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EVALUATION OF DRIVER BEHAVIOR AT HIGHWAY-RAILROAD GRADE CROSSINGS BASED ON ENVIRONMENTAL CONDITIONS AND DRIVER DEMOGRAPHICS

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By

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List of Abbreviations

ANOVA	Analysis of Variance
AWS	Advance Warning Sign
FRA	Federal Railroad Administration
HRGC	Highway-Railroad Grade Crossing
ITS	Intelligent Transportation System
Michigan Tech	Michigan Technological University
MTTI	Michigan Tech Transportation Institute
MUTCD	Manual on Uniform Traffic Control Devices
RID	Roadway Information Database
SHRP 2 NDS	Strategic Highway Research Program 2 Naturalistic Driving Study
TCD	Traffic Control Device
TRB	Transportation Research Board

Abstract

Although the total number of highway-railroad grade crossing (HRGC) accidents has significantly decreased in recent decades, they remain as one of the highest causes of injuries and fatalities in rail transportation. It is known that driver behavior is the leading cause for accidents at HRGCs, but there is less understanding on the reason for these inappropriate behaviors. This research uses the Strategic Highway Research Program 2 Naturalistic Driving Study (SHRP 2 NDS) data and a behavior scoring methodology developed at Michigan Technological University (Michigan Tech), to evaluate driver behavior when traversing HRGCs. More specifically, it uses a two-sample t-test to determine whether there is a statistically significant difference in driver behavior based on weather condition, driver demographics (gender and age) and time of day. It also further divides the HRGCs to three subgroups based on the traffic control devices (TCD) and performs similar analysis for each subgroup.

The research has identified that while statistically significant differences were absent in majority of the tested scenarios, they do exist between some of the compared categories. Especially, both male and female drivers received lower behavior scores during the night compared to the day and female drivers received lower behavior scores under rain and higher behavior scores in snow condition. In contrast to the researcher’s expectation, the data did not show any significant difference in average behavior scores of male versus female drivers. When considering the impact of TCD types on driver behavior, it was found that except for the "snow" condition, there was very little variability between behavior scores under various weather conditions.

Keywords: Highway-railroad grade crossing (HRGC), driver behavior, naturalistic driving study, grade crossing safety.

1 Introduction

1.1 Background

Highway-Railroad Grade Crossings (HRGCs) are locations where a highway (road or street), and its associated pathways and sidewalks, cross one or more railroad tracks at grade. HRGCs are often called level crossings or at-grade crossings in the literature. HRGCs may be public or private. Public highway authorities have regulatory responsibilities to assess the physical condition and safety needs of public HRGCs while private HRGCs are not maintained by public authorities and are not intended to be used by the public. According to the U.S. Federal Railroad Administration (FRA), there was a total of 211,631 public and private HRGCs operating in the United States in 2015 [1].

Together with trespassing incidents, HRGCs accidents have been the greatest source of injuries and fatalities related to rail transportation. From 2010 to 2014, an average of nearly 2,100 accidents per year have taken place at such crossings in the United States, leading into more than 250 fatalities each year [1]. Due to severity of accident at HRGCs, a motorist is 40 times more likely to be killed if he/she is involved in a vehicle-train accident than in any other type of highway collision [2].

Because of numerous safety efforts, the total number of HRGCs accidents has significantly decreased over the last decades. A 30 percent decline was reported in total number of accidents between 2005 and 2009 (Figure 1). However, the number of HRGCs accidents has increased slightly since 2009, most likely due to the traffic volume [1]. Therefore, HRGC accidents continue to levy a heavy toll on the public and the railroad industry.

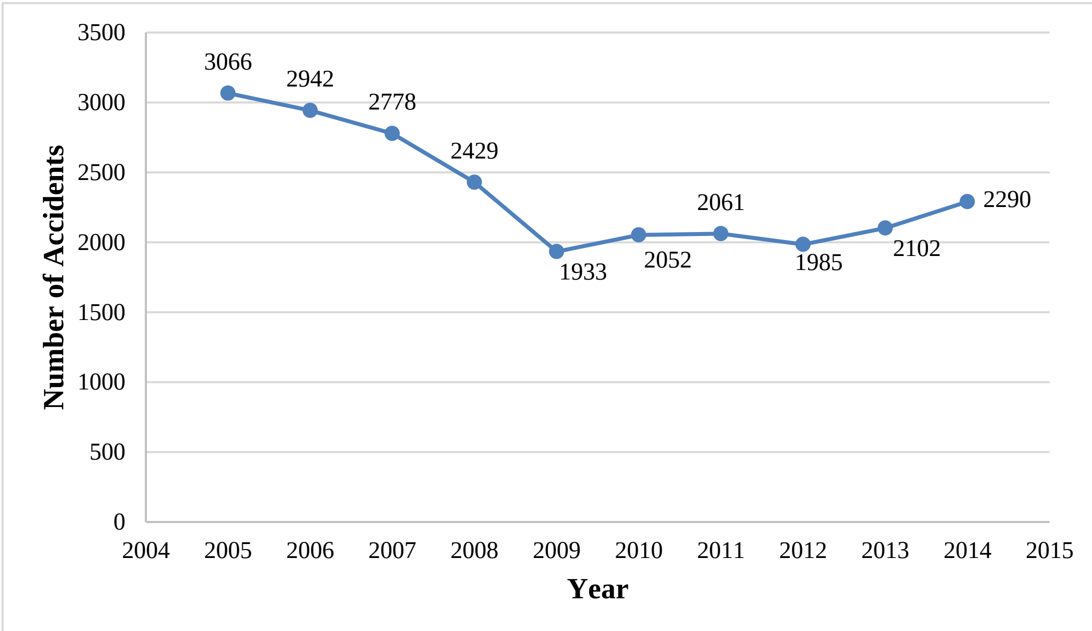


Figure 1. Number of Annual HRGC Accidents, 2005-2014 [1].

Drivers' behavior and their reaction to the surrounding conditions and traffic control devices (TCDs) at HRGCs are key elements in both cause and prevention of accidents. FRA's 2016 report on HRGC accidents shows that 94 percent of train-vehicle collisions can be attributed to driver behavior or poor judgment, implying that risky behavior (or lack of defensive driving) by drivers is likely to increase the possibility of an accident at HRGCs[3]. Previous studies on HRGCs accidents have also indicated several other factors that increase the accident risk at HRGCs. These factors include rail and highway traffic volumes, train speeds, number of tracks and highway lanes, HRGCs angle, TCD type, driver demographics and time of day [1]. Three of the identified factors affecting accident risk at HRGCs and specifically selected for study in this research are weather conditions, driver demographics (gender and age) and time of day.

As driving and responding to TCDs under different environmental conditions are largely visual tasks, poor visibility condition due to the adverse weather (rain, fog, or snow) or nighttime place additional demands on drivers and their ability to collect necessary visual information may be drastically reduced. The driving task involves several activities such as guiding the vehicle within the road, detecting other vehicles and/or non-motorized users, and judging their speed and position. In addition, conditions such as wet pavement, impaired visibility, heavy or frozen precipitation, high winds, and extreme temperatures reduce the capabilities of vehicles [4].

From driver demographics perspective (gender and age), FRA's record of accidents indicates that male and younger drivers were at higher risk of accidents at HRGCs. 70 percent of HRGC accidents within 2005-2014 period involved male drivers and 59 percent involved drivers who were 20 to 49 years of age [1]. Another study performed in Canada found that out of 155 fatal accidents since 1993, 26-64 old male drivers had the highest fatal accident frequency (49%) and female drivers aged 26-64 had the next highest frequency (17.4%) [5].

This study continues the safety investigation at HRGCs, but instead of concentrating on accident events, it uses a large sample of naturalistic driving data from people successfully traversing HRGCs. The goal is to evaluate whether driver behavior during traversals reveals any risky patterns that might explain the higher occurrence of accidents in certain environmental conditions and within certain demographic groups.

The following section describes the problem statement, the research objective and the study hypotheses. Chapter 2 provides a summary of past studies performed on HRGCs safety, human factors contributions to HRGC accidents, environmental impacts on human behavior and driver behavior based on driver demographics (gender and age). The methodology and data sources used in this research are provided in Chapter 3 and the results of the analysis are presented in Chapter 4. Chapter 5 provides a discussion of the results and compares the results with research hypotheses. Chapter 6 contains the research conclusion and recommendations for future research.

1.2 Problem Statement

Previous research on HRGC safety has either used accident reports to predict situations when HRGC accidents are more likely to happen or used traffic volumes and infrastructure conditions as an indicator of the risk level at crossings [1]. In other words, many past studies on HRGCs safety have concentrated on after the fact analysis of accident events. Other methods, such as external video recordings and roadside/in-vehicle observations have also been used, but they provide only partial data of the driving event (internal or external) and tend to have too limited sample sizes for developing large scale trends [6]. One aspect that has not been investigated extensively in the past methods is the numerous potentially unsafe driving events that may have preceded each accident event. It's believed that analysis of driver behavior and better understanding on what different drivers do during daily traversals at HRGCs under various conditions may help in better identification of scenarios that seem to increase the accident risks at HRGCs. If one better understands types of risky behaviors that drivers show at HRGCs and conditions that encourage/increase those risky behaviors, more effective methods to reduce such behaviors and eventually improve safety at HRGCs may become possible.

1.3 Research Objective

The objective of this research was to perform quantitative evaluation on the level of defensive driving behavior during HRGCs traversals. The study uses data from the Strategic Highway Research Program 2 Naturalistic Driving Study (SHRP2 NDS), together with an evaluation methodology developed at Michigan Tech. It concentrates on three key parameters, weather conditions, time of day and driver demographics analysis, and compares the statistical significance of the outcomes at various conditions. The study hypotheses are as follows:

1. Considering the impact of environmental conditions on driving task in general, the research expects that inclement weather conditions (snow, rain, fog) and traversals during night lead into changes in the level of defensive driving.
2. Driver demographics (gender and age) affects driver response to the TCDs at HRGCs, implying that some age and gender categories of drivers could be more

vulnerable to HRGC accidents. The second hypothesis of this study is that there will be a difference in the level of defensive driving between gender and age groups.

3. We expect that driver behavior or the level of defensive driving in non-accident situations align with the findings of previous accident-based studies. If the level of defensive driving is lower under certain parameters, it suggests that one reason for accidents may be in increased level of risky behavior by drivers in such situations.

2 Literature Review

HRGCs safety is a major research topic for the rail industry due to the high concentration of accidents at HRGCs. Much of the past literature has concentrated either on the impacts of various TCDs and other safety technologies, or on the impact of human behavior on HRGC accidents. The following sections will first introduce the current warning systems at the crossings, followed by past studies and methodologies for HRGCs safety research, concentrating on human factors. Finally, specific research on driver behavior as it relates to weather conditions, time of day and driver demographics (gender and age) is reviewed.

2.1 HRGC Safety and Traffic Control Devices

Just like intersecting roads need traffic control devices (TCDs) to guide drivers through conflicting movements and prevent accidents, HRGCs also require TCDs to allow safe and efficient operation of both railway and highway traffic. Since the highway users are always in the yielding position, warnings at HRGCs concentrate on drivers of roadway vehicles. Based on the type of TCDs recommended by the Manual on Uniform Traffic Control Devices (MUTCD), TCDs can be divided into two categories: active and passive warning [7, 8]. Passive TCDs are the minimum traffic control applications that must be installed in all grade crossings, however, an engineering and traffic investigation is required to determine the need and application of active devices at any given highway-rail grade crossing [9]. The need and selection of traffic control devices at a HRGCs is determined jointly by the railroad company, highway agency and authority with jurisdiction [5].

Passive and active warning devices at HRGCs can be further broken down into additional subcategories, as outlined in Figure 2. TCDs with passive warning devices have been divided to three different categories, crossbuck only, crossbuck with stop sign, and crossbuck with yield sign. For HRGCs with active warning devices, two different categories have been considered in this research: HRGCs with flashing lights only, and HRGCs with both flashing lights and gates.

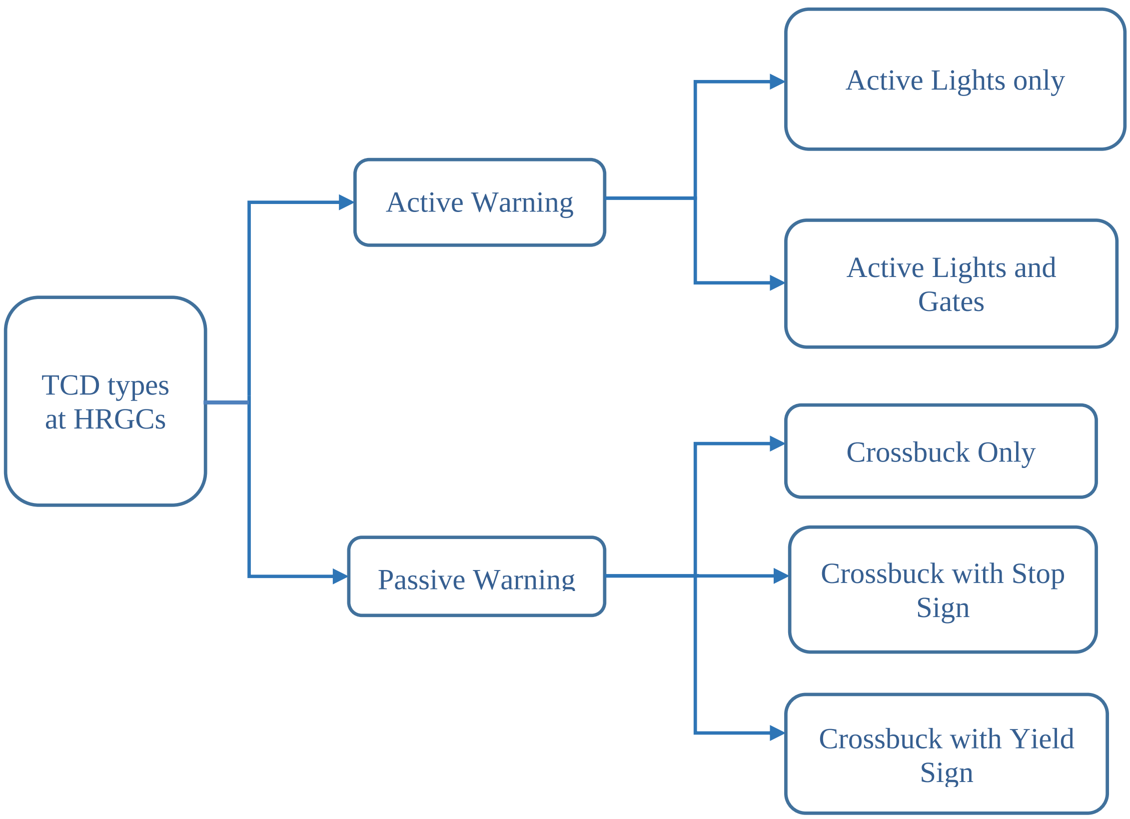


Figure 2. Breakdown of HRGCs Warning Devices.

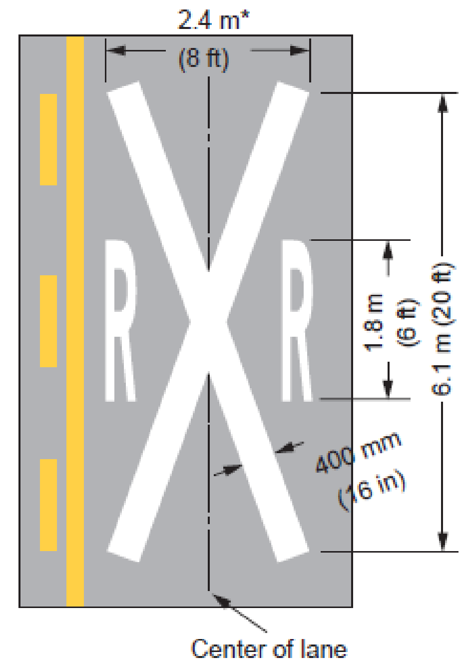
2.1.1 HRGCs with Passive Warning Devices

HRGCs with passive TCDs provide stationary warning devices that do not change in response to train presence. Their message remains constant and drivers are expected to obey the traffic signs and exercise defensive driving to cross safely [8]. The lack of active warning devices at HRGCs places the responsibility of safety on the drivers. Table 1 lists the most common traffic control devices present at passive HRGCs.

Table 1. Common Traffic Control Devices for HRGCs with Passive TCDs [10].

TCD Name	Sign
W10-1: Advance Warning Signs	
R15-1: Crossbuck	

Crossbuck with Yield Sign and Number of Tracks	
Crossbuck with Stop Sign and Number of Tracks	

HRGC Pavement Marking	

On the approach to the HRGCs, the driver must first be aware that HRGC exists. Drivers must be warned of a HRGCs presence early enough so they have time to scan for trains and stop in time if necessary [5]. The round, yellow advance warning sign (AWS) is designed to provide such awareness before each HRGC [7]. Sight distance, including the visibility down the tracks in each direction, is critical to the driver before reaching the crossing. Trees, buildings, and geometry should not be within the recommended sight distances to facilitate the detection of approaching trains by drivers [9].

In addition to the AWS, pavement markings warn drivers of the approaching HRGC. AWS and pavement marking locations depend on posted speed, environment, and road type. The crossbuck sig provides the final indication to the driver about to the HRGCs. In addition, a multiple track sign under the crossbuck tells the driver the number of tracks to expect when there is more than a single track. Stop lines are required at all HRGCs and indicate where the driver should stop.

2.1.2 Active Warning Devices and Other Safety Applications

At HRGCs with active warning devices, the passive warning devices are complemented with bells, flashing lights and in many cases gates. Additional active warnings, such as wayside horns may also be present. In a HRGC with active traffic control devices, a warning system begins functioning only when a train approaching the HRGC is detected. Figure 3 shows an example of flashing lights and gates used with active TCDs.

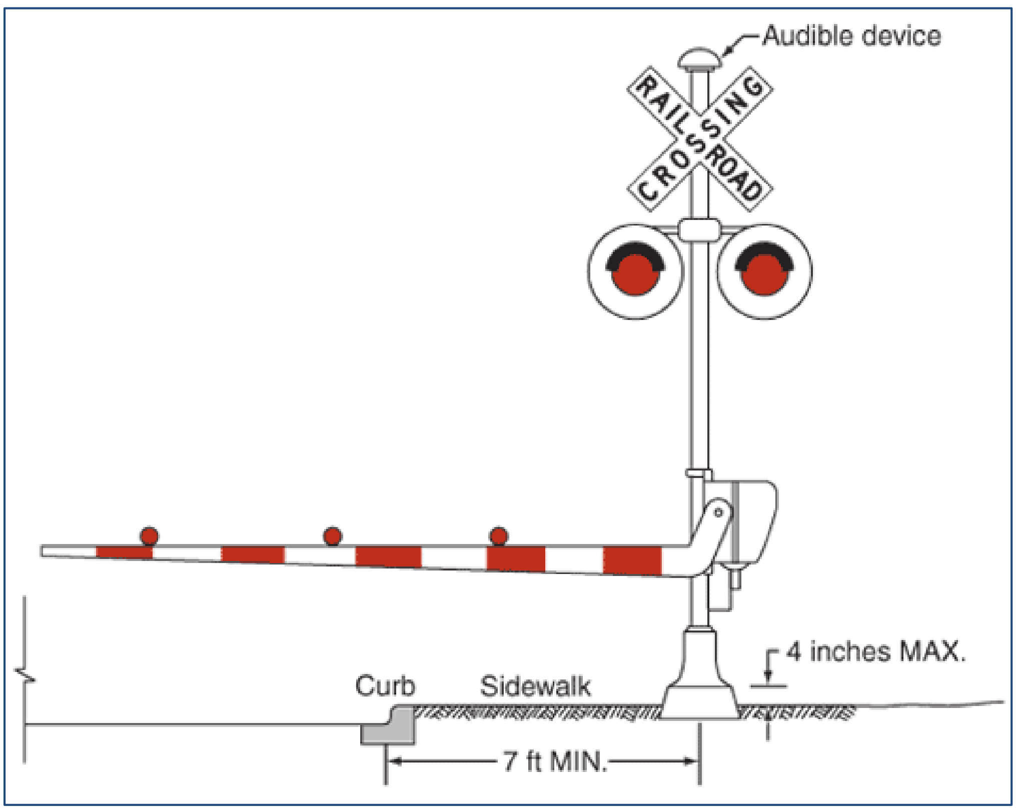


Figure 3. Active HRGC with Lights and Gates [10].

Conversion of HRGCs from passive to active TCDs has proven to substantially reduce the number of accidents, but it has not eliminated all the accident at HRGCs. In addition, upgrading each passive grade crossing to active TCDs costs several hundred thousand dollars (from $100,000 to over $400,000), so it is not feasible to upgrade all crossings to include active HRGCs [5, 11]. Therefore, despite the higher safety risk of HRGCs with passive TCDs, they will remain a part of the rail transportation network for the distant future.

In addition to using conventional TCDs at HRGCs and grade separation when it is feasible, there has been many other efforts and advancements in using recent technologies such as intelligent transport system (ITS) to improve safety and efficiency of traffic at HRGCs. As the crossings used for this study did not have any such technologies implemented, those are excluded from the literature review and discussion.

2.2 Past Studies on HRGC Safety

Literature review revealed four main research approaches that have been used in the past for HRGCs safety and driver behavior analysis at HRGCs. Past work by Muhire identified these methods and some of the shortcomings of each one for the evaluation of driver behavior at HRGCs (Table 2) [6].

Table 2. Methodologies used in the Past to Study HRGC Safety [6].

Method	Name	Approach	Disadvantage
1	Post-accident Analysis	Uses statistical analysis of the reports describing conditions at which accidents have happened.	Accident Frequency at HRGC is extremely low compared to the number of traversals. The data obtained from accident report may not represent "average" driver behavior at HRGCs.
2	External Data Recording	Cameras and sensors are used to record vehicle movements traversing HRGCs. Videos are analyzed later to determine factors contributing to HRGC safety.	This method collects data about the vehicle rather than driver action. Driver behavior or action can't be obtained from recorded videos, only vehicle movement parameters.
3	Roadside Observation	A live researcher collects data on driver behavior and vehicle movement through a roadside direct observation.	This also collect data about the vehicle rather than driver behavior. In addition to that, the results and recommendations from this type of study cannot be applied in areas other than the specific locations where the research has been performed.
4	Direct Observation	This method places a live observer inside the vehicle to record driver action during HRGCs traversals.	Presence of a researcher in the vehicle influences driver behavior from a naturalistic condition to a situation where the driver is performing in a test condition. Also, complexity of creating such studies typically limits the sample sizes.

Much of the past literature related to driver behavior at HRGCs has focused on an analysis of accidents that has occurred. Post-accident analysis method tries to infer accident cause from the analysis of statistics describing the condition at which the accident has happened. For example, the accident data from 393 HRGCs in California found that male drivers were involved in 75% of accidents between 2000-2004 [12]. In a similar manner, FRA's 2017 accident report found that most of HRGCs accidents happen when weather is clear [1]. However, the same report also shows that the accident frequency at HRGCs is extremely low (around one accident per 14 million traversals) when compared to the total number of traversals at these locations. Therefore, the post-accident analysis method fails to present a comprehensive and reliable understanding of accident causes and human factors behind accidents at HRGCs.

External data recording procedure is also used by researchers to perform analysis of safety at HRGCs [13, 14]. In this method, the data is recorded from outside the vehicle during HRGCs traversals by means of video cameras and/or sensors and analyzed later to determine factors contributing to safety. The main shortcoming of this method is its concentration on information about the vehicle movements rather than the driver actions and behavior inside the vehicle. In addition, the outcomes of this type of study only apply to conditions existing at the particular HRGC studied.

In the third method, a human researcher collects data on driver behavior and vehicle movement through a roadside observation. This method is mostly used in small-scale projects, mainly due to cost limitations of extensive studies. This method has the same shortcoming as the external data recording procedure, as data collected from roadside observation could be only about the vehicle movements rather than the driver action and the results and recommendations cannot be applied in areas other than the specific locations where the research was performed [15].

The fourth method places a human observer inside the vehicle to record driver performance and action during traversing HRGCs [15]. Even though this method provides data from direct observation of the driver behavior, the presence of a researcher in the vehicle has been proven to influence driver behavior, creating a situation where the driver is aware that they are performing in a test condition [6].

All methodologies discussed tend to have limitations, such as poor reliability of the data gathered, human errors, and/or high cost of implementation. Naturalistic driving studies that monitor driver behavior using in-vehicle cameras/sensors provide yet another promising methodology for driver behavior analysis that avoids many of the previously mentioned drawbacks [6]. The technique allows the observation of driving behavior under conditions as close to normal situations as possible by taking advantage of various technologies and by performing the data collection over an extended period of time without a presence of other humans [16]. Although the cost of implementing the naturalistic driving study method can be significant, the accuracy and completeness of data received is expected to be high. The data recorded over the course of study is then available for further analysis in the future. For instance, a naturalistic driving study conducted in 2014 revealed that young driver crash risk increases with the duration of longest glance away from the forward roadway [17].

2.3 Highway-Railroad Grade Crossing Safety Research

As noted earlier, a variety of past studies have investigated HRGCs safety. In the U.S., the 1994 HRGC Safety Action Plan introduced a 10-year goal to reduce HRGCs accidents and fatalities by 50 percent (to less than 2,500 accidents and 300 fatalities). Another example of safety related actions was the State Highway-Rail Action Plans that were required from ten states with the highest number of HRGCs accidents over a 3-year period (2006, 2007, and 2008) [18, 19]. Despite all efforts in the past decades, HRGC safety is still a major safety concern and an average of 2,100 HRGCs accidents were recorded in the United States from 2010 to 2014, most of them involving a collision between a motor vehicle and a train [1].

Rail human factors research has grown over the past two decades [20] and driver behavior continues to be a research topic of interest as a contributor to the HRGCs safety [8]. Several studies in literature have linked human factors and the HRGC accidents and have tried to understand a meaningful relationship between driver risky behaviors and HRGCs accidents. FRA's 2008 report, for example, shows that a large portion of HRGCs accidents results from the driver error [21] One study used 5,528 public HRGCs extracted from FRA database and explored a comprehensive list of risk factors including driver demographics (age and gender). The study found that female drivers were in a higher risk of injuries and fatalities compared to male drivers and showed that young and middle aged drivers were in less risk of injuries and fatalities at HRGCs [22]. However, a more recent report by FRA in 2017 showed that male and younger drivers were at much higher risk of accidents [1].

Evaluating the relationship between the TCDs at HRGCs and driver behavior, a study conducted by Tey, Ferreira and Wallace indicated that drivers behave differently with respect to different warning systems and revealed the weaknesses of passive warning devices at HRGCs [23]. Another study found that drivers' low expectancy of hazardous conditions at HRGCs resulted in failure-to-recognize the presence (or approach) of a train in passive grade crossings [24]. A driving simulator study performed at the University of Tennessee also found that there were less violations if "Stop" signs were used at HRGCs. In addition, drivers were more likely to look for an upcoming train, reduce speed and/or stop, when compared to either cross buck signs or yield signs [10].

In addition to gender and age characteristics, human factors such as fatigue, destructions and familiarity have been proved to affect driver behavior at HRGCs. An Australian study in 2000 indicated that 86 percent of drivers killed in HRGCs accidents were people who lived close to the accident location, implying that familiarity of HRGC may be a contributing factor [23]. In 2002, an extensive study in Canada analyzed HRGC safety using 19 years of HRGCs accident records. Figure 4 summarizes the main HRGCs accident contributors found in this study [5].

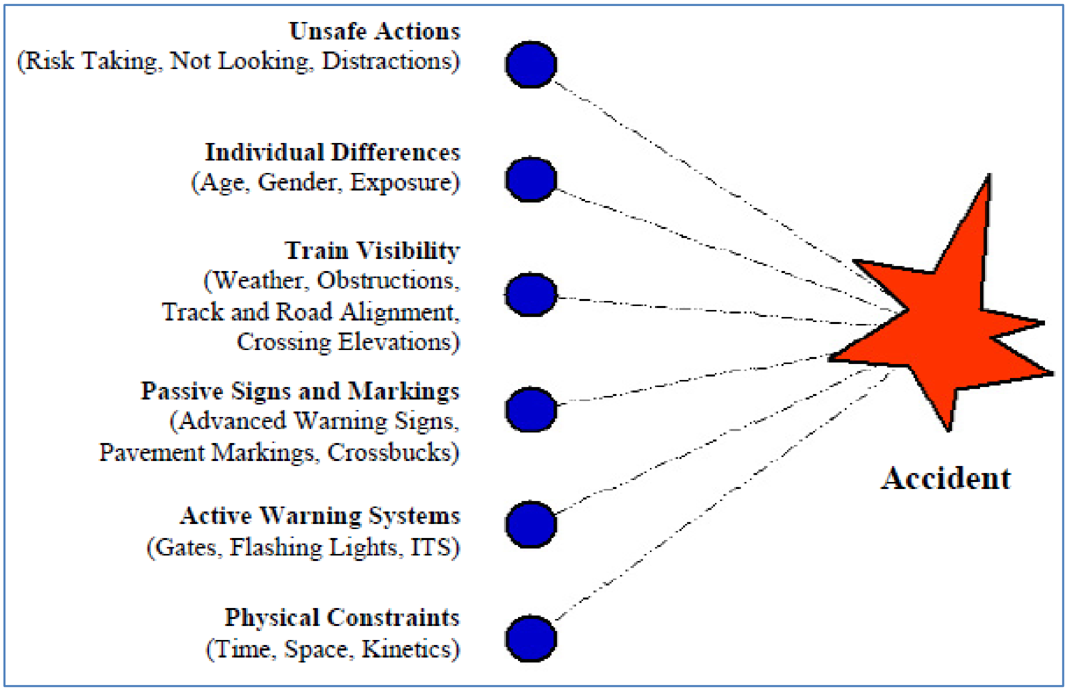


Figure 4. HRGCs Accident Contributors [5].

Investigating the causes on why HRGC safety has improved over the past the 30 years, a study performed by Mok and Savage found that 40 percent decrease in the number of collisions and fatalities at HRGCs is due to factors external to the HRGCs, such as reduced drunk driving and improved emergency medical response. Another study of driver behavior at 37 HRGCs in Michigan revealed the possible association between past crash histories and traffic violations, suggesting that driver violations data may be used to develop countermeasures to improve safety at HRGCs [13].

2.4 Role of Weather Conditions on Driver Behavior and Safety at HRGCs

Several studies have been completed related to weather impact on driver behavior in highways, as well as at HRGCs. One study of US public grade crossings used FRA data and examined ten years of accidents nationwide (1998 to 2007) and found that collisions are more likely to occur during the day and in clear weather conditions [13].

FRA's 2017 accident report [1] on HRGCs accidents also indicated that most accidents between 2005-2014 occurred when the weather was clear with good visibility (Table 3). The study concluded that weather condition has smaller but not negligible effect on accident frequency at HRGCs.

Table 3. Number of Accidents by Weather Conditions, 2005-2014 [1].

		Year											
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total	%
Weather	Clear	2,165	2,089	1,932	1,699	1,343	1,384	1,409	1,436	1,447	1,526	16,430	69.5%
	Cloudy	581	550	554	450	371	419	420	373	417	471	4,606	19.5%
	Rain	187	201	176	153	134	131	135	122	144	163	1,546	6.5%
	Fog	45	46	44	36	25	40	21	21	30	32	340	1.4%
	Sleet	11	14	4	10	4	2	4	3	2	11	65	0.3%
	Snow	77	42	68	81	56	76	72	30	62	87	651	2.8%
		3,066	2,942	2,778	2,429	1,933	2,052	2,061	1,985	2,102	2,290	23,638	100.0%

In general, studies have found that precipitation impacts pavement friction, visibility distance and lane obstruction, causing a reduction in roadway capacity and traffic speed and increasing both delays and accident risks [13]. Studies also show that visibility challenges (clear day, fog, etc.) resulting from different weather situations have higher impact on driving performance of older adults [4].

A study in Shanghai, China, found that rainy conditions result in significantly negative impacts on traffic safety, as driver visibility is affected during the rain [25]. Table 4 presents a risk index developed in the study to indicate the driving safety risk under each weather condition. The index used the percentage of accidents divided by the percentage of days in corresponding weather category as its foundation and suggested that snowy and rainy conditions ranked first and second on the list, implying driving under these two conditions could be much riskier compared to other weather conditions.

Table 4. Risk Index Analysis under Different Weather Condition [25].

	Weather conditions	Sun	Rain	Fog	Cloud	Snow	Strong Wind
Annual accident distribution	Number of accidents	794	117	111	32	26	5
	Percentage(%) of accidents	73.18	10.78	10.23	2.95	2.40	0.46
Annual weather distribution	Number of days	273	25	42	16	5	4
	Percentage(%) of days	74.79	6.85	11.51	4.38	1.37	1.10
Average daily accident rate		2.91	4.68	2.64	2.00	5.20	1.25
Risk index		0.98	1.57	0.89	0.67	1.75	0.42

2.5 Role of Time of Day on Driver Behavior and Safety at HRGCs

Previous studies and accident reports indicate that time of day has impact on accident frequency at grade crossings. Street lights at grade crossings have been shown in a study to reduce nighttime vehicle train accidents by 52 percent over no lighting. This indicates that low visibility or perceptual difficulties during the night increase the accident risk at HRGCs [5]. In a report released in 2017, FRA compares the percentage of HRGCs accidents from 4pm to 8pm in December (when it is generally dark outside) with the percentage of accidents within the same period of time in June (when it is still light outside) from 2004 to 2015 [1]. The report shows higher percentage of accidents from 4pm to 8pm in December compared to June showing that darkness is most likely responsible for the higher number of accident in December for the studied hours. In order to exclude the impact of weather condition differences for December and June, the study evaluated darkness effects in northern and southern states separately and found that darkness has impact on both regions.

2.6 Driver Demographics Role on Safety at HRGCs

Drivers' age and gender have been identified as contributing factors to violations of driving rules at HRGCs, which in turn are strongly related to accident likelihood at these locations[23]. It has also been found that braking responses at road intersections are gender and age-related, but little research has been conducted specifically on braking at HRGCs [23].

Attitude and driving style are found to be affected by gender and age. FRA's investigation based on drivers' behavior studies from 1990-2006 indicated that male drivers were involved in more HRGCs accidents (77 percent of fatal accidents) and committed more violations than female drivers (64 percent). Young and older drivers were also reported to be involved in more HRGCs accidents than middle-aged drivers [21]. After normalizing the grade crossing accidents by the mile traveled and calculating the relative age risk, FRA's 2017 report shows that male drivers were still involved in more accidents in HRGCs (nearly 75 percent) compared to female drivers (Figure 5) [1].

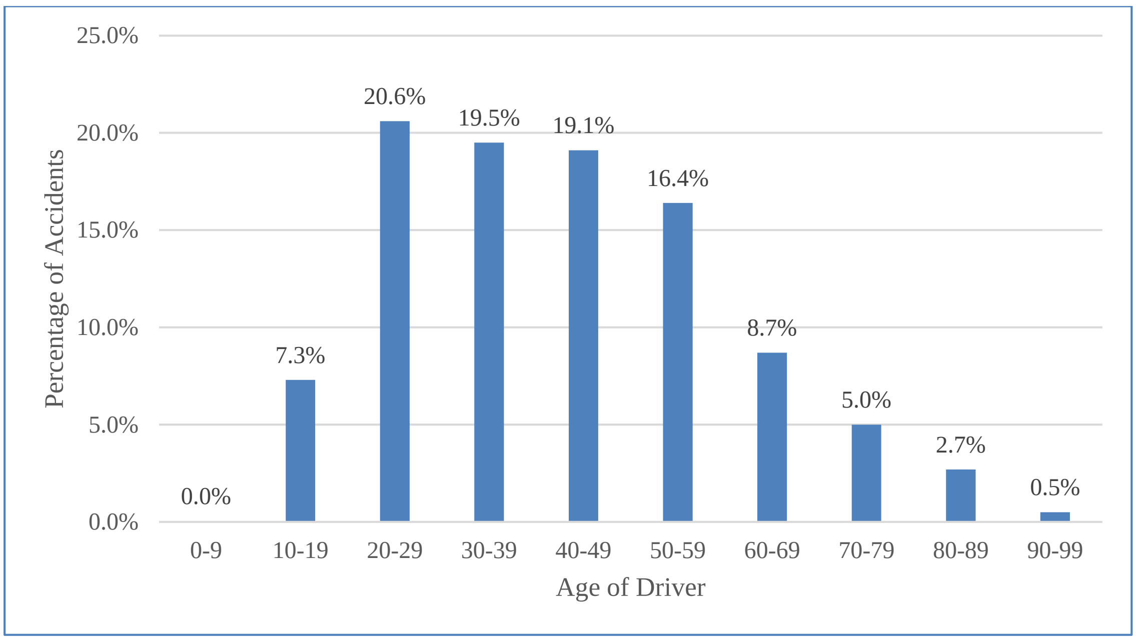


Figure 5. HRGC Accidents by Age Group, 2005-2014 [1].

A Canadian study also indicated that male drivers (aged 26-64) had the highest fatal accident frequency at HRGCs (49 percent) and female drivers (aged 26-64) had the second highest accident frequency (17.4 percent) [5].

Another study, performed in California on crash data for 393 public HRGCs from 2000-2004 found that male drivers were overrepresented in 12 out of the 13 age categories, with an overall average of nearly 75% [26]. Figure 6 shows that for male and female drivers, the age groups of 26-30 and 31-35 has the highest number of accidents respectively, although the number of accidents for female drivers are still much lower than the number of accidents for male drivers in all categories.

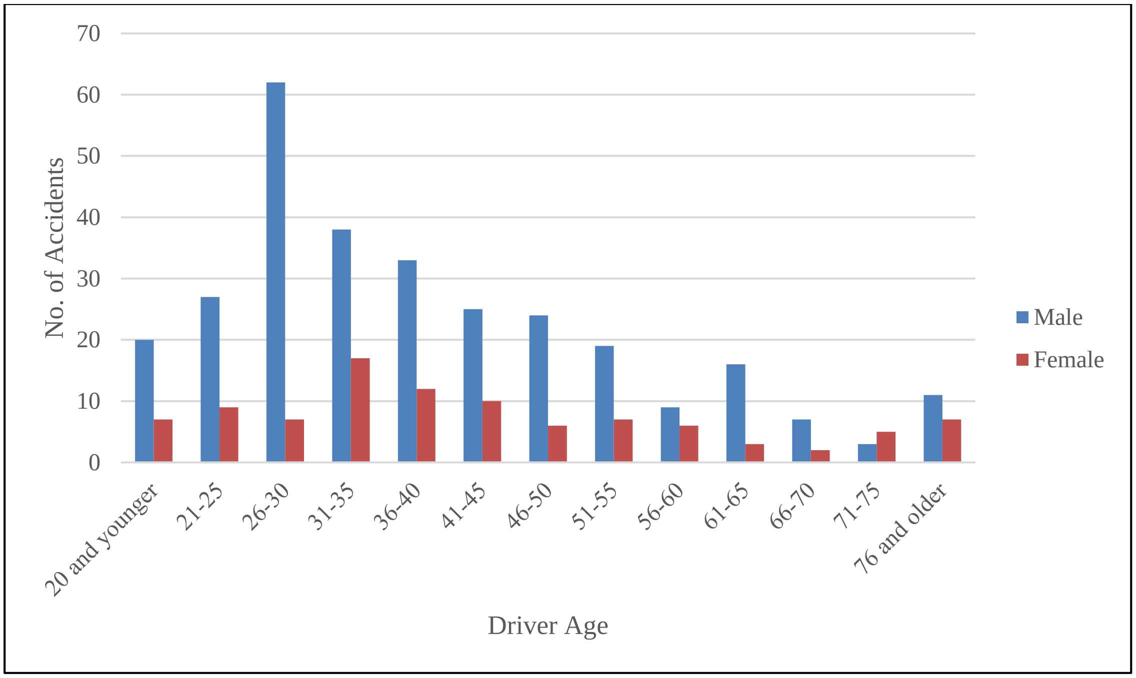


Figure 6. Age and Gender of Drivers Involved in Crashes at Public HRGCs in California (2000-2004) [26].

3 Data Sources and Methodology

This study concentrates on the effects of weather and demographic factors on driver behavior at HRGCs. It uses the data obtained by Michigan Tech as part of an on-going effort to study the driver behavior and safety at HRGCs and a quantitative behavior score [27] that was also developed at Michigan Tech as the main methodology for the analysis.

Figure 7 provides a detailed flowchart of the steps taken in the research process and the critical data used in each step. The following section describes the data sources and the methodologies in more detail.

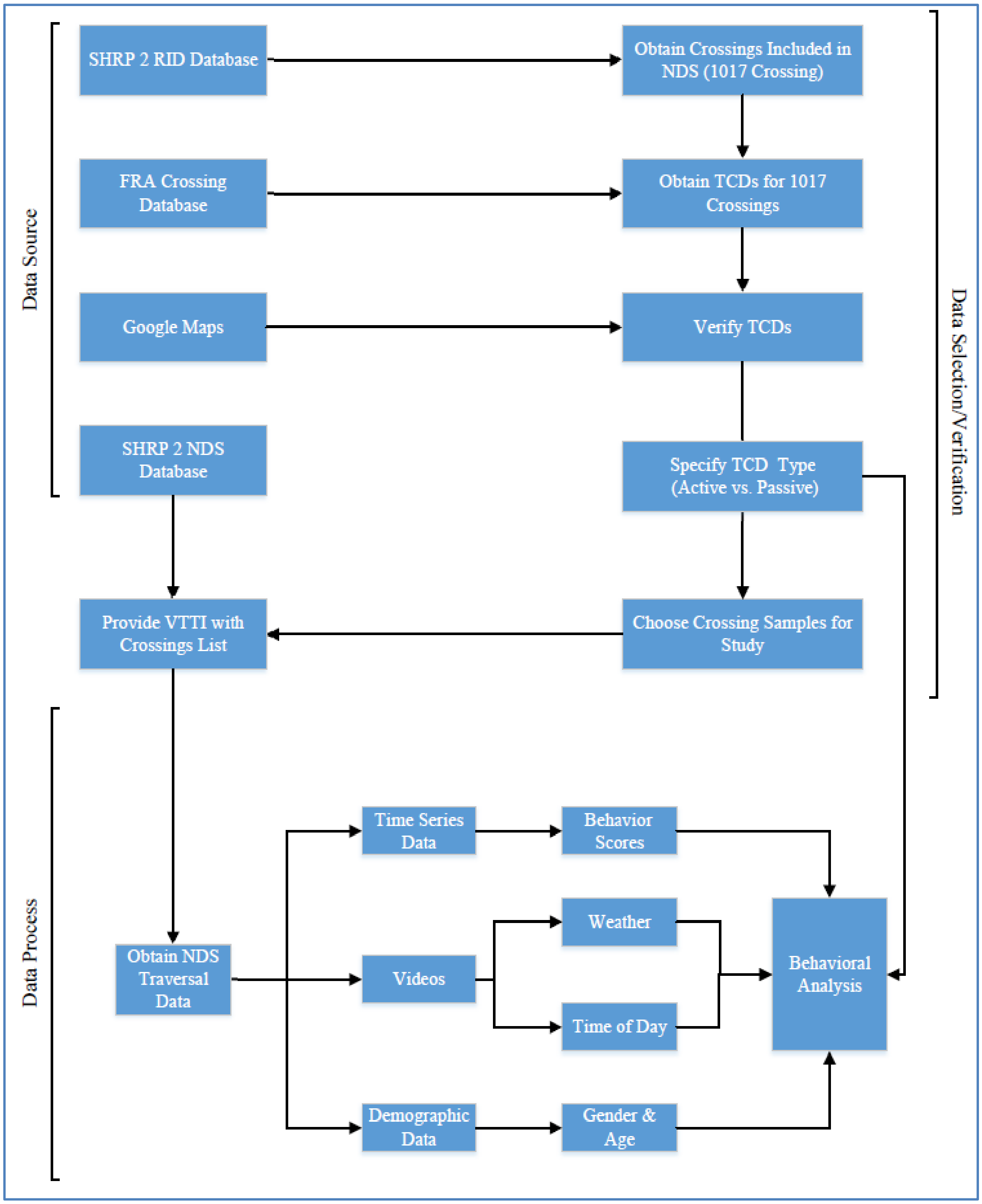


Figure 7. Data Sources and Research Task Relationships.

3.1 Data Sources and Data Selection

Three main data sources were used for this study; SHRP 2 Naturalistic Driving Study (NDS) database, SHRP 2 Roadway Information Database (RID), and FRA Grade Crossing Inventory Database. Google Maps and forward video streams of the NDS data were used to verify TCDs at selected HRGCs.

3.1.1 SHRP 2 NDS and SHRP 2 RID Databases

The SHRP 2 NDS, funded by Transportation Research Board (TRB), captured driving performance of unsupervised participants from six different states in the United States; Florida, Indiana, New York, North Carolina, Pennsylvania and Washington. The study was conducted 2010-2013 and included approximately 3,500 participants and more than five million trips [6]. The database is stored in a secure data enclave at the Virginia Tech Transportation Institute (VTTI) and is accessible for researchers across the US [14].

The Roadway Information Database (RID) was developed under the same program (SHRP 2) [28]. The overall focus was to provide the roadway and route information on trips taken by the NDS participants [29]. The RID was used in our study to identify HRGCs that were traversed by the SHRP 2 NDS study participants. A total of 1,017 HRGCs identified in the RID were then used to select crossings for study (Table 5).

Table 5. Number of Crossings per State in the RID [30].

State	Number of Crossings in NDS
Florida	295
Indiana	104
New York	181
North Carolina	168
Pennsylvania	61
Washington	208
Total	**1,017**

3.1.2 FRA Grade Crossing Inventory Database

The FRA indicates that there were 129,582 public HRGCs and 80,073 private HRGCs in the United States in 2015 [31]. Each crossing is identified in the FRA inventory database by its FRA crossing ID and can be described by different data fields that provide crossing information ranging from their ownership to their geometric configurations. In this study, crossing ID was used as a linking field in a programming algorithm to match the available data from each HRGC in the FRA inventory with the corresponding HRGCs in the RID database. The presence of lights and/or lights with gates were used to separate HRGCs with active warning devices from those with passive ones.

3.1.3 Google Maps and Forward Camera Videos and Selection of HRGCs for Analysis

Google Maps were used to verify the status of TCDs at all 1,017 HRGCs during the NDS study period. The forward facing videos were used to confirm that the warning devices in the FRA inventory matched the devices in place at the time of study [6].

Based on the information from RID database, FRA Crossing Inventory database, and verification using Google maps, 306 crossings were selected for the study. The selection was based on key parameters such as type of TCDs, configuration of nearby intersections and the number of accidents that had taken place at these crossing in recent years.

3.2 Obtained Data and Data Processing

After selecting the crossings described in the previous section and choosing sample size, NDS data from over 12,000 traversals was obtained from Virginia Tech Transportation Institute (VTTI). The final sample included 9,128 individual traversals across 286 HRGCs containing the necessary data to develop a behavior score for the analysis. The data set included an average of approximately 40 traversals per selected HRGC and this number was felt to be adequate for statistically valid results [30].

The raw data obtained from VTTI included video recordings from forward facing cameras, time series data consisting of vehicle speed, vehicle acceleration/deceleration, head rotation and other data shown in Table 6. Driver demographics were downloaded separately from VTTI enclave. The raw data was processed to obtain various parameters needed for the development of behavior scores.

Table 6. Data Fields Obtained from VTTI

NDS Trip Data		
Head Rotation and position	Vehicle Speed	Vehicle Accelerations
GPS Location	Day and Time	Brake and Throttle
Age Group	Gender	Forward Video
Forward Camera Videos		
Weather	Day/Night	Traffic Conditions
Crossing Position	Other Crossing Features	Crossing Conditions
Sun in Face		

3.2.1 Time Series Data (for Behavior Score)

In a previous research study completed at Michigan Tech [6], a three-point "compliance score" (later renamed as "behavior score") methodology was developed to quantitatively evaluate driver behavior when approaching a HRGC. The score uses a combination of head rotation and vehicle speed changes obtained from the NDS time series data to evaluate whether the driver has looked for a train and slowed down to prepared to stop, if a train were present. The score consisted of one point for scanning to the right, one point for scanning to the left and one point for appropriate speed reduction while approaching HRGCs [6]. All three activities had to be performed within predetermined analysis range to receive a full score at the HRGCs. The goal of the behavior score was to translate qualitative driver behavior data into quantitative data suitable for statistical analysis. Table 7 shows a summary of the behavior score calculation for driver behavior analysis.

Table 7. Driver Behavior Score Calculation Parameter [6].

Driver Behavior Action	**Points Awarded**
Visual scan for train to the right	+1
Visual scan for train to the left	+1
Significant speed reduction	+1
Total Possible Score	**+3**

A MATLAB code was developed to process the data and calculate the behavior score. After discarding traversals from the dataset that did not have adequate or reliable data, the scanning and speeding actions were evaluated for each traversal. The analysis range was twice the standard reaction time before the last point to start braking with ability to come to a complete stop before the crossing (Figure 8).

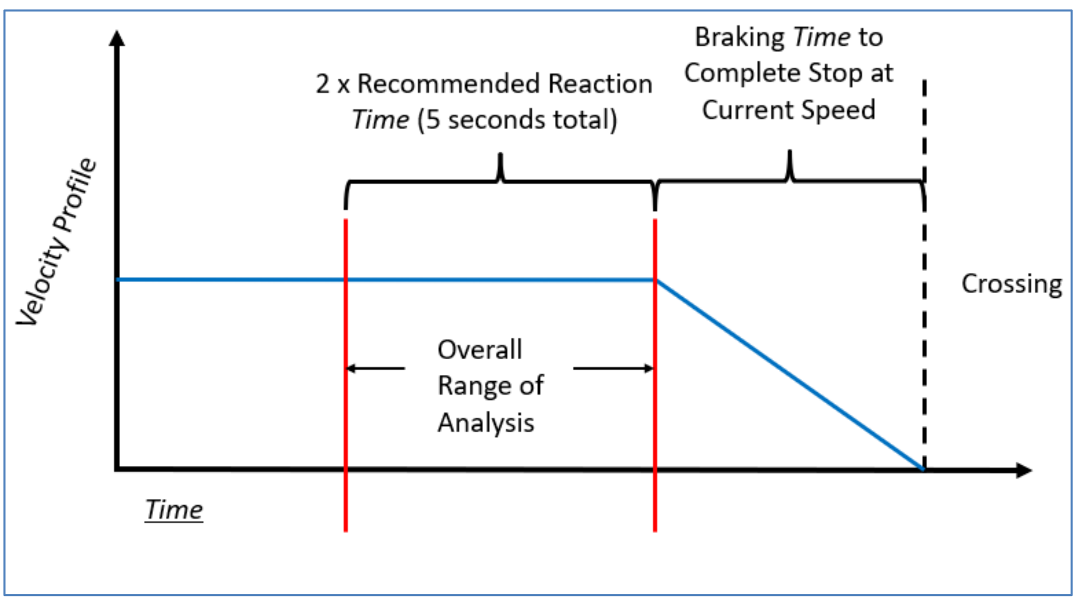


Figure 8. Driver Behavior Score Analysis Range.

The driver behavior score was evaluated based on velocity and head rotation profiles within the following thresholds (Figure 9):

1. A speed reduction score of +1 was given to drivers when a speed reduction of more than 10 percent of initial speed was observed within the analysis range. Drivers received score of zero if the speed reduction of more than 10 percent was not observed, or it did not occur within the specified analysis range. The 10 percent speed reduction was chosen based on engineering judgment.
2. A visual scanning score of +1 was given to drivers when the head rotation for left or right directions was more than 8 degrees and the head pitch (head rotation up and down) was less than 8 degrees within the analysis range. The 8 degrees criteria was selected based on previous studies [6, 32].

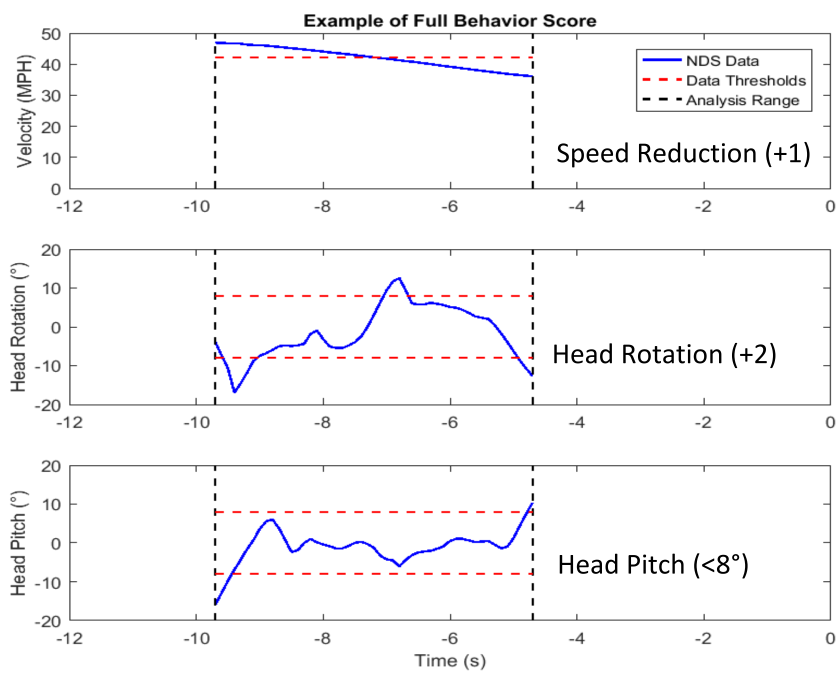


Figure 9. Example Behavior Score Calculation [27].

An average behavior score value for each specific crossing location was calculated and used for the analysis of driver behavior in this study.

In order to obtain weather information for each HRGC traversal, the video recordings obtained from VTTI were manually reviewed and the weather condition at the time of traversing was recorded as one of the five possible conditions, e.g. clear, cloud, fog, rain and snow. In addition, the time of day for each traversal was also categorized as either daytime or nighttime.

The driver demographic information was downloaded separately from the VTTI data enclave and were first divided into male and female categories and then further refined into seven age groups (16-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75+) for the analysis.

3.3 Behavioral Analysis

The average behavior score was extracted to compare driver behavior (behavior scores) in several situations. The basic analysis concentrated on weather, demographics (gender and age) and time of day data. The same parameters were further explored with respect to different TCD types. Finally, combined weather, demographic and time analysis were performed. For example, drivers' behavior in rainy conditions at night was investigated as one category. Table 8 provides a summary of the different scenarios analyzed in this study.

Table 8. Behavior Analysis Procedure

Behavioral Analysis		
1	Basic Analysis	▪ Weather Analysis ▪ Demographic Analysis (Gender and Age) ▪ Time of Day Analysis
2	Analysis Divided between TCDs	▪ Weather Analysis ▪ Demographic Analysis (Gender) ▪ Time of Day Analysis
3	Combined Analysis	▪ Weather and Demographics (gender & age) ▪ Weather and Time of Day ▪ Demographics (Gender & Age) and Time of Day

A single factor one-way ANOVA (Analysis of Variance) with a confidence interval of 95 percent (P(T<=t) two-tail) was used to test the null hypothesis of the average behavior scores for several categories. If the ANOVA test statistics indicated that there was significant difference between the average behavior scores, a statistical two-sample t-test assuming unequal variances was used to determine the statistical significance of different condition pairings. Each pair being tested was assumed to be normally distributed and the assumption of unequal variances was made due to the significant difference in the number of sample points for each pair of data. Since the sample size for some situations (weather condition, gender and age, etc.) was less than 30, it would be insufficient for other statistic tests, such as Z test for equality of data means. T-test on the other hand can be used for any size of data samples to determine, if the mean/average is statistically different for two data points.

4 Data Analysis

This chapter presents the average behavior scores for the various scenarios analyzed in the study, as well as their statistical significance. The data from 9,128 traversals across 286 crossings were used to evaluate drivers' behavior based on environmental conditions and driver demographics. In the first four sections of this chapter (4.1 to 4.4), sample size, average behavior scores and standard deviations are presented based on weather, time of day and demographics (gender and age). The last section on this chapter (4.5) concentrates on the results of analysis conducted to determine the statistical significance between parameters.

4.1 Weather Impact Analysis of Driver Behavior at HRGCs

The literature review indicated that weather condition is one of the parameters that affects driver behavior in general, as well as at HRGCs [1, 25]. This section presents the analysis of changes in driver performance observed under different weather conditions.

4.1.1 Weather Impact on Driver Behavior Across Entire Sample

Table 9 shows the number of traversals, average behavior scores and standard deviations for the entire sample, for different weather conditions and Figure 10 is a graphical representation of behavior scores. The results show that on average, drivers received higher behavior scores in snow, followed by clear, cloudy, rainy and foggy conditions. Due to the small sample size, the fog condition was excluded from further analysis.

Table 9. Sample Size, Average Behavior Score and SDT Based on Weather Condition (Entire Sample).

Weather Condition	#Traversals	Average Behavior Score	STD
Clear	8,379	1.39	0.84
Cloudy	221	1.33	0.87
Fog	7	1.14	0.64
Rain	428	1.28	0.83
Snow	91	1.60	0.88

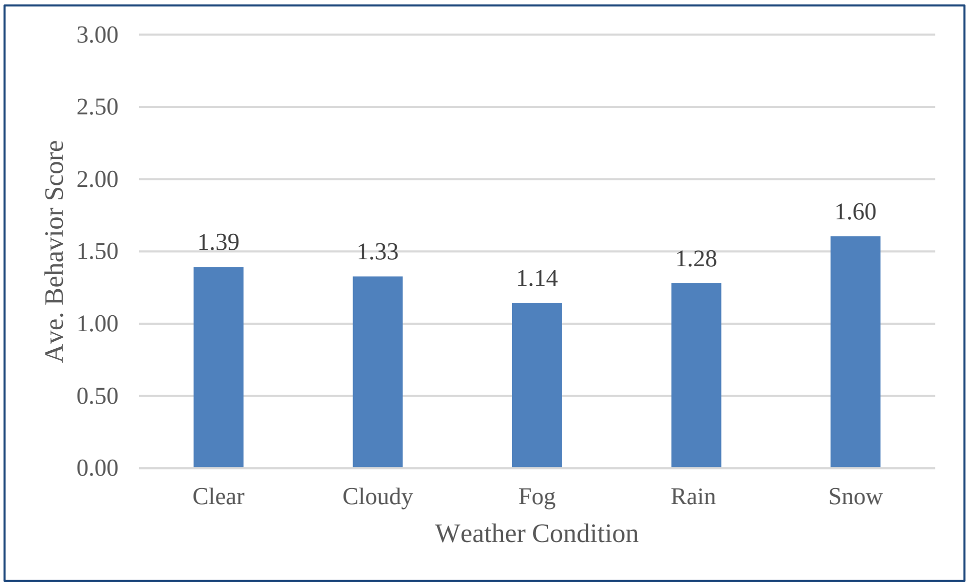


Figure 10. Average Behavior Score versus Weather Condition (Entire Sample).

4.1.2 Weather Impact on Driver Behavior Based on TCDs.

In a previous Michigan Tech study , it was found that driver behavior score was affected by the TCDs present at the crossings [6]. When weather is included in the analysis, the TCDs at the crossing are increasingly important as inclement weather may further degrade opportunities for defensive driving, especially at locations with passive TCDs where visual observation of a train is the first line of defense.

The behavior scores under different weather conditions were evaluated separately based on the TCDs at each HRGC. Table 10 and Figure 11 present the sample sizes, average behavior scores, standard deviations and graphical plots of driver behavior with respect to different TCD category.

Table 10. Sample Size, Average Behavior Score and STD Based on Weather and TCD.

	Passive			**Lights Only**			**Lights and Gates**		
Weather	**#Traversals**	**Score**	**STD**	**#Traversals**	**Score**	**STD**	**#Traversals**	**Score**	**STD**
Clear	631	1.42	0.85	1,273	1.40	0.85	6,475	1.39	0.83
Cloudy	68	1.41	0.84	7	1.29	0.70	148	1.29	0.89
Rain	77	1.31	0.87	65	1.14	0.82	6,475	1.30	0.82
Snow	6	1.67	0.94	12	1.08	0.64	148	1.68	0.87

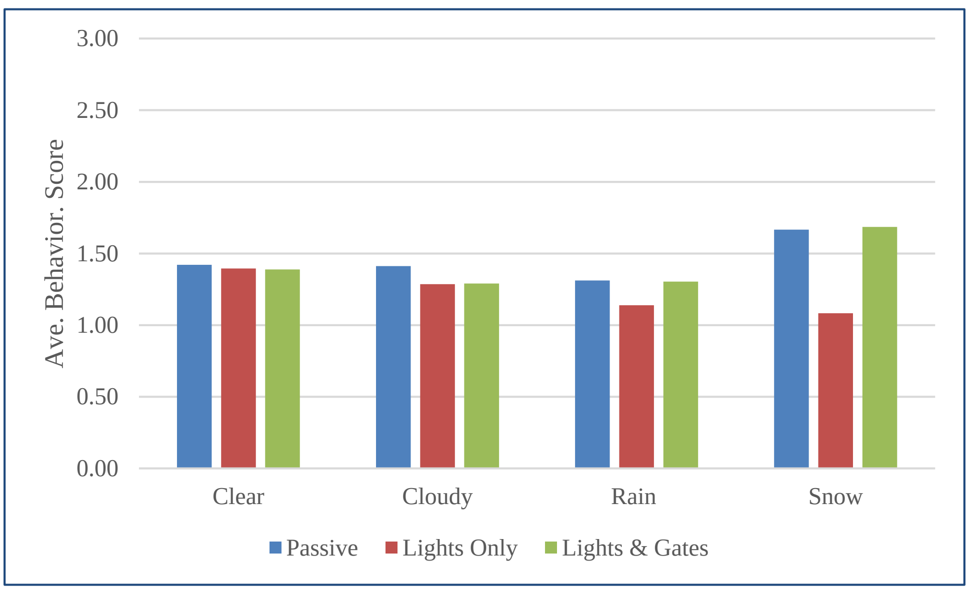


Figure 11. Average Behavior Score versus Weather Condition.

The data in Table 8 shows that with the exception of “snow” condition, there is little variability between scores under various weather conditions and TCDs.

4.2 Time of Day Impact Analysis of Driver Behavior at HRGCs

Previous studies show that time of day at which a driver traverses HRGCs has impact on HRGC safety. Nighttime driving has been shown to be associated with more HRGC accidents per traffic volume [1]. This section briefly evaluates driver behavior at HRGCs in terms of behavior score for different times of day, for the entire population of the data, and with respect to each TCD category.

4.2.1 Time of Day Impact on Driver Behavior Across Entire Sample

Using the forward video stream, the data was divided into day and nighttime traversals. Dusk and dawn were not considered as separate categories due to subjectivity of selection for such situations. Table 11 shows the sample size, behavior score and standard deviation for daytime and nighttime driving conditions. Overall, the data shows drivers receive higher behavior scores during the day compared to the nighttime traversing.

Table 11. Sample Size, Behavior Score and STD Based on Time of Day (Entire Sample).

Time of Day	**#Traversals**	**Ave. Score**	**Standard Deviation**
Day	7,560	1.41	0.84
Night	1,568	1.26	0.84

4.2.2 Time of Day Impact on Driver Behavior Based on TCDs

Similar to the weather and demographic data analysis, three types of TCDs was considered for time of day analysis of driver behavior scores at HRGCs (Table 12 and Figure 12). The data shows that drivers receive higher behavior scores during the day compared to the nighttime traversing across all TCD types. In addition, the data shows that drivers receive lowest behavior scores during the night at HRGCs with lights only TCDs.

Table 12. Sample Size, Behavior Score and STD based on Time of Day and TCD Types.

Time/TCD	**Passive**			**Lights Only**			**Lights & Gates**		
	#Trav.	**Score**	**STD**	**#Trav.**	**Score**	**STD**	**#Trav.**	**Score**	**STD**
Day	645	1.44	0.87	1104	1.44	0.83	5811	1.41	0.83
Night	138	1.29	0.78	254	1.13	0.86	1176	1.28	0.83

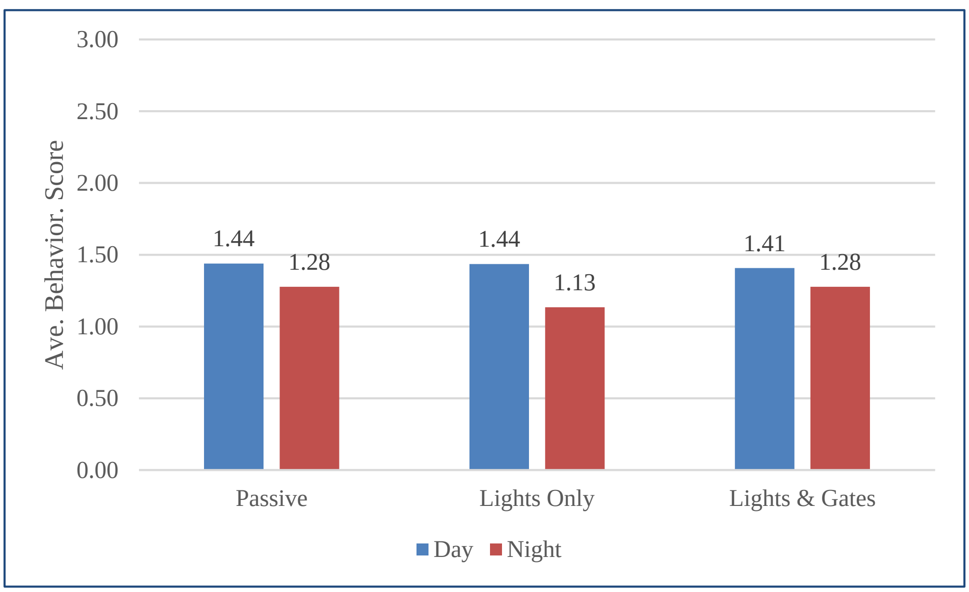


Figure 12. Average Behavior Score based on Time of Day and TCD Types.

4.3 Driver Demographic Impact Analysis of Driver Behavior at HRGCs

The literature indicated that gender and age are meaningful parameters influencing the risk of accidents at HRGCs. The following will investigate the behavior scores based on driver demographics.

4.3.1 Driver Demographic Impact Across Entire Sample

For the purposes of demographic data analysis of driver behavior at HRGCs, the average behavior score for male and female groups was calculated to determine differences. Table 13 indicates sample size, average behavior scores and standard deviation for male and female drivers. The data shows that the average scores between male and female scores are almost identical across the sample.

Table 13. Sample Size, Behavior Score and STD Based on Gender (Entire Sample).

Gender	**#Traversals**	**Average Behavior Score**	**STD**
Male	4,515	1.38	0.83
Female	4,512	1.39	0.85

Demographic data was further explored to look at how the behavior score changes with respect to different age group drivers. Table 14 indicates the sample size, behavior score and standard deviation for different age groups of male and female drivers. The behavior scores are also presented in Figure 13.

Table 14. Sample Size, Behavior Score and STD based on Gender and Age.

Age Group	Male			Female		
	#Traversals	Score	STD	#Traversals	Score	STD
16-19	458	1.36	0.83	570	1.32	0.83
20-29	1,265	1.40	0.79	1613	1.38	0.85
30-39	414	1.39	0.82	324	1.44	0.81
40-49	429	1.43	0.83	421	1.52	0.82
50-59	481	1.30	0.88	510	1.37	0.86
60-69	574	1.37	0.85	565	1.38	0.88
70+	885	1.40	0.83	481	1.40	0.85

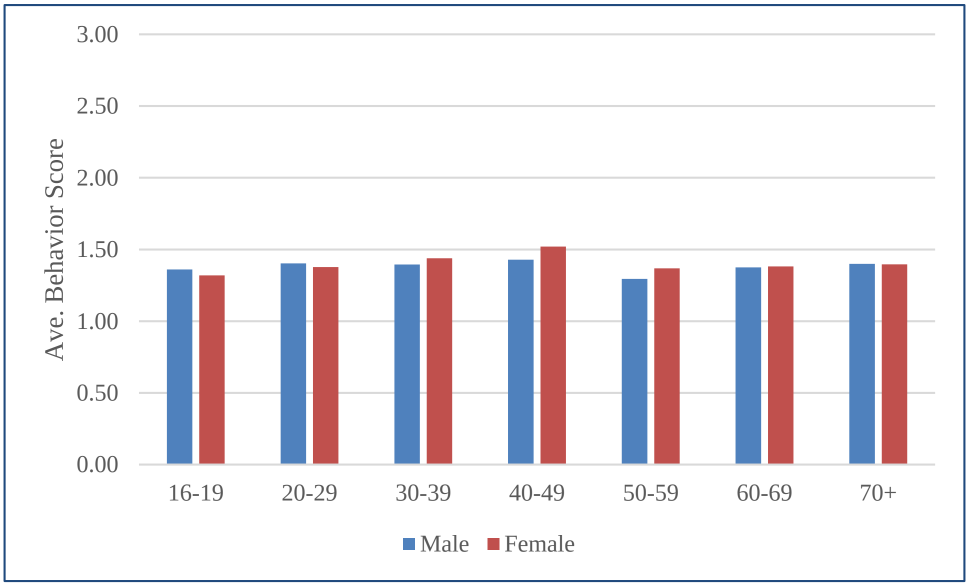


Figure 13. Driver Behavior Score based on Gender and Age.

For both female and male drivers, the data presented in Figure 16 shows minor differences in average behavior scores of different age group drivers. The data indicates that middle aged drivers (40-49 years old) receive somewhat higher behavior score in both gender categories, especially among female drivers.

4.3.2 Driver Demographic Impact on Driver Behavior Based on TCDs.

Demographic data was further divided into different TCD types at HRGCs. Table 15 shows the sample size, behavior score, and standard deviation based on gender and TCD types. The data in Table 15 is graphically shown in Figure 14 below.

Table 15. Sample Size, Average Behavior Score and STD based on Gender and TCDs.

Gender	Passive			Lights Only			Lights and Gates		
	#Trav.	**Score**	**STD**	**#Trav.**	**Score**	**STD**	**#Trav.**	**Score**	**STD**
Male	424	1.38	0.86	640	1.34	0.85	3,451	1.39	0.82
Female	349	1.46	0.84	712	1.41	0.85	3,451	1.38	0.85

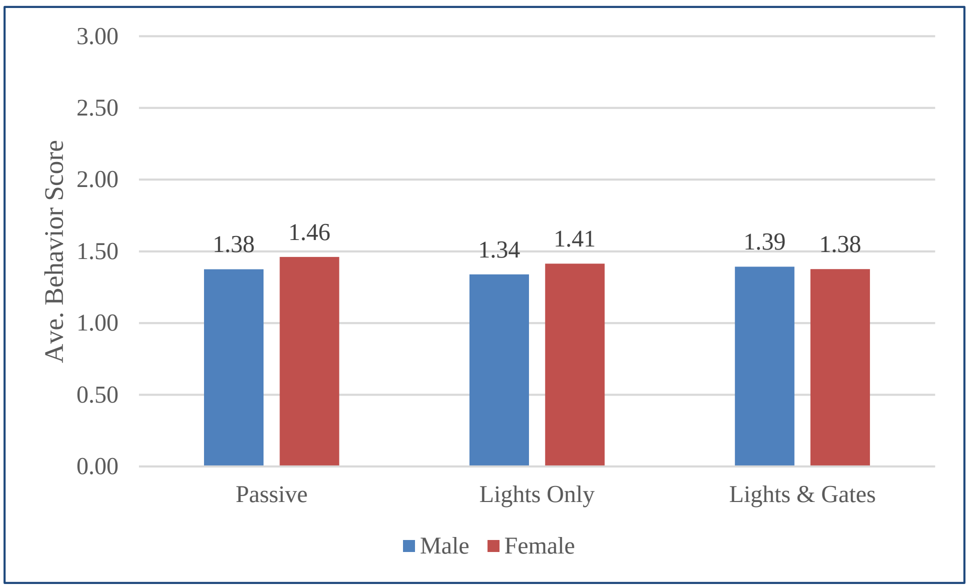


Figure 14. Average Behavior Score based on Gender and TCDs.

While differences were fairly minor, Figure 14 indicates female drivers receive higher behavior scores in HRGCs with passive and lights only TCDs when compared to male drivers. The difference is negligible for lights and gates TCDs.

4.4 Combined Weather, Demographic and Time of Day Analysis

This section combines the effects of weather, demographics (gender and age) and time of day on driver behavior at HRGCs.

4.4.1 Combined Weather and Time of Day Analysis

Another perspective of driver behavior at HRGC is to combine the impact of weather conditions and time of day of traversal. The combinations of two different traversal times (day, night) and four weather conditions (clear, cloudy, rain, snow) are considered in this section. Table 16 shows the sample size, average behavior scores and standard deviation based on time of day and weather condition. Due to uncertainties on identifying cloudy weather during the night, the nighttime traversals in cloudy conditions was considered as "clear weather" in the analysis. The data presented in Table 16 shows drivers receive highest behavior scores in snow condition for both day and nighttime traversing. Figure 15 provides a histogram plot of the data in Table 16.

Table 16. Sample Size, Average Behavior Score and STD based on Time of Day and Weather Condition.

	Day			**Night**		
Weather	**#Traversal**	**Score**	**STD**	**#Traversal**	**Score**	**STD**
Clear	6,933	1.42	0.83	1,446	1.25	0.84
Cloudy	215	1.32	0.86			
Rain	333	1.27	0.84	92	1.32	0.81
Snow	73	1.64	0.88	18	1.44	0.83

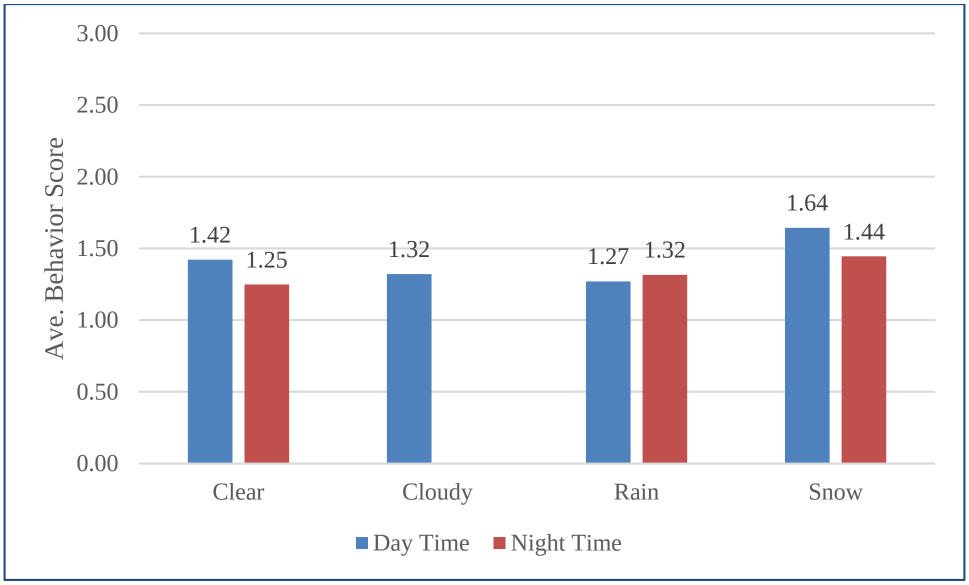


Figure 15. Average Behavior Score based on Weather and Time of Day.

4.4.2 Combined Weather and Demographic Analysis

In previous sections, it was found that different weather conditions have some impact on driver behavior at HRGCs. This section provides a more in-depth evaluation on whether weather condition impacts average behavior scores when drivers are divided to different age and gender groups. Table 17 indicates drivers' average behavior scores based on driver gender and weather conditions. As the data shows, both female and male drivers receive lower behavior scores under cloudy and rain conditions compared to clear and snow conditions, but the difference is higher among females. The behavior scores are presented in Table 17 and in Figure 16.

Table 17. Sample Size, Behavior Score and STD based on Gender and Weather.

Weather	Male			Female		
	#Traversal	Score	STD	#Traversal	Score	STD
Clear	4,169	1.38	0.83	4,121	1.40	0.85
Cloudy	88	1.42	0.85	135	1.27	0.88
Rain	203	1.32	0.84	216	1.23	0.82
Snow	53	1.58	0.86	36	1.61	0.92

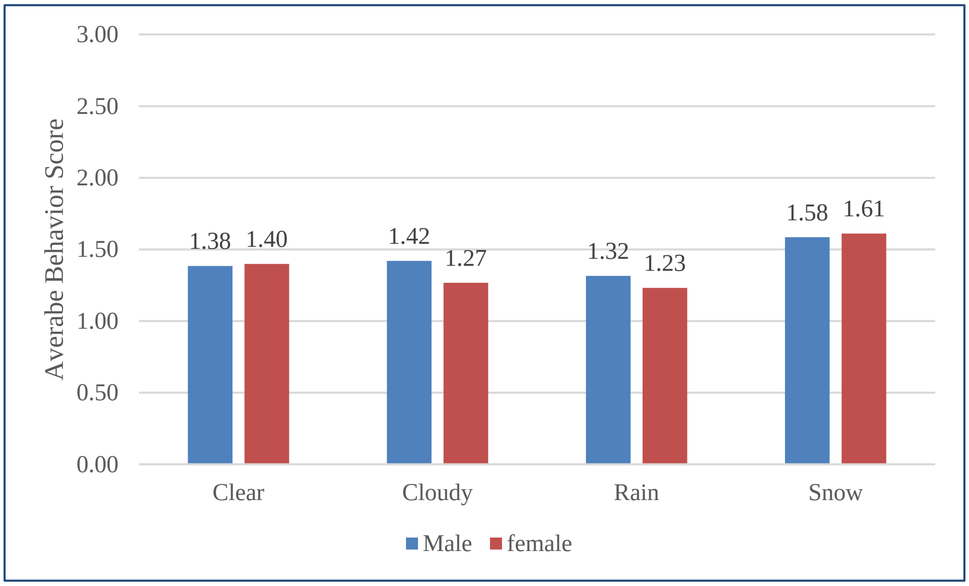


Figure 16. Male vs. Female Drivers Based on Weather Conditions.

4.4.3 Combined Demographic and Time of Day Analysis

For the time of day analysis of driver behavior based on demographics, two time of day categories of traversing HRGCs are used (day and night). Table 18 shows the sample size, behavior scores and standard deviation for male and female drivers with respect to time of day traversing. The data indicates both male and female drives receive higher behavior scores during the day compared to the nighttime traversing. The average behavior scores are presented in Table 18 and Figure 17.

Table 18. Sample Size, Average Behavior Score and Standard Deviation Based on Gender and Time of Day.

Gender	Day			Night		
	#Traversal	Score	STD	#Traversal	Score	STD
Male	3,733	1.42	0.83	782	1.23	0.83
Female	3,745	1.41	0.85	767	1.27	0.84

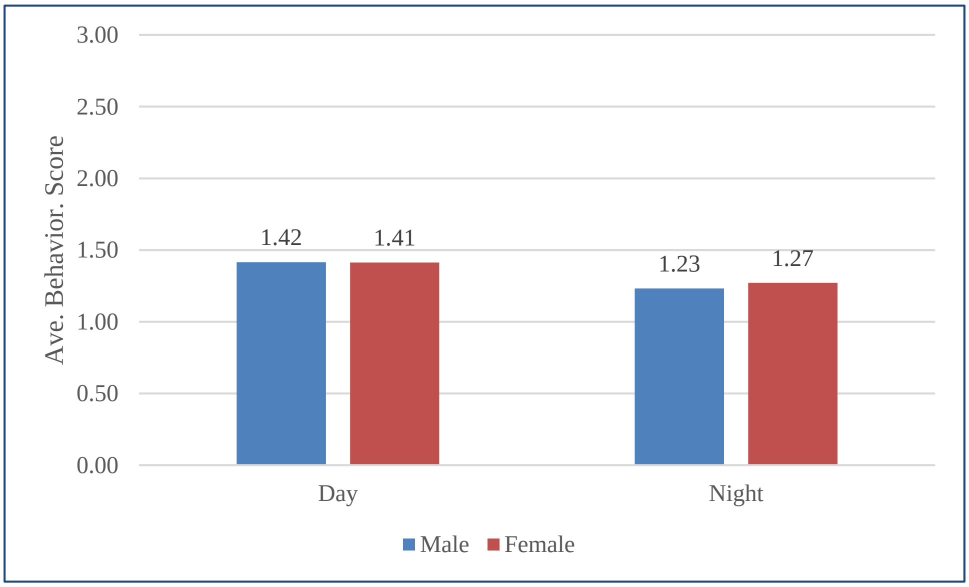


Figure 17. Average Behavior Score based on Time of Day and Driver Gender.

4.5 Summary of Statistical Test Results

As described in the methodology, a single factor ANOVA hypothesis test was performed to determine if the differences observed between average behavior scores of drivers under more than two different conditions were statistically significant. If the ANOVA test specified a significant difference between groups of average behavior scores, a null hypothesis of $P(T \leq t)$ two-tail t-test with a significance level of 0.05 (95 percent confident interval) was performed. In the t-test, a statistical significance was reached, if P(T≤t) two-tail was less than the selected significance level (0.05).

This section presents the summary of condition pairs that were tested for the 95 percent statistical significance difference between the average scores. If preceding ANOVA test did not suggest significant difference the any of the pairs, no t-test was performed. The pairings without t-test are presented as a diagonal line in the following tables. If the pairing showed statistical significance in 95 percent confidence interval, the value is presented in “bold” letters. ANOVA test values and detailed tables of the statistical tests for all condition pairs/categories are included in Appendix A. It should be noted that as numerical results in this report is presented in two decimal places, all numbers smaller than 0.01 are shown as <2E-03.

Table 19 below provides a summary of t-test results for the weather conditions and highlights in bold condition pairs for which a statistical significance was reached.

Table 19. Summary of Statistical Test Results for Weather Conditions

Condition Pair	**P(T<=t) two-tail**			
Weather per TCDs				
	Entire Sample	**Passive**	**Lights Only**	**Lights & Gates**
Clear vs. Cloudy	0.28		0.72	0.19
Clear vs. Rain	**<2E-03**		**0.02**	0.09
Clear vs. Snow	**0.02**		0.14	**<2E-03**
Cloudy vs. Rain	0.51		0.64	0.88
Cloudy vs. Snow	**<2E-03**		0.57	**<2E-03**
Rain vs. Snow	**<2E-03**		0.80	**<2E-03**
TCD Types Under Each Weather Condition				
Clear				
Passive vs. Lights Only vs. Lights & Gates				
Cloudy				
Passive vs. Lights Only vs. Lights & Gates				
Rain				
Passive vs. Lights Only vs. Lights & Gates				
Snow				
Passive vs. Lights Only	0.25			
Passive vs. Lights & Gates	0.97			
Lights Only vs. Lights & Gates	**<2E-03**			

Per ANOVA test, there is no significant difference between average drivers' behavior scores for passive HRGCs under any weather conditions. For the HRGCs with lights only as shown in the Table 19, the difference in average behavior scores are statistically significant for only one comparison pairing (clear versus rain). For HRGCs with lights and gates, three out of six categories are significantly different from each other. This is partially because this type of TCD is most common in the sample and the same pairings are statistically significant for the entire sample as well. When comparing driver behavior across all TCD types for each weather condition, the only statistically significant difference is at HRGCs with lights only compared to lights and gates TCDs under snow conditions.

Table 20 provides the details of t-test and ANOVA single factor test results for comparison between age groups, first as gender neutral and then separately for male/female groups.

Table 20. Summary of Statistical Test Results for Driver Age Groups

Condition Pair	**P(T<=t) two-tail**		
	Entire Sample	**Male**	**Female**
16-19 vs. 20-29	0.09		0.16
16-19 vs. 30-39	0.06		**0.04**
16-19 vs. 40-49	**<2E-3**		**0.01**
16-19 vs. 50-59	0.92		0.34
16-19 vs. 60-69	0.28		0.22
16-19 vs. 70+	0.08		0.14
20-29 vs. 30-39	0.45		0.22
20-29 vs. 40-49	**<2E-03**		**<2E-03**
20-29 vs. 50-59	0.08		0.85
20-29 vs. 60-69	0.71		0.90
20-29 vs. 70+	0.73		0.67
30-39 vs. 40-49	0.15		0.17
30-39 vs. 50-59	**0.05**		0.24
30-39 vs. 60-69	0.35		0.34
30-39 vs. 70+	0.68		0.48
40-49 vs. 50-59	**<2E-03**		**0.01**
40-49 vs. 60-69	**<2E-03**		**<2E-03**
40-49 vs. 70+	**0.04**		**0.03**
50-59 vs. 60-69	0.25		0.80
50-59 vs. 70+	0.07		0.62
60-69 vs. 70+	0.54		0.80

The data presented in Table 20 does not show any significant different in average behavior scores of different age groups of male drivers. For female drivers however, five different age group pairings show statistical significance when compared to the 40-49 age group (considering 16-19 vs 30-39 an outlier). The same five age groups show statistical significance from each other across the entire sample.

When gender differences are compared within each age group, there are no significant differences between any of the groups (Table 21).

Table 21. Driver Demographics (Male vs. Female Age Groups)

Condition Pair	**Age Group**	**P(T<=t) two-tail**
Male vs. Female	16-19	0.43
	20-29	0.39
	30-39	0.47
	40-49	0.11
	50-59	0.19
	60-69	0.88
	70+	0.94

For the time of day analysis, the statistical test results were significant for day versus night condition across the entire sample as well as with respect to TCDs indicting lower behavior scores for the night compare to day (Table 22). The data also shows driver behavior does not change with respect to TCDs during the day.

Table 22. Summary of Statistical Test Results for Time of Day Analysis

Condition Pair	**P(T<=t) two-tail**		
Entire Sample			
Day vs. Night	**<2E-03**		
TCDs In General			
	Passive	Lights Only	Lights & Gates
Day vs. Night	**0.05**	**<2E-03**	**<2E-03**
All TCDs			
Time of Day and TCDs			
	Passive vs. Lights Only	Passive vs. Lights & Gates	Lights Only vs. Lights & Gates
Daytime			
Nighttime	0.07	0.87	**0.02**

When weather and demographics are compared (Table 23), the data does not show any significant difference in the average behavior scores for the male drivers. However, there are significant differences in average behavior scores of female drivers indicating lower scores during the rain and higher scores in snow condition.

Table 23. Summary of T-Test Results for Weather and Demographics Combination.

Condition Pair	**P(T<=t) two-tail**		
	Entire Sample	**Male**	**Female**
Clear vs. Cloudy	0.28		0.09
Clear vs. Rain	**0.01**		**<2E-03**
Clear vs. Snow	**0.02**		0.18
Cloudy vs. Rain	0.51		0.71
Cloudy vs. Snow	**0.01**		**0.05**
Rain vs. Snow	**<2E-03**		**0.03**

Considering weather and time of day combinations (Table 24), there is no significant difference in average behavior scores of drivers for the nighttime driving based on ANOVA test results. However, the data shows differences in average behavior scores during the day indicating lower scores during the rain and higher scores in snow condition.

Table 24. Summary of Statistical Test Results for Weather and Time of Day.

Condition Pair	**P(T<=t) two-tail**		
	Entire Sample	**Day**	**Night**
Clear vs. Cloudy	0.28	0.09	
Clear vs. Rain	**0.01**	**<2E-03**	
Clear vs. Snow	**0.02**	**0.04**	
Cloudy vs. Rain	0.51	0.50	
Cloudy vs. Snow	**0.01**	**0.01**	
Rain vs. Snow	**<2E-03**	**<2E-03**	

Finally, for the driver gender and time of day combination (Table 25), the data does not indicate any significant differences in average behavior scores of male or female drivers with respect to time of day. However, when we compare the behavior during the day versus during night, both females and males show statistically significant difference in behaviors.

Table 25. Summary of Statistical Test Results for Driver Gender and Time of Day.

With Respect to Time	
Male vs. Female	P(T<=t) two-tail
Day	0.89
Night	0.37
With Respect to Gender	
Day vs. Night	P(T<=t) two-tail
Male	**<2E-03**
Female	**<2E-03**

5 Hypothesis and Discussion

Chapter 4 provided the quantitative results of both average behavior scores for the various scenarios analyzed in this study and condition pairs for which two-tail t-test with a significance level of 0.05 (95 percent confident interval) was met. This chapter provides a brief discussion of those results and tests them against the three-hypotheses established in the beginning of the study.

1. *Considering the impact of environmental conditions on driving task in general, the research expects that inclement weather conditions (snow, rain, fog) and nighttime lead into changes in the level of defensive driving.*

   In terms of the average behavior scores, the results obtained from this study supports the hypothesis, but only in a limited and inconsistent manner. The results show that drivers received significantly higher behavior scores in snow compared to clear, cloudy and rain conditions. Previous studies have indicated that rainy weather causes negative impact on traffic safety due to low visibility[25] and per FRA accident reports, December, January and February have been identified as the months with the highest HRGCs accident rates [1]. This study also indicated that drivers received lower behavior scores during rain when compared to clear and snow conditions – i.e. an indication of less defensive driving. Therefore, if the lower behavior score is considered to increase the risk of an accident, our results would support the literature trends in rainy conditions, but not in snowy conditions. It is also worth mentioning that drivers received the lowest behavior scores in fog, however, due to the small sample size, this condition was excluded from the study. From time of day perspective, the trends were more consistent. The results indicated that drivers receive lower behavior scores during the night compare with day. Drivers also receive lower behavior scores during the night across all TCD types. This outcome supports previous studies explaining visibility condition has impact on driver behavior and increases accident rate at HRGCs [5].

2. *Driver demographics (gender and age) affects driver response to the TCDs at HRGCs, implying that some age and gender categories of drivers could be more vulnerable to HRGC accidents. The second hypothesis of this study was that there will be a difference in the level of defensive driving between gender and age groups.* Previous studies have shown driver demographics, specifically gender and age, has impact on HRGCs safety indicating that male and younger drivers are involved in more accidents compared to female and middle-aged drivers. In contrast to the researcher's expectation, the data did not show any significant difference in average behavior scores between male and female drivers. The most significant difference obtained in this study was the higher behavior scores for female drivers (40-49 years). When one excludes this group, the data does not show a clear difference among gender and age groups and as such no clear difference in level of defensive driving. Thus, the results did not support the hypothesis and this study did not reveal why certain demographic/age groups are more prone to accidents.

3. *As the third hypothesis of this study, we expect that driver behavior in non-accident situations aligns with the findings of previous accident-based studies. If the level of defensive driving is lower under certain parameters, it suggests that one reason for accidents may be the increased level of risky behavior by drivers in such situations.* One of the objectives of this research was to evaluate whether NDS data shows any differences in the level of defensive driving based on the parameters identified by previous accident-based studies. The results of this research support the findings to some extent. Especially, rain and nighttime were found to be associated with lower level of defensive driving at most of HRGCs types and as such, a potential increasing factor for accident risks. Both scenarios have been found to correlate with increased accident risk in past studies as well. On the other hand, other parameter comparisons (such as male versus female drivers) did not support the findings of past studies.

6 Conclusion and Recommendation for Future Work

Although the number grade crossing accidents has significantly decreased in recent decades, they remain as one of the highest causes of injuries and fatalities in rail transportation. It is known that driver behavior is the leading cause for accidents at HRGCs, but there is less understanding on what causes the inappropriate behavior by drivers as they approach the HRGCs. Using naturalistic driving study data from SHRP 2 NDS, the primary objective of this research was to use a quantitative methodology developed at Michigan Tech to determine if the weather, time of day and demographic parameters affect driver behavior at HRGCs. A literature review was performed to document past studies/reports that have investigated the impact of weather conditions, time of day and driver demographics (gender and age) parameters on safety and accidents at HRGCs.

The criteria utilized in this research for evaluation of driver behavior was a three-point behavior score that evaluates drivers' visual scanning for the train and speed adjustment while approaching HRGCs. A higher behavior score was considered to be associated with more defensive driving behavior and as such reduce the accident risk at HRGCs. The results of this study were compared against the hypotheses of observing differences in driver behavior with respect to different weather conditions, time of day and driver demographics (gender and age).

This research found that drivers received higher behavior scores in snow compared to clear, cloudy and rain conditions. In addition, rain and cloudy conditions received lower scores than clear conditions, but they did not consistently reach statistical significance. The most consistent trend found in this study was the difference between drivers' behavior during the day compared to the night. All drivers received significantly lower behavior scores during the night (across all TCDs) compared to the day. Overall, the findings provide limited support to the previous accident-based reports indicating that weather condition and time of day affect the accident risk at HRGCs. The evidence is more clear and consistent for time of day analysis while weather conditions show more inconsistency.

With respect to the driver demographics, this study did not show any significant difference in average behavior scores of male and female drivers. As such, it did not provide any insight to past study results that indicate higher risks for young male drivers. Both male and female drivers received significantly low behavior scores during the night compared to the day. However, female drivers received higher behavior scores in snow and lower scores during the rain conditions while male drivers did not show any significant difference in behavior scores with respect to weather conditions. This study also showed that for some reasons, one group of female drivers (40-49 years) received highest behavior scores while traversing HRGCs.

The researcher believes that better understanding driver behavior at HRGCs during non-accident traversals will provide insight to the causal factors by drivers that may contribute to or explain the accident risks at HRGCs. Naturalistic driving study data provides opportunity for large-scale observation of driving behavior by taking advantage of technology and by collecting data over an extended period of time. This study initiated the use of NDS data for HRGC research, but there are various opportunities to expand the approach. Some of the limitations with this study and suggestions for future research on this topic include:

- The methodologies developed here could be used with a larger sample size to improve the analysis of the driver behavior at HRGCs. Due to small sample size, some of the parameters initially considered for the analysis were excluded from study. For example, the data in this research indicated that drivers receive the lowest behavior scores under fog conditions, but due to smaller sample size, the fog condition had to be excluded from the statistical analysis. On the other hand, a larger sample size may also reveal or strengthen the trends as the sample size impacts in the outcomes of statistical tests.
- As this research concentrated on visual scanning and speed adjustment behavior only, other parameters that affect drivers could be used to more accurately evaluate driver behavior at HRGCs. Brake/gas pedal depression data, for example, could be used to supplement (or replace) the speed reduction data used in the speed score to more accurately evaluate drivers' speeding behavior.
- Comparison of crossings with lowest and highest behavior scores might provide interesting observations on potential similarities or differences that may affect the driving habits at specific crossings.
- A similar study at the roadway intersections close to the HRGCs could be carried out using the same NDS data. Comparing drivers' behavior in HRGCs with

roadway intersections can validate or contradict the patterns observed at grade crossings, allowing an interesting comparison between behavior at highway-highway versus highway-railway intersections.

7 Disclaimer

The findings and conclusions of this paper are those of the authors and do not necessarily represent the views of the VTTI, SHRP2, the Transportation Research Board, or the National Academies.

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9 Appendix A - Statistical Test Results

The detailed statistical test analysis results obtained throughout this research is presented in this section for further information.

9.1 Test Results for Weather Analysis

Table A.1 ANOVA Test for Different Weather Conditions.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Clear	8379	11661	1.39	0.70
Cloudy	223	296	1.32	0.76
Rain	428	548	1.28	0.69
Snow	91	146	1.60	0.772

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	10.145	3	3.38	4.80	0.003	2.60
Within Groups	6409	9117	0.70			
Total	6419	9120				

Table A.2. Summary of T-Test for Different Weather Conditions (Entire Sample).

Condition Pair	df	t Stat	P(T≤ t) two-tail	t Critical two-tail
Clear vs. Rain	233	1.09	0.28	1.97
Clear vs. Cloudy	472	2.70	0.01	1.97
Clear vs. Snow	92	-2.29	0.02	1.99
Rain vs. Snow	432	0.66	0.51	1.97
Rain vs. Cloudy	166	-2.54	0.01	1.97
Cloudy vs. Snow	127	-3.22	<2E-3	1.98

Table A.3 ANOVA Test for Different Weather Condition (Passive).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Clear	631	1.42	0.72
Cloudy	68	1.41	0.72
Rain	77	1.31	0.77
Snow	6	1.67	1.07

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.22	3	0.41	0.56	0.64	2.09
Within Groups	568	778	0.73			
Total	569	781				

Table A.4. ANOVA Test for Different Weather Condition (Lights Only).

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Clear	1273	1776	1.39	0.72
Cloudy	7	9	1.28	0.57
Rain	65	74	1.13	0.68
Snow	12	13	1.08	0.45

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	5.20	3	1.73	2.42	0.063	2.088
Within Groups	968	1353	0.72			
Total	974	1356				

Table A.5. Summary of T-Test for Different Weather Conditions (Lights Only TCDS).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Clear vs. Cloudy	6	0.38	0.72	1.94
Clear vs. Rain	71	2.44	0.02	1.67
Clear vs. Snow	11	1.60	0.14	1.80
Cloudy vs. Rain	8	0.49	0.64	1.86
Cloudy vs. Snow	11	0.59	0.57	1.80
Rain vs. Snow	18	0.25	0.80	1.73

Table A.6. ANOVA Test for Different Weather Condition (Lights & Gates).

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Clear	6475	8988	1.39	0.69
Cloudy	148	191	1.29	0.79
Rain	286	373	1.30	0.67
Snow	73	123	1.68	0.77

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9.81	3	3.27	4.69	0.003	2.08
Within Groups	4866	6978	0.69			
Total	4876	6981				

Table A.7. Summary of T-Test for Different Weather Conditions (Lights & Gates).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Clear vs. Cloudy	153	1.32	0.19	1.65
Clear vs. Rain	311	1.69	0.09	1.65
Clear vs. Snow	73	-2.87	0.01	1.67
Cloudy vs. Rain	277	-0.16	0.88	1.65
Cloudy vs. Snow	145	-3.12	<2E-3	1.66
Rain vs. Snow	106	-3.34	<2E-3	1.66

Table A.8. ANOVA Test Based on Weather Condition and TCDS (Clear).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Passive	631	1.42	0.72
Lights Only	1273	1.40	0.72
Lights & Gates	6475	1.39	0.70

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F critical*
Between Groups	0.66	2	0.33	0.47	0.62	2.30
Within Groups	5874	8376	0.70			
Total	5874	8378				

Table A.9. ANOVA Test Based on Weather Condition and TCDS (Cloudy).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Passive	68	1.41	0.72
Lights Only	7	1.29	0.57
Lights & Gates	148	1.29	0.79

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.70	2	0.35	0.46	0.63	2.33
Within Groups	168	220	0.77			
Total	169	222				

Table A.10. ANOVA Test Based on Weather Condition and TCDS (Rain).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Passive	77	1.31	0.77
Lights Only	65	1.14	0.68
Lights & Gates	286	1.30	0.68

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.55	2	0.77	1.11	0.33	2.32
Within Groups	295	425	0.69			
Total	296	427				

Table A.11. ANOVA Test Based on Weather Condition and TCDS (Snow).

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Passive	6	10	1.67	1.067
Lights Only	12	13	1.08	0.45
Lights & Gates	73	123	1.68	0.77

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.75	2	1.87	2.50	0.08	2.36
Within Groups	66	88	0.75			
Total	69	90				

Table A.12. ANOVA Test Based on Weather Condition and TCDS (Snow).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Passive vs. Lights Only	153	1.32	0.19	1.65
Passive vs. Lights & Gates	311	1.69	0.09	1.65
Lights Only vs. Lights & Gates	73	-2.87	0.01	1.67

9.2 Test Results for Demographic Analysis

Table A.13. Summary of T-Test for Male vs. Female Drivers (Entire Sample).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Male vs. Female	9020	-0.28	0.78	1.65

Table A.14. ANOVA Test Summary for Different Age Group Drivers (Entire Sample).

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
16-19	1028	1375	1.33	0.69
20-29	2878	3996	1.38	0.67
30-39	737	1042	1.41	0.66
40-49	850	1253	1.47	0.68
50-59	992	1323	1.33	0.75
60-69	1140	1570	1.37	0.74
70+	1364	1907	1.39	0.70

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	12.60	6	2.10	2.992	0.006	1.775
Within Groups	6305	8982	0.70			
Total	6318	8988				

Table A.15. Summary of T-Test for Different Age Group Drivers (Entire Sample).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
16-19 vs. 20-29	1796	-1.69	0.09	1.65
16-19 vs. 30-39	1600	-1.92	0.06	1.65
16-19 vs. 40-49	1813	-3.55	<2E-3	1.65
16-19 vs. 50-59	2004	0.10	0.92	1.65
16-19 vs. 60-69	2156	-1.09	0.28	1.65
16-19 vs. 70+	2225	-1.75	0.08	1.65
20-29 vs. 30-39	1149	-0.75	0.45	1.65
20-29 vs. 40-49	1384	-2.65	0.01	1.65
20-29 vs. 50-59	1643	1.73	0.08	1.65
20-29 vs. 60-69	2008	0.38	0.71	1.65
20-29 vs. 70+	2628	-0.35	0.73	1.65
30-39 vs. 40-49	1558	-1.46	0.15	1.65
30-39 vs. 50-59	1636	1.96	0.05	1.65
30-39 vs. 60-69	1630	0.93	0.35	1.65
30-39 vs. 70+	1545	0.42	0.68	1.65
40-49 vs. 50-59	1821	3.54	<2E-3	1.65
40-49 vs. 60-69	1868	2.54	0.01	1.65
40-49 vs. 70+	1823	2.09	0.04	1.65
50-59 vs. 60-69	2084	-1.16	0.25	1.65
50-59 vs. 70+	2091	-1.80	0.07	1.65
60-69 vs. 70+	2401	-0.61	0.54	1.65

Table A.16. ANOVA Test for Different Age Group (Male Drivers).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
16-19	458	1.36	0.69
20-29	1265	1.40	0.63
30-39	413	1.39	0.68
40-49	429	1.43	0.69
50-59	481	1.30	0.78
60-69	574	1.37	0.72
70+	884	1.40	0.70

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	5.68	6	0.95	1.38	0.22	1.78
Within Groups	3086	4497	0.69			
Total	3092	4503				

Table A.17. ANOVA Test for Different Age Groups Drivers (Female Drivers)

SUMMARY

Groups	Count	Sum	Average	Variance
16-19	570	752	1.31	0.69
20-29	1613	2221	1.37	0.72
30-39	324	466	1.43	0.65
40-49	421	640	1.52	0.67
50-59	510	698	1.36	0.73
60-69	565	781	1.38	0.76
70+	480	670	1.39	0.72

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	11.30	6.00	1.88	2.62	0.02	1.78
Within Groups	3212	4476	0.72			
Total	3224	4482				

Table A.18. Summary of T-Test for Different Age Groups Drivers (Female Drivers)

Condition Pair	df	t Stat	P(T<=t) two-tail		t Critical two-tail
16-19 vs. 20-29	1015	-1.41	0.16	1.65	16-19 vs. 20-29
16-19 vs. 30-39	688	-2.09	0.04	1.65	16-19 vs. 30-39
16-19 vs. 40-49	913	-3.78	<2E-3	1.65	16-19 vs. 40-49
16-19 vs. 50-59	1057	-0.96	0.34	1.65	16-19 vs. 50-59
16-19 vs. 60-69	1129	-1.24	0.22	1.65	16-19 vs. 60-69
16-19 vs. 70+	1010	-1.46	0.14	1.65	16-19 vs. 70+
20-29 vs. 30-39	477	-1.23	0.22	1.65	20-29 vs. 30-39
20-29 vs. 40-49	674	-3.16	<2E-3	1.65	20-29 vs. 40-49
20-29 vs. 50-59	848	0.19	0.85	1.65	20-29 vs. 50-59
20-29 vs. 60-69	960	-0.13	0.90	1.65	20-29 vs. 60-69
20-29 vs. 70+	783	-0.43	0.67	1.65	20-29 vs. 70+
30-39 vs. 40-49	700	-1.36	0.17	1.65	30-39 vs. 40-49
30-39 vs. 50-59	717	1.18	0.24	1.65	30-39 vs. 50-59
30-39 vs. 60-69	718	0.96	0.34	1.65	30-39 vs. 60-69
30-39 vs. 70+	717	0.71	0.48	1.65	30-39 vs. 70+
40-49 vs. 50-59	909	2.75	0.01	1.65	40-49 vs. 50-59
40-49 vs. 60-69	935	2.53	0.01	1.65	40-49 vs. 60-69
40-49 vs. 70+	891	2.23	0.03	1.65	40-49 vs. 70+
50-59 vs. 60-69	1066	-0.26	0.80	1.65	50-59 vs. 60-69
50-59 vs. 70+	985	-0.50	0.62	1.65	50-59 vs. 70+
60-69 vs. 70+	1024	-0.25	0.80	1.65	60-69 vs. 70+

Table A.19. Summary of T-Test for Male vs. Female Drivers for Different TCDs

Male vs. Female	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Passive	749	-1.40	0.16	1.65
Lights Only	1336	-1.63	0.10	1.65
Lights & Gates	9020	-0.28	0.78	1.65

Table A.20. Summary of T-Test for Male vs. Female Drivers Within Different Age Groups

Male vs. Female	df	t Stat	P(T<=t) two-tail	t Critical two-tail
16-19	982	0.79	0.43	1.65
20-29	2794	0.85	0.39	1.65
30-39	700	-0.72	0.47	1.65
40-49	848	-1.61	0.11	1.65
50-59	981	-1.32	0.19	1.65
60-69	1134	-0.15	0.88	1.65
70+	965	0.07	0.94	1.65

Table A.21. ANOVA Test for Driver Behavior within Different TCDs (Male Drivers).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Passive	424	1.38	0.75
Lights Only	640	1.34	0.72
Lights & Gates	4515	1.38	0.69

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.13	2	0.56	0.81	0.44	2.30
Within Groups	3871	5576	0.69			
Total	3872	5578				

Table A.22. ANOVA Test for Driver Behavior within Different TCDs (Female Drivers)

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Passive	349	1.46	0.71
Lights Only	712	1.41	0.72
Lights & Gates	4512	1.39	0.72

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.96	2	0.98	1.37	0.25	2.30
Within Groups	4002	5570	0.72			
Total	4004	5572				

9.3 Test Results for Time of Day Analysis

Table A.23. Summary of T-Test for Day vs. Nighttime Driving (Entire Sample).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Day vs. Night	2,267	6.82	<2E-3	1.65

Table A.24. Summary of Test for Day vs. Nighttime Driving for Different TCDs.

Day vs. Night	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Passive	215	1.99	0.05	1.65
Lights Only	370	5.07	<2E-3	1.65
Lights & Gates	1685	4.84	<2E-3	1.65

Table A.25. ANOVA T-Test for Daytime Driving Within Different TCDs.

SUMMARY

Groups	Count	Sum	Average	Variance
Passive	645	928	1.44	0.75
Lights Only	1104	1585	1.44	0.70
Lights & Gates	5811	8177	1.41	0.70

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.19	2	0.59	0.85	0.43	2.30
Within Groups	5295	7557	0.70			
Total	5296	7559				

Table A.26. ANOVA T-Test for Nighttime Driving Within Different TCDs.

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	138	178	1.29	0.62
Column 2	254	288	1.13	0.74
Column 3	1176	1503	1.28	0.70

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4.52	2	2.26	3.24	0.04	2.31
Within Groups	1090	1565	0.70			
Total	1094	1567				

Table A.27. Summary of T-Test for Nighttime Driving Within Different TCDs.

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Passive vs. Lights Only	304	1.82	0.07	1.65
Passive vs. Lights & Gates	175	0.17	0.87	1.65
Lights Only vs. Lights & Gates	363	-2.43	0.02	1.65

9.4 Test Results for Combined Weather and Time of Day Analysis

Table A.28. ANOVA Test for Different Weather Conditions (Daytime).

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Clear	6933	9856	1.42	0.69
Cloudy	215	284	1.32	0.74
Rain	333	423	1.27	0.70
Snow	73	120	1.64	0.78

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	13	3	4.33	6.1957	0.0003	2.08
Within Groups	5280	7550	0.70			
Total	5293	7553				

Table A.29. Summary of T-Test for Different Weather Conditions (Daytime).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Clear vs. Cloudy	227	1.69	0.09	1.65
Clear vs. Rain	364	3.22	<2E-3	1.65
Clear vs. Snow	73	-2.13	0.04	1.67
Cloudy vs. Rain	448	0.68	0.50	1.65
Cloudy vs. Snow	121	-2.71	0.01	1.66
Rain vs. Snow	102	-3.29	<2E-3	1.66

Table A.30. ANOVA Test for Different Weather Conditions (Nighttime).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Clear	1454	1.25	0.70
Rain	95	1.32	0.67
Snow	18	1.44	0.73

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.04	2	0.52	0.74	0.48	2.31
Within Groups	1093	1564	0.70			
Total	1094	1566				

9.5 Test Results for Combined Demographics and Time of Day Analysis

Table A.31. Summary of T-Test for Male vs. Female Drivers Based on Time of Day.

Male vs. Female	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Day	7472	0.14	0.89	1.65
Night	1544	-0.90	0.37	1.65

Table A.32. Summary of T-Test for Day vs. Night Driving for Male and Female Drivers.

Day vs. Night	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Male	1131	5.62	<2E-3	1.65
Female	1103	4.23	<2E-3	1.65

9.6 Test Results for Combined Weather and Demographics Analysis

Table A.33. ANOVA Test for Different Weather Conditions (Male Drivers).

SUMMARY

Groups	*#Traversals*	*Ave. Score*	*Variance*
Clear	4168	1.38	0.68
Cloudy	88	1.42	0.73
Rain	203	1.32	0.70
Snow	53	1.58	0.75

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.22	3	1.07	1.56	0.20	2.09
Within Groups	3092	4508	0.69			
Total	3095	4511				

Table A.34. ANOVA Test Different Weather Conditions (Male Drivers)

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Clear	4121	5766	1.39	0.71
Cloudy	135	171	1.26	0.77
Rain	216	266	1.23	0.68
Snow	36	58	1.61	0.87

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9.58	3	3.19	4.45	0.0040	2.09
Within Groups	3232	4504	0.718			
Total	3241	4507				

Table A.35. Summary of T-Test for Different Weather Conditions (Female Drivers).

Condition Pair	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Clear vs. Cloudy	142	1.72	0.09	1.66
Clear vs. Rain	239	2.91	<2E-3	1.65
Clear vs. Snow	36	-1.36	0.18	1.69
Cloudy vs. Rain	270	0.37	0.71	1.65
Cloudy vs. Snow	53	-1.99	0.05	1.67
Rain vs. Snow	45	-2.29	0.03	1.68