers 1/more experienced drivers 0)	-0.15 (*)	-0.13 (p=0.07)
Urban Arterial	0.28 (***)	0.30 (***)
Roadside Restrictions	0.29 (***)	0.27 (***)
Environmental Conditions	0.42 (***)	0.42 (***)
Multilane Median-Separated Facility	-0.27 (***)	-0.28 (***)
Moderate Vehicle Density	0.13 (**)	0.13 (**)
Urban Arterial: Roadside Restrictions	0.13 (**)	0.13 (**)
Urban Arterial: Moderate Vehicle Density	0.21 (**)	0.24 (**)
Urban Arterial: Moderate Vehicle Density	-0.09 (*)	-0.09 (p=0.06)
Roadside Restrictions: Multilane Median-Separated Facility	-0.35 (***)	-0.34 (***)
Roadside Restrictions: Moderate Vehicle Density	-0.17 (***)	-0.16 (**)
Environmental Conditions: Multilane Median-Separated Facility	-0.27 (***)	-0.29 (***)
* p<0.05, ** p<0.01, *** p<0.001	Multiple R-Squared: 0.63	Multiple R-Squared: 0.63

Table 3-9: Linear Regression Predictive Model 3 and Model 4 with Time following Licensure as an Independent Variable

Significant Predictors	Model 5: HS (107 subjects, n = 100 images)	Model 6: College/Festival (181 subjects, n = 100 images)		
	Estimate (significance)	Estimate (significance)		
(Intercept)	1.93 (***)	2.08 (***)		
Simulated (0) / On-Road (1)	0.57 (***)	0.61 (***)		
Urban Arterial	0.29 (***)	0.22 (**)		
Roadside Restrictions	0.21 (**)	0.22 (**)		
Environmental Conditions	0.42 (***)	0.42 (***)		
Multilane Median- Separated Facility	-0.27 (***)	-0.21 (**)		
Moderate Traffic Density	0.13 (*)	—		
Urban Arterial: Environmental Conditions	0.21 (*)	_		
Roadside restrictions: Multilane Median- Separated Facility	-0.34 (*)	-0.32 (*)		
Roadside Restrictions: Moderate Vehicle Density	-0.14 (*)	-0.15 (*)		
Environmental Conditions: Multilane Median- Separated Facility	-0.27 (**)	-0.20 (*)		
	Multiple R-Squared: 0.61	Multiple R-Squared: 0.58		
* p<0.05, ** p<0.01, *** p<0.001				

 Table 3-10: Linear Regression Predictive Model 5, High School Only, and Model 6

 College/Festival Only High School Participants versus College/Festival Participants

	Model 7: 1–6 Months (30 subjects, n = 100 images)	Model 8: 7–12 Months (26 subjects, n = 100 images)
Significant Predictors $(\alpha = 0.05)$	Estimate (significance)	Estimate (significance)
(Intercept)	1.82 (***)	1.90 (***)
Simulated (0) / On-Road (1)	0.55 (***)	0.59 (***)
Urban Arterial	0.24 (***)	0.30 (***)
Roadside Restrictions	0.19 (*)	0.21 (**)
Environmental Conditions	0.39 (***)	0.44 (***)
Multilane Median-Separated Facility	-0.22 (**)	-0.27 (***)
Traffic Density	—	0.14 (*)
Urban Arterial: Moderate Vehicle Density		0.22 (*)
Roadside Restrictions: Multilane Median-Separated Facility	-0.29 (*)	-0.32 (*)
Roadside Restrictions: Moderate Vehicle Density	-0.15 (*)	-0.12 (*)
Environmental Conditions: Multilane Median-Separated Facility	-0.20 (*)	-0.27 (**)
	Multiple R-Squared: 0.56	Multiple R-Squared: 0.62
* p<0.05, ** p<0.01, *** p<0.001		

Table 3-11: Linear Regression Predictive Model 7, High School with 1–6 months following Licensure and Model 8, High School with 7–12 Months following Licensure High School Participants: 1–12 Months following Licensure

3.4.5 Implications of Findings

This study shows that drivers with varied lengths of time since licensure, particularly those with the least (under 12 months) versus those with the highest (over 15 years) have statistically significant differences in ratings of perceived complexity, but generally appear to perceive specific roadway factors similarly within roadway environments. The exception is that younger drivers' perceived complexity tended to be

more influenced by the difference between urban and non-urban environments. As noted, more experienced drivers tended to rate images as more complex than novice drivers, demonstrating a possible impact of experience on driver perception and/or visual search patterns, as discussed in detail above. This study supports the existing literature suggestions that time elapsed following licensure may play a role in driver behavior differences, while raising the possibility that some of these differences may be attributed to perceived complexity and visual perception variances between novice and experienced drivers. However, confounded in this finding is that, for the given data, time elapsed following licensure is highly correlated with age, thus it is not possible with these data to distinguish between influence of age and the driving experience on perceived complexity.

In addition, multiple factors potentially influenced perceived complexity. For example, environmental conditions had some of the highest impacts on perceived complexity. Also, drivers had a tendency to rate images with rural characteristics as less complex and urban characteristics as more complex. Similarly, a greater sense of openness in an image decreased perceived complexity, with younger drivers being most sensitive to this factor. As an illustration, roadside barriers increased perceived complexity, while a multiple-lane facility could have the opposite influence. A potential correlate of this observation could be the younger drivers are failing to perceive the complexity (i.e., risks) of driving in non-urban environments, thus increasing their likelihood of an incident. This observation may highlight a need to place more emphasis on highlighting the challenges of rural and freeway conditions in driver education aimed at younger drivers and is worthy of additional research. For freeway facilities, moderate traffic also had the potential to provide path guidance, reducing perceived complexity. Previous efforts by the research team also explored the importance of the development of work zone delineation devices forced on path guidance. The complexity findings provide additional support to the need to strengthen the path identification aspects of traffic control devices.

Finally, for the given image set, there is a bias toward lower perceived complexity on the simulated images. This could indicate that simulator studies may potentially fail to capture the complexity of the real world. While it is critical that future efforts explore the potential impact of this finding on the transferability of simulator results to the real world, the next section of this report will provide and summarize the initial insights regarding this topic from the current study.

3.5 Perceived Complexity of Simulated vs. On-road Environments

Driving simulation is widely accepted to be an important research tool in a wide array of fields, but the application of research findings often hinges on simulator validation and fidelity. However, simulator validation studies frequently indicate relative differences in driver behavior (Blaauw 1982; Godley, Triggs, and Fildes 2002; Törnros 1998; Mullen et al. 2011; Kaptein, Theeuwes, and van der Horst 1996; Riener 2010). Given that the perception of roadway complexity has been found to impact drivers' behavior and performance (Young et al. 2009; Horberry et al. 2006; Brookhuis, de Vries, and de Waard 1991; Schiessl 2008; Teh et al. 2014; Zeitlin 1995; Edquist, Rudin-Brown, and Lenné 2012; Stinchcombe and Gagnon 2010; Paxion, Galy, and Berthelon 2014), the research team hypothesized that relative differences reported in simulator validation studies may be influenced by differences in driver-perceived complexity of simulated versus on-road environments.

3.5.1 Simulator Fidelity and Validation

Since the initial development of vehicle simulation, beginning with flight simulators in the early 20th century, rapidly increasing computational power and technological advances have facilitated continued research and development in the arena of improved simulator fidelity (Page 2000; Fisher et al. 2011; Allen 2000; Allen, Rosenthal, and Cook 2011). Fundamentally, simulator fidelity is defined from the perspective of the driver, and is a measure of the realism of the simulated experience, relative to on-road driving. It is often decomposed into physical, psychological, and perceptual fidelity, all of which examine the ability of the simulator to provide relevant cues that mimic on-road driving. Despite noteworthy advances in simulator fidelity, fundamental differences between onroad and simulated driving remain, and those disparities have not yet been remedied through technological progress. These disparities include: (1) perceptual limits, such as spatial and temporal resolution; (2) physical limits, such as restricted range of motion; and (3) psychological limits, such as motivators for driving (i.e., driving for a purpose) that are difficult to replicate in simulator experiments (Greenberg and Blommer 2011; Ranney 2011; Andersen 2011; Espie, Gauriat, and Duraz 2005). As such, persistent constraints in fidelity may also contribute to remaining gaps in driver behavior between simulator and on-road environments (Ranney 2011). Attempts to control for resolution, luminance, and contrast limitations of driving simulator monitors relative to real-world visual capabilities were considered in the design of the study presented here; therefore, static images were used in an attempt to reduce visual fidelity limitations as a potential confounding factor between simulated and on-road metrics in this study (Andersen 2011).

Concurrent with research and development in simulator fidelity, simulator validation studies have been, and continue to be, executed with the goal of examining the suitability of various simulators for use in driver training, as well as for widespread applications in medical, psychological, and engineering research (Allen, Rosenthal, and Cook 2011; Mullen et al. 2011). Simulator validity is most frequently defined along physical and behavioral lines. Physical validity indicates the exactness of the simulator in reproducing the on-road vehicle and behavioral validity represents the consistency of driver behavior such as speed, lateral deviation, and brake onset between simulator and on-road environments (Mullen et al. 2011). The large body of literature makes it apparent that simulator validation is a significant research hurdle, exacerbated by evidence that validation is specific to the task, scenario, and simulator, and differs depending on the objective of each study (Allen, Rosenthal, and Cook 2011; Mullen et al. 2011; Kaptein, Theeuwes, and van der Horst 1996; Riener 2010). However, the challenges of simulator validation are not novel to researchers in this field. As a result, many studies target relative validity, which refers to scale and directional consistencies between simulator and on-road driving behavior and performance, as sufficient for the specific purposes of the research (Blaauw 1982; Godley, Triggs, and Fildes 2002; Törnros 1998; Mullen et al. 2011; Kaptein, Theeuwes, and van der Horst 1996; Riener 2010). As such, the researchers in this study hypothesized that differences in driver-perceived complexity of simulated roadways relative to on-road environments could contribute to the relative disparities in driver behavior that are often reported in simulator validation studies.

3.5.2 Analysis of Perceived Complexity Ratings of Simulated versus On-road Environments

Perceived complexity ratings across the participant samples are analyzed and discussed within this section, with a focus on differences between simulated and on-road environments.

3.5.2.1 <u>Range of Complexity in On-road and Simulated Roadway Environments</u>

One objective of this portion of the study was to identify the respective ranges of complexity that can be achieved in simulated roadways as compared to on-road environments. The data summary presented in Table 2-3 illustrates that participants responded in the range of 1 to 5 for both on-road and simulated roadway environment images, regardless of the question posed or participant sample. This implies that it is possible to design simulated roadway environments that may be perceived to achieve complexities over a range similar to that of on-road environments. Given that in the experimental design, the selection of images for the on-road and simulated roadway environments cannot be verified as existing in the same proportions for each rating level (i.e., 1, 2, 3, 4, and 5), statistical comparisons (e.g., chi-squared tests of independence for categorical variables) between simulated and on-road environment images are not meaningful and, thus, are not considered. However, statistical analyses on a between-question and between-institution basis for simulated versus on-road environments are presented in the following sections.

3.5.2.2 Examining Sample Differences in Perceived Complexity Ratings

The distributions of ratings for on-road and simulated roadway environments across the four participant samples are shown in Figure 3-7. The chi-squared analysis for the ratings of perceived complexity between institutions produced significant χ^2 values ($\chi^2 =$ 1010.9 and 374.5, df = 12, p < 0.001, $\alpha = 0.05$), indicating that the distribution of ratings differs significantly between at least some of the different institutional participant samples for both on-road and simulated roadway environments. This suggests that in modeling driver perception in roadway environments, it may be useful to differentiate driver models based on participants' demographic characteristics such as level of driving experience, age group, or land-use characteristics of the group's driving range (i.e., suburban, rural, urban, etc.). Some of this was discussed previously in Section 3.4.



Figure 3-7: Distributions of (a) On-road and (b) Simulated Roadway Environment Complexity Ratings by Institution of Origin

3.5.2.3 <u>Examining Task and Visual Complexity Question Differences in Ratings</u>

Median differences between the task and visual complexity questions (median difference = task complexity median - visual complexity median) for each of the 100 images were calculated to examine response differences between simulated and onroad environments. These median differences are shown in Figure 3-8. Executing the sign test for the simulated roadway environments indicated that there are not significant differences between responses to the task and visual complexity questions for simulated environments in the aggregate data (n = 25 images $\times 4$ samples = 100 images, p = 0.62, $\alpha = 0.05$). On-road environments were found to have significant differences between the questions (n = 75 images \times 4 samples = 300 images, p = 0.013*, α = 0.05), with the results showing that 21.9% of the on-road median differences had greater visual complexity ratings than task complexity ratings, and 16.3% of the median differences represented one rating point of difference in the visual complexity relative to the task complexity ratings. In contrast, 8% of the median differences for simulated environments represented higher visual complexity ratings as compared to task complexity ratings, with 2.7% of those differences showing the visual complexity question as being one rating point above the task complexity question (see Figure 3-8).

These differences between simulated and on-road questions may be attributable to differences in the specific roadway environments that the researchers selected to compose the simulated and on-road image sets used in this experiment. It is also possible that these dissimilarities are due to differences in sample size between the simulated and on-road environments. Regardless, the differences observed here should be taken into consideration when studying on-road versus simulated driver behavior, and should be examined in future studies. As previously noted, median differences of 0 between questions were randomly allocated as positive or negative signs (Kvam and Vidakovic 2007).



Figure 3-8: Median Differences between Task and Visual Complexity Questions for (a) On-road and (b) Simulated Environments

3.5.2.4 <u>Comparing Descriptive Models for Simulated and On-road Environments</u>

Beta-distributed descriptive models were developed and compared for both the simulated and on-road environments, and those results are presented here. For the simulated roadway environments, the coefficient of determination (\mathbb{R}^2) ranged from 0.92 to 0.99, while \mathbb{R}^2 for the on-road environments ranged from 0.81 to 0.995, with the exception of the one previously discussed image (see Section 2.2.2). As such, it was determined that the beta distribution was able to model perceived complexity ratings on a roadway environment basis with excellent goodness of fit across both simulated and on-road environments. The overall variance of the beta-distributed fits for simulated
roadway environments was 0.032, with an adjusted mean of 2.11. Similarly, the overall variance of the beta-distributed fits for on-road roadway environments was 0.035, with an adjusted mean of 2.31. As such, using the mean and variance parameters of the beta-distributed fits supports the conclusion reached earlier regarding the consistency of achievable perceived complexity between simulated and on-road environments. Beta-distributed fits for the simulated and on-road environments are shown in Figure 3-9.



Figure 3-9: Probability Density Functions of Beta-distributed Fits for Perceived Complexities of (a) On-road and (b) Simulated Roadway Environments

3.5.3 Implications from Findings

This study demonstrated that it is possible to achieve the same range of perceived complexity in simulated and on-road environments, given the scale used; however, participants' demographic characteristics and/or the type of complexity of the environment (i.e., task versus visual) may affect driver-perceived complexities of simulated versus on-road environments. The study also indicated that drivers potentially perceive roadway environment factors, such as urban arterial roadways and poor driving conditions, differently in simulated relative to on-road environments for the given image set. These findings indicate that simulator experimental design may be improved through the development of scenarios that are equivalent in perceived complexity to the desired on-road environments, rather than the typical method of scenario creation that focuses on technical and visually similar replication of on-road environments. A better understanding of driver perception differences between simulated and on-road environments can potentially improve the validity of simulator studies. This work lays the foundation for future research on the impact of the roadway environment on driver perception of complexity, behavior, and performance in driving simulated experiments. The next chapter begins the process of determining factors influencing the driver's perceived complexity of simulator scenarios.

4. Driver-Perceived Complexity of Dynamic, Simulated Roadway Environments

This phase of the study aimed to examine driver-perceived complexity of simulated roadway videos using a full factorial experimental design that featured high and low levels of five roadway factors: *Work Zone Treatment, Traffic, Roadway Objects, Lane Configuration,* and *Urban/Rural Environments.* These factors were chosen to align with the roadway factors (i.e., *Urban Environment, Moderate Traffic Density,* etc.) previously discussed, from factors identified in previous efforts by the research team, and from findings from relevant literature.

4.1 Selected Roadway Factors

A discussion of the five roadway factors examined within this experiment is presented in this section. Factor levels were designed based on differential visual and/or task complexity attributes associated with each factor (see Table 4-1).



Table 4-1: Low and High Levels of Roadway Factors

4.1.1 Work Zone Treatment Factor

Work zone channelizing devices were selected as a factor for this experiment based on a series of studies previously executed by the research team. These studies found that driver performance in correctly identifying work zone diverges improved when perceptual Gestalt principles of continuity and closure were applied to work zone channelizing devices. Accuracy in identifying work zone diverges was found to be highest for portable concrete barriers (PCB), which are closed and continuous (i.e., providing the greatest path guidance), and lowest for misaligned work zone drums, which are neither closed nor continuous (Hunter et al. 2014; Greenwood et al. 2016). Similarly, response times were lowest for work zones delineated with PCB, and highest for the misaligned drums (Xu et al. 2015; Hunter et al. 2014). Supporting literature indicates that driver confusion and risk of intrusion into work zones decreases with the use of longitudinal channelizing devices such as PCB (Finley et al. 2011; Bryden, Andrew, and Fortuniewicz 2000). Thus, in this study, the low level of the Work Zone Treatment factor used PCB, while the high level used misaligned (± 2 feet) work drums spaced 40 feet apart.

4.1.2 Traffic Factor

This factor refers to increased vehicles and vehicular maneuvers in proximity to the driver. A series of naturalistic and driving simulated studies has found that increased traffic negatively impacts driver performance as measured through:

- increased workload (Brookhuis, de Vries, and de Waard 1991; Teh et al. 2014;
 Schiessl 2008; Zeitlin 1995) and physiological strain (Schiessl 2008);
- decreased speed adherence (Kaber et al. 2012);

- increased deviations from average lane position (Kaber et al. 2012);
- reduced performance on secondary tasks such as the peripheral detection task (PDT) and situational awareness questions conducted while driving (Teh et al. 2014; Schiessl 2008; Kaber et al. 2012); and
- increased probability of collision following an error (Brookhuis, de Vries, and de Waard 1991).

Decreases in performance were exacerbated in situations where a lane change either occurred in close proximity to the driver or the driver was asked to maneuver lane changes (Stinchcombe and Gagnon 2010; Teh et al. 2014; Schiessl 2008). Numerous studies executed using crash reports have found that an increase in average annual daily traffic (AADT) contributes to increases in motor vehicle crashes (Abdel-Aty, Keller, and Brady 2005; Abdel-Aty and Radwan 2000; Milton and Mannering 1998; Hadi et al. 1995; Karlaftis and Golias 2002; Mohamedshah, Paniati, and Hobeika 1993). AADT is also a parameter in the Highway Safety Manual's (HSM) Predictive Method, which quantitatively forecasts crashes for specific types and functional classes of roadways (*Highway Safety Manual* 2010).

This factor differs from the *Moderate Traffic Density* factor as discussed in the static image experiments in Chapter 3. In that analysis, a potential benefit was noted under moderate traffic conditions; however, that was primarily for multilane freeway images. Rural and urban images did not witness similar decreases in perceived complexity, with increases in perceived complexity in some instances. To allow for the factorial design in this experiment, all videos are for four-lane facilities (i.e., two-lane each direction); however, a lane in each direction is restricted for a work zone. This

eliminates the ability to test for the moderate traffic impacts on perceived complexity seen in Chapter 3 in multilane freeway scenarios. Future efforts will seek an experiment design targeted at this factor.

Level of service (LOS), a qualitative characterization of traffic on a scale from A to F, is used to describe the overall nature of travel captured in the high and low levels of this factor (*Highway Capacity Manual Volumes 1 and 2* 2010). The low level of the *Traffic* factor in this experiment approximated LOS A in the opposing lane, where a small number of vehicles (i.e., 9 vehicles per minute per lane) traveled freely and maintained large headways. The high level of the *Traffic* factor approximated LOS D for both the opposing and traveled lanes, and consisted of a steady stream of vehicles (i.e., 36 vehicles per minute per lane) with reduced headways in the opposing lane, as well as a lead vehicle in the lane of travel and a turning vehicle that emerged from a right-hand side street without an appropriate gap to the external driver.

4.1.3 Roadway Objects Factor

The presence of roadway objects reflects existing research that reports negative relationships between increased visual clutter and driver performance measures. Ho et al. found that visual clutter increased reaction time and error rates in a visual search experiment that asked participants to locate specific stimuli in roadway environments (Ho et al. 2001). This concept is reinforced by general visual search theories that indicate that the length of time needed for visual search increases with the presence of increased numbers of objects (Zhang and Lin 2013). Several studies have also examined visual clutter in the form of advertising billboards, finding that it causes drivers to spend more time looking away from the road and, thus, increases reaction time to road signs (Edquist

et al. 2011), and adversely affects lateral control, workload, and speed control for drivers (Young et al. 2009; Horberry et al. 2006). In addition, researchers have found that driver performance is negatively affected in roadway environments such as intersections (Cantin et al. 2009; Hadi et al. 1995; Stinchcombe and Gagnon 2010) and urban roads (Cantin et al. 2009; Edquist, Rudin-Brown, and Lenné 2012; Kaber et al. 2012; Abdel-Aty and Radwan 2000), where visual clutter is inherently greater than in other environments. The *Urban/Rural* factor was examined independently of the *Roadside Objects* factor, and is discussed further in Section 4.1.5.

In the design of this experiment, roadway objects represented construction equipment and workers present in the work zone. The low level of the factor contained no objects in the work zone, while the high level contained cement mixers and dump trucks, as well as stationary and mobile construction workers performing a variety of tasks (see Figure 4-1).



Figure 4-1: Roadway Objects Present in Work Zone

4.1.4 Lane Configuration Factor

In the context of this experiment, lane configuration was manipulated as a representation of increased task complexity, which has also been found to have negative relationships with driver performance. Increased task complexity in roadway literature is commonly described by Fastenmeier's taxonomy, which qualitatively describes levels of roadway complexity as being composed of high/low levels of information processing and vehicle handling demands (Fastenmeier 1995). The scale has been applied in experimental studies that report greater cognitive workloads (Stinchcombe and Gagnon 2010), increased PDT, and increased miss rates when information-processing and vehicle-handling demands are increased (Patten et al. 2006). Additionally, as noted in 4.1.2, the presence of lane maneuvers by vehicles in proximity to the driver or by the driver has been shown to reduce driver performance measures such as workload and PDT performance (Stinchcombe and Gagnon 2010; Teh et al. 2014; Schiessl 2008).

In this experiment, the *Lane Configuration* factor was manipulated with work zone lane closures, increasing in handling (i.e., task) complexity for drivers maneuvering through the work zones. In the low level of this factor, the external lanes in both directions of travel were closed for the roadway construction work zone using temporary traffic control (e.g., work drums or PCB). In the high level, the work zone shifts from the external lane to the internal lane, forcing the vehicle to merge right to avoid the work zone in the left lane of travel. Figure 4-2 provides a closer view of the lane merge conditions for the high level of this factor.

65



Figure 4-2: Left: High Level of Lane Configuration Factor for PCB; Right: High Level of Lane Configuration Factor for Work Drums

4.1.5 Urban versus Rural Roadway Factor

Urban/rural environments represent a common parameter in roadway safety studies; however, individual features of these environments often vary substantially across experiments. For example, Kaber at al. defined urban environments as characterized by increased traffic (i.e., 11 vehicles per minute per lane), pedestrians, densely located buildings, and six lanes of travel. Rural roadways in the aforementioned study featured very low traffic (i.e., 2–3 vehicles per minute per lane), reduced pedestrians and buildings, and four lanes of travel. Kaber et al. reported that the urban environments resulted in reduced situational awareness, reduced speed adherence, and increased lane deviations (Kaber et al. 2012). Edquist et al. defined urban environments as having low setback, dense buildings, absence of green space, and presence of on-street parking, and they reported that the urban environment with empty on-street parking resulted in increased workload, increased lateral deviations from edge of pavement, and more variable and lower speeds relative to the arterial environment studied (Edquist, Rudin-Brown, and Lenné 2012). Stinchcombe and Gagnon examined driver differences in an urban environment with traffic, pedestrians, parked cars, tall buildings, and intersections, as compared to a low-complexity environment that contained none of those features. They found that the urban environment resulted in reduced PDT performance for drivers (Stinchcombe and Gagnon 2010). Within the static image study reported in Chapter 3 the *Urban Environment* consistently contributed to higher perceived complexity scores.

Within this study, the urban/rural differences were limited to buildings, setbacks, and green space. The rural factor was characterized by wide-open green spaces interspersed with vegetation, and the urban roadway environments featured dense buildings along the roadside with low setbacks and sparse green space.

4.2 Experiment Method: Dynamic Roadway Environments

This experiment was conducted at the Georgia Institute of Technology, and Institutional Review Board approval was obtained prior to implementation. Detailed here is a brief overview of participant involvement, followed by experimental design and implementation procedures.

4.2.1 Overview of Participants

The participant pool consisted of students enrolled in undergraduate psychology courses. Participants were reimbursed with extra credit to be applied toward the psychology course in which they were enrolled at the time of the experiment. To be eligible for inclusion, participants were required to hold a valid driver's license, have at least two years of driving experience, and have normal or corrected-to-normal vision. Six participants were removed from the data set; of those, four were removed due to sustained signs of inattention to the experiment (e.g., falling asleep or looking away from the experiment while the video stimuli were playing). An additional two participants were removed from the data set due to observed responses that occurred solely in the first 20% range of the scale provided. The final participant pool for analysis consisted of 63 participants, of whom 52.4% identified as female, 47.6% identified as male, and 96.8% were in the 18–24 age group, with the remainder in the 25–34 age group.

4.2.2 Experimental Design

This experiment was designed as a 2⁵ full factorial experiment with high and low levels of the five roadway factors studied: *Work Zone Treatment, Traffic, Roadway Objects, Lane Configuration*, and *Urban/Rural Environments*. The roadway environment consisted of two lanes in each direction of travel, separated by a double yellow centerline. Depending on the *Lane Configuration* factor, either the internal or external lane in each direction of travel was obstructed by temporary traffic control (i.e., work zone treatments), which resulted in one available lane in each direction of travel (see Figure 4-2). Self-reported ratings of perceived complexity were collected across 32 simulated roadway videos, and each video contained a unique combination of either high or low levels of the five roadway factors (see Table 4-1). Participants saw two randomized repetitions of the 32 videos, for a total of 64 videos over the course of the experiment. The simulated scenarios were designed using the Interactive Scenario Authoring Tool® (ISAT), and videos were recorded using the National Advanced Driving Simulator

MiniSim[®] at a driver-controlled speed of 50 miles per hour. Each video was 20 seconds in length, and began and ended at approximately the same distance stations within the scenarios.

4.2.3 Experiment Implementation

The experiment was implemented using Inquisit® 3, a stimulus presentation and data acquisition platform, which allowed for the presentation of each video, followed by a rating screen. The rating screen consisted of a visual analog (i.e., slider) scale that ranged from low to high complexity, and participants were asked to rate the complexity of the video they had just seen. The experiment began with a waiver of documentation of consent, followed by a Snellen eye exam (i.e., standard eye chart), brief instructional period, and practice video. A self-timed break occurred at the midpoint of the experiment between the two repetitions of videos. The experiment ended with a demographic survey that collected a variety of information including participants' age range, number of years driving, country of licensure, etc. Participants were debriefed following the experiment.

4.3 Results

Presented here is a descriptive model of the ratings' distributions, followed by within-factor, and main and interaction effects analyses on perceived complexity ratings of the dynamic roadway environments shown. The ratings of complexity for each roadway video were obtained on a continuous scale ranging from 1 to 1000 (low to high complexity). To examine ratings distributions, responses were binned in intervals (i.e., bin widths) of 200. This experiment included two replications of the experimental stimuli for which Pearson's chi-squared test of independence indicated no significant differences

69

in the rating distributions ($\chi^2 = 2.7$, df = 4, p = 0.604, $\alpha = 0.05$) between replications (see Figure 4-3). As a result, these replications are combined (i.e., mean rating per video) for each participant for the remainder of the analyses discussed within this paper.



Figure 4-3: Ratings Distributions for Experiment Replications 1 and 2

4.3.1 Descriptive Model of Perceived Complexity

The beta distribution was found to fit the rating distributions for each roadway video well, with R² values ranging from 0.84 to 0.998. Beta distribution parameters were estimated for the ratings distributions using the Statistics and Machine Learning Toolbox in Matlab® 2014, and R: The R Project for Statistical Computing was used to generate and plot the beta-distributed probability density functions for each of the 32 videos in this experiment (see Figure 4-4). Figure 4-4 indicates that the videos generally represented the complexity spectrum provided, taking into account all participants' ratings. Figure 4-5a shows the beta-distributed fit for the complexity ratings of the video with all low

levels of roadway factors ($\mathbb{R}^2 = 0.98$), and Figure 4-5b shows the beta-distributed fit for the video with all high levels of roadway factors ($\mathbb{R}^2 = 0.97$). As previously discussed, the beta distribution is a good choice for modeling perceived complexity ratings because it is a bounded distribution that is described by two shape parameters (α , β) (Hahn and Shapiro 1994). Given that the beta distribution is defined over the interval (0,1), for this experiment, the perceived complexity ratings were binned in intervals of 200 and discretized to simulate the process used for the static roadway environments. A low pass filter was applied to the data to reduce variability within each bin; for example, ratings over the interval 1 to 200 were assigned to the equivalent interval of 0 to 0.2, after which the ratings in this interval were set to 0.1 to represent the midpoint of that interval.



Figure 4-4: Probability Density Functions of Beta-Distributed Fits for Perceived Complexities of 32 Roadway Videos





Figure 4-5: (a) Beta-distributed Fit for Roadway Video with Low Levels across All Factors ($\mathbf{R}^2 = 0.98$); (b) Beta-distributed Fit for Roadway Video with High Levels across All Factors ($\mathbf{R}^2 = 0.97$)

4.3.2 Within-Factor Analyses of Perceived Complexity Ratings

Pearson's chi-squared tests of independence were executed to identify overall ratings distribution differences between the high and low levels of each roadway factor. As summarized in Table 4-2, the ratings distributions differed significantly between the high and low levels for the *Work Zone Treatment, Traffic, Roadway Objects*, and *Lane Configuration* factors. The *Urban/Rural* factor was found to a have a p-value slightly

greater than the significance value of 0.05, and thus the within-factor effect is not reported as significant. Ratings distribution graphs for each factor are shown in Figure 4-6, Figure 4-6, and Figure 4-6.

Roadway	Levels of	(D	R Density o	Pearson's Chi- Squared Test				
Factors	Factors	1– 200	200– 400	400– 600	600– 800	800– 1000	$\alpha = 0.05$	
Work Zone Treatment	High	0.08	0.20	0.37	0.27	0.07	$\chi 2 = 135.7,$	
	Low	0.22	0.27	0.32	0.16	0.02	p < 0.001	
Traffic	High	0.05	0.17	0.40	0.31	0.07	$\chi 2 = 300.9,$	
	Low	0.25	0.31	0.30	0.13	0.01	p < 0.001	
Roadway Objects	High	0.11	0.22	0.35	0.26	0.07	$\chi 2 = 75.4,$	
	Low	0.20	0.25	0.35	0.18	0.02	p < 0.001	
Lane Configuration	High	0.10	0.21	0.35	0.28	0.06	$\chi^2 = 102.7,$	
	Low	0.21	0.26	0.34	0.16	0.02	p < 0.001	
Urban/ Rural	High	0.15	0.23	0.33	0.24	0.05	$\chi 2 = 8.7,$	
	Low	0.16	0.25	0.36	0.20	0.03	p = 0.07	

Table 4-2: Ratings Distribution Comparisons for High/Low Roadway Factor Levels



Ratings Distribution for Workzone Treatment Factor

Figure 4-6: Ratings Distributions for Roadway Factors

Ratings of Perceived Complexity

200-400 400-600 600-800 800-1000

0.0

1-200



Ratings Distribution for Roadway Objects Factor



Ratings Distribution for Lane Configuration Factor

Figure 4-7: Ratings Distributions for Roadway Factors



Ratings Distribution for Urban/Rural Factor



4.3.3 Main and Interaction Effects of Factors

The main and interaction effects of factors in two-level factorial experiments are represented by the difference between ratings averages for low and high levels of each factor (Kutner et al. 2005). Results indicated that all factors yielded positive main effects with *Traffic* having the greatest effect, followed by the effects of *Work Zone Treatment*, *Lane Configuration, Roadway Objects*, and *Urban/Rural* factors (see Table 4-3 and Figure 4-7). Significant interaction effects are also reported in Table 4-3. The positive interaction effects indicate the presence of drums in the work zone with increased lane maneuvering and the presence of drums in the work zone with increased roadway objects result in increased perceived complexity of the roadway environment. The *Urban/Rural* setting also interacted with the *Lane Configuration* factor to increase perceived complexity ratings. The interaction of *Traffic* with *Roadway Objects, Lane*

Configuration, and *Work Zone Treatment*, individually, all resulted in decreased perceived complexity ratings.

Roadway Factors	Effects (High–Low)		
Traffic	169		
Work Zone Treatment	121		
Lane Configuration	98		
Roadway Objects	79		
Urban/Rural	20		
Work Zone Treatment–Roadway Objects	23.2		
Work Zone Treatment-Lane Configuration	20.4		
Urban/Rural–Lane Configuration	15		
Traffic-Roadway Objects	-22.4		
Traffic–Lane Configuration	-18.4		
Work Zone Treatment–Traffic	-12.4		

Table 4-3: Effects Table of Roadway Factors onPerceived Complexity



Figure 4-9: Main Effects of Roadway Factors on Perceived Complexity

4.3.4 Effects of Demographic Variables on Perceived Complexity Rating Distributions

Differences in perceived complexity ratings between gender, driving frequency, and driving experience were also examined. Pearson's chi-squared test of independence indicated no significant differences between ratings distributions for males and females $(\chi^2 = 2.4, df = 4, p = 0.660, \alpha = 0.05)$, but found significant differences across ratings distributions for various weekly driving frequencies of participants ($\chi^2 = 38.3, df = 12, p < 0.001, \alpha = 0.05$). Significant differences were also found for drivers with less than 5 years of experience as compared to drivers with 5 to 10 years of experience ($\chi^2 = 19.8, df = 4, p < 0.001, \alpha = 0.05$). Results from these analyses are summarized in Table 4-4.

Demographic Variables	Question	Percentage of Sample	(D	Chi- Squared Test					
	Choices	(%)	1– 200	200– 400	400– 600	600– 800	800– 1000	α = 0.05	
Gender	Male	47.6	0.16	0.24	0.34	0.22	0.05		
	Female	52.4	0.15	0.23	0.36	0.22	0.04	$\chi 2 = 2.4,$ df = 4, p = 0.66	
	Choose Not to Answer	0	N/A	N/A	N/A	N/A	N/A		
Number of Times Participants Drive per Week	0–1	22.2	0.14	0.27	0.39	0.17	0.03		
	2–5	38.1	0.13	0.23	0.36	0.24	0.05	$\chi 2 = 38.3,$ df = 12, p < 0.001	
	6–10	25.4	0.17	0.23	0.34	0.22	0.04		
	10+	14.3	0.23	0.22	0.26	0.23	0.07		
Driving Experience (years)	< 5	76.2	0.14	0.25	0.36	0.21	0.04	$\chi 2 = 19.8,$ df = 4, p < 0.001	
	5–10	23.8	0.19	0.19	0.31	0.25	0.06		
	11–15	0	N/A	N/A	N/A	N/A	N/A		
	>15	0	N/A	N/A	N/A	N/A	N/A		

Table 4-4: Ratings Distribution Comparisons for Demographic Variables

4.4 Discussion of Findings

Results from this study indicated that *Traffic* had the greatest main effect on perceived complexity ratings, followed by *Work Zone Treatment, Lane Configuration, Roadway Objects*, and the *Urban/Rural* factors. The interactions between *Work Zone Treatment* and *Roadway Objects*, between *Work Zone Treatment* and *Lane Configuration*, and between *Urban* and *Lane Configuration* had positive effects on perceived complexity ratings, although their estimated coefficients are smaller than the previously discussed predictors for the main effects. Thus, the effect on perceived complexity of a change in lane configuration or addition of roadway objects is greater in a work zone with lower path guidance (i.e., drums) than higher path guidance (i.e., PCB).

Similar effects are seen given lane configuration in urban versus rural environments. The interactions between *Traffic* and *Roadway Objects, Traffic* and *Lane Configuration,* and *Traffic* and *Work Zone Treatment* yielded negative coefficients. These results potentially suggest that traffic and these factors are not independent and their impact on perceived complexity is not the sum of each factor's individual impact. The co-existence of traffic with these factors requires an adjustment of the overall perceived complexity of the environment (i.e., not additive effects). This is very similar to ongoing research in crash modification factors where the impact of multiple factors is found not to be multiplicative in the determination of their influence on the number of crashes.

The Urban/Rural factor did not have a significant difference between its ratings distributions (i.e., within-factor analysis) for the low and high levels of this factor. This would appear to be in conflict with the findings from the static experiment results reported in Chapter 3. However, when the static and dynamic experiment results are taken together, this may suggest that the *Urban Environment* factor may not result in a perceived complexity difference in simulated environments, whereas a difference may exist in actual on-road environments. This finding may suggest a perceptual difference between simulated and on-road environments, particularly in urban environments, that should be considered in the design of simulator experiment, all video images contained a work zone. It is also possible that the presence of a work zone is confounded with the urban variable, as many of the urban characteristics (e.g., curb and gutter, lack of shoulders) are muted by the work zone. A secondary study should be conducted to explore the urban variable in a simulated environment without a work zone.

The finding that work drums increase perceived complexity relative to portable concrete barriers could foreshadow a possible reason for the reduction in driver performance in the vicinity of work zones delineated with work drums. This result also agrees well with the research team's previous studies on work zone delineation. Overall, these results provide a foundation for the design of simulator experiments that further examine the effects of traffic and work zone configuration on driver behavior and performance. They also provide an understanding of some of the perceptual shifts that occur in the presence of specific roadway environment factors—shifts that may result in increased risk of likelihood of driver error and, ultimately, crashes.

The chi-squared tests suggest that driving frequency and driver experience are variables that may influence perceived complexity ratings of drivers, and should be monitored in driver behavior and performance studies. The densities of ratings indicate that as driving frequency and experience increases, participants increased their ratings at the extremes, reporting more of the roadway videos as being very simple or very complex. This effect is particularly noticeable in the upper two rating ranges, where the drivers who reported driving 0–1 times per week had fewer ratings than drivers who reported driving 10 or more times per week. This finding is mirrored in the comparison between drivers who have less than 5 years of experience relative to those with 5–10 years of experience. These results are similar to those reported for the static environments experiment, where it was found that experienced drivers (i.e., those with greater than 2 years of experience) perceived *static* roadway environments as being more complex than did drivers with less than two years of experience (Shaw et al. 2015b).

5. Conclusions and Recommendations

Summaries of results from the static and dynamic roadway environments experiments are presented here, followed by potential applications and future research directions.

5.1 Static Roadway Environments Experiments

A primary finding of the static roadway environments experiments was that simulated images, for this data set, were more likely to have a lower rating than the onroad images. While the underlying cause for the lower complexities of the simulator images is uncertain, the findings indicate a potential bias in that simulator scenarios may be failing to capture sufficient complexity when used to evaluate real-world treatments.

Among the factors considered, *Environmental Conditions, Urban Arterial*, and *Roadside Restrictions* were all seen to affect perceived complexity. The *Environmental Conditions* factor highlights the potential importance of the presence of heavy vehicles, inclement weather, and lighting conditions. Interestingly, the highest *Environmental Conditions* factor values were for the simulator inclement weather images, highlighting weather conditions as a possible means to increase complexity in a simulator scenario. The *Urban Arterial* factor indicates that as the urban characteristics of an image increased (or decreased) participants tended to assign higher (or lower) complexity ratings. *Roadside Restrictions* (i.e., barrier separation, delineation devices, work zones, etc.) also contributes to higher complexity rating, potentially indicating the impact of an increasingly constrained roadway image.

The consideration of interaction effects between factors allowed further discernment of how these factors influence a driver's perception. For instance, a sense of openness in the image can reduce perceived complexity. This includes partially negating the additional complexity introduced by environmental conditions. An interesting application of this finding could be support for context-sensitive roadside design guidance that allows for objects closer to the road in some instances. Such objects likely create an increased sense of constraint (i.e., complexity) on the part of the driver and raise the awareness, potentially increasing safety. However, the objects must be traversable and not hinder sight distance, thus limiting potential downside impacts on safety. Future efforts should consider confirmation of this potential application.

For freeway facilities, moderate traffic also had the potential to provide path guidance, reducing perceived complexity. Previous efforts by the research team explored the importance of the development of work zone delineation devices on path guidance. The complexity findings provide additional support to the need to strengthen the path identification aspects of traffic control devices, particularly in work zones.

When considering driver experience, this study shows that drivers with varied lengths of time since licensure, particularly those with the least (under 12 months) versus those with the highest (over 15 years), have statistically significant differences in ratings of perceived complexity, but generally appear to perceive specific roadway factors similarly within roadway environments. More experienced drivers tended to rate images as more complex than novice drivers, demonstrating a possible impact of experience on driver perception and/or visual search patterns. However, confounded in this finding is that, for the given data, time elapsed following licensure is highly correlated with age; thus, it is not possible to distinguish between influence of age and the driving experience on perceived complexity.

Younger drivers' perceived complexity tended to be more influenced by the difference between urban and non-urban environments. A greater sense of openness in an image decreased perceived complexity, with younger drivers being most sensitive to this factor. A potential correlate of this observation could be the younger drivers are failing to perceive the complexity (i.e., risks) of driving in non-urban environments, thus increasing their likelihood of an incident. This observation may highlight a need to place more emphasis on the challenges of rural and freeway conditions in driver education aimed at younger drivers and is worthy of additional research.

5.2 Dynamic, Simulated Roadway Environments Experiment

Results from the dynamic roadway environments study indicated that *Traffic* had the greatest effect on perceived complexity ratings, followed by *Work Zone Treatment, Lane Configuration, Roadway Objects*, and the *Urban/Rural* factors. Also, the effect on perceived complexity of a change in lane configuration or addition of roadway objects is greater in a work zone with lower path guidance (i.e., drums) than higher path guidance (i.e., PCB). This finding could foreshadow a possible reason for the reduction in driver performance in the vicinity of work zones delineated with work drums. This result also agrees well with the research team's previous studies on work zone delineation. Also, many of the factors influencing perceived complexity are likely not independent and their impact on perceived complexity is not the sum of each factor's individual impact. The co-existence of factors requires an adjustment of the overall perceived complexity of the environment (i.e., not additive effects).

Overall, these results provide a foundation for the design of simulator experiments that further examine the effects of traffic and work zone configuration on driver behavior and performance. They also provide an understanding of some of the perceptual shifts that occur in the presence of specific roadway environment factors—shifts that may result in increased risk of likelihood of driver error and, ultimately, crashes.

5.3 Applications of Findings

The findings from this research project can be applied within several contexts to further the safety of multiple driver groups across varied roadway environments. First, the study of perceived complexity differences between simulated and on-road environments showed that while the same range of complexity can be achieved between simulated and on-road environments, simulator studies may need to adjust (e.g., overcomplicate) images to achieve equivalent levels of perceived complexity for the comparable factors in on-road environments. These findings also provide context for interpreting simulator study results, and applying these results to on-road environments.

Overall, the findings support existing driver performance literature and suggest that reduced driver performance observed in the presence of certain roadway factors/attributes may be due in part to an increased risk associated with perception of these factors that is separate from the exposure risk associated with the presence of these factors in the roadway environment.

Additionally, the identification of roadway factors that most significantly influence perceived complexity for various driver demographic groups can be used to guide road safety audits executed for roadway system locations with high crash rates. Finally, this project has shown that integrating the discussion of complex driving environments into driver training for new drivers may benefit this vulnerable demographic of road users.

5.4 Future Directions

The work presented here provides a strong foundation for corollary human factors in transportation engineering research, safety, and operations initiatives. Results from the simulated and on-road environment studies provide a basis for future driving simulator studies to explore in greater detail the most significant factors that were found to influence driver perception, and particularly to make the connection between perception of complexity and driver performance measures such as lane deviations, speed adherence, and cognitive workload. A next step that would also add significant insight to this work is the study of the roadway factors that impact crash rates using available crash data. This knowledge would allow for a deeper understanding of how shifts in transportation system users' psychological and perceptual assessments of their environment affect performance and safety on a larger scale.

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Appendix A: Roadway Characteristics Classification Analysis

Items	Rotated Factor Matrix					
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
Curb and Gutter	1.076	0.282	-0.046	0.036	0.082	
Drainage Ditches	-0.882	0.058	0.019	-0.002	-0.034	
Roadside Buildings	0.846	0.079	-0.054	-0.051	0.044	
Sidewalk	0.824	-0.084	-0.082	-0.015	0.054	
Urban/Rural	0.666	-0.09	-0.17	-0.304	0	
Street Lights	0.527	-0.058	-0.39	-0.101	0.023	
Paved Shoulders	-0.444	0.179	0.164	-0.08	0.154	
Rural Facilities	-0.427	-0.146	-0.163	-0.312	0.039	
Guardrail	-0.413	-0.01	-0.051	0.095	0.247	
Driveways	0.331	-0.083	-0.002	0.109	0.027	
Crosswalks	0.287	-0.086	-0.135	-0.021	0.038	
Barrier-Separated	0.139	1.329	-0.046	-0.338	0.041	
Non–Work Zone Delineation Devices	-0.066	0.828	-0.065	-0.172	0.025	
Trucks/Heavy Vehicles	-0.169	-0.063	0.786	-0.021	0.074	
Weather	-0.216	-0.007	0.627	-0.137	0.096	
Light (Time of Day)	-0.022	-0.112	0.563	-0.158	0.091	
Roadside Vegetation	-0.288	-0.137	-0.319	0.017	0.132	
Hydrants	-0.017	-0.114	-0.136	-0.117	0.073	
Medians	-0.169	-0.343	-0.141	0.985	0.009	
Decorated Medians	0.02	-0.201	-0.07	0.643	0.058	
Double Yellow Centerline	0.004	-0.327	0.141	-0.582	-0.026	

 Table A-1: Rotated Pattern Matrix: Maximum Likelihood Extraction with Promax

 Rotation

Items	Rotated Factor Matrix						
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5		
Number of Lanes	0.068	0.133	0.195	0.31	0.044		
Low Traffic	0.105	0.005	0.122	0.044	0.893		
No Traffic	-0.139	-0.1	-0.158	-0.019	-0.823		
Telephone Wires and Poles	-0.095	0.272	-0.114	0.114	-0.048		
Freeway Facility	-0.238	0.265	-0.179	0.246	-0.023		
Work Zone Diverges/ Maneuvering	0.05	0.017	-0.125	-0.095	0.033		
Work Zones	-0.132	0.361	-0.069	0.032	-0.025		
Constrained/Narrow Lanes	-0.091	-0.192	0.044	-0.11	0.151		
Parked Cars	0.221	-0.054	0.103	-0.076	-0.237		
Heavy Traffic	-0.066	0.125	-0.002	-0.126	-0.091		
Scenic Roadside Attractions	0.188	-0.15	-0.149	-0.017	0.085		
Signalized Intersections	-0.06	0.029	-0.059	0.061	0.036		
Overhead Signs	-0.013	0.171	-0.008	-0.147	0.08		
Centerline: Passing Allowed	-0.007	-0.166	-0.026	-0.015	0.062		
Noise Barriers/Fencing	-0.011	-0.011	-0.011	0.094	0.098		
Bridge Infrastructure	-0.298	0.133	-0.161	-0.229	0.036		
Horizontal Curvature	-0.051	0.2	-0.137	0.112	0.055		
Pedestrians	0.305	-0.049	0.047	-0.046	-0.054		
Pavement Markings	-0.07	-0.158	0.311	-0.093	-0.065		
Arterial Facility	0.489	-0.124	0.247	0.075	0.032		
Static Signage	0.097	-0.24	-0.239	0.122	0.078		
Vertical Curvature	0.009	-0.05	-0.169	0.023	0.02		