ABSTRACT

SCHROEDER, BASTIAN JONATHAN. A Behavior-Based Methodology for Evaluating Pedestrian-Vehicle Interaction at Crosswalks. (Under the direction of Dr. Nagui Rouphail.)

This dissertation explores the interaction of pedestrians and drivers at unsignalized crosswalks in an event-based data collection and analysis approach. Through logistic regression techniques the microscopic data are used to derive predictive models for driver yielding and pedestrian crossing behavior. The analysis found that pedestrian and driver decision-making processes are sensitive to the dynamic profile of the vehicle, pedestrian characteristics and other concurrent events at the crosswalk. By relating the yield outcome to the dynamic state of the vehicle, a region of vehicle dynamics constraints was defined where virtually no yields are observed. Pedestrian assertiveness was found to be a key variable for promoting yielding behavior and increasing the likelihood of a pedestrian crossing. A contrast of the behavioral models for driver yielding and pedestrian crossing found a generally better model fit for the latter category. It is reasoned that the pedestrian decision is strongly influenced by the temporal duration to the point of conflict and the consequences of a poor decision. With a lack of enforcement, a driver is more easily swayed in the decision of whether or not to yield. The pedestrian crossing data are thus more consistent than the yielding data, resulting in models with greater statistical power. The evaluation of two pedestrian crossing treatments found that the treatments resulted in expected increases in the likelihood of drivers yielding, but also promoted more aggressive pedestrian behavior. For a pedestrian-actuated treatment, the effect on yielding was found to be greater following activation. The predictive models for two geometrically different mid-block crossings showed sufficient similarities, which suggests that the development of generic yielding and crossing models is feasible. The results of this research demonstrated the viability of the data collection approach and gave promise for expandability of the method to other applications. The research is meaningful in the context of modern microsimulation models, where the resulting models can be applied to describe the interaction of the driver and pedestrian modes.

A Behavior-Based Methodology for Evaluating Pedestrian-Vehicle Interaction at Crosswalks

by
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DEDICATION

To My Family

BIOGRAPHY

Bastian Jonathan Schroeder was born on August 18, 1980 in Frankfurt, Germany. He grew up in Kriftel, Germany and received his Abitur high school diploma from the Main-Taunus Schule in Hofheim, Germany in 1999. He immigrated to the United States in February 2000 and enrolled as an undergraduate at North Carolina State University in the fall of 2000. In May 2004, he graduated with a Bachelor of Science in Civil Engineering and a Bachelor of Science in Multidisciplinary Studies. Mr. Schroeder continued his graduate career at NCSU where he received a Master of Civil Engineering in December 2005. Since that time he had been working on his Ph.D. degree under the supervision of Dr. Nagui Rouphail in the Department of Civil, Construction, and Environmental Engineering at North Carolina State University. He started working as a research associate at the Institute for Transportation Research and Education in January 2008. Mr. Schroeder resides in Raleigh, NC with his wife Theresa and his son Aedon.

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LIST OF ABBREVIATIONS

Response Variables

GO – Pedestrian Event is GO (crossing was initiated). Also the binary outcome of the pedestrian event (GO=1, NOGO=0)
HY – The outcome of the vehicle event is a hard yield, indicating that the driver slowed down to a full stop to create a crossing opportunity for the pedestrian
LAG_EVENT - Pedestrian Event is a Lag (First Event after arriving at the crosswalk)
NOGO – Pedestrian Event is NO-GO (no crossing event)
NY – The outcome of the vehicle event is a Non Yield
SY – The outcome of the vehicle event is a Soft Yield, indicating that the driver slowed down for the pedestrian, but did not come to a full stop
YIELD – The binary outcome of the yield event (Yield=1, Non-Yield=0)
Y_ORDERED – The categorical outcome of the yield event with three ordered outcomes (3=HY=hard yield, 2=SY=soft yield, 1=NY=non-yield)
Y_TYPE - The binary type of the yield event outcome (HY=1, SY=0)

Discrete Explanatory Variables

ADY – Presence of an adjacent yield in the opposite direction; ADY=1 if a vehicle in the opposite lane has already yielded for the pedestrian at the crosswalk
AST – The pedestrian is assertive; AST=1 if the pedestrian exhibits assertive behavior in the approach of the crosswalk, indicated for example through fast walking pace
COM – Indication of non-verbal communication between driver and pedestrian; COM=1 if there is evidence of non-verbal interaction (waving, raising hand to say 'Thank You') between the driver and pedestrian
DECEL_TAU – The deceleration rate threshold is satisfied; DECEL_TAU=1 if the deceleration rate necessary to come to a full stop before the crosswalk is greater than 10ft/sec^2
DSC – Presence of an downstream conflict; DSC=1 if a vehicle is stopped downstream of the crosswalk or if there is heavy traffic in the circulating lane preventing immediate entry into the circle (Roundabout Only)
ENTRY – Indication of whether the event occurred at the entry leg of the roundabout (Entry = 1) or at the exit leg (Entry = 0) - (Only applicable for roundabout site)
FLASH – Indication whether the flashing beacon was actuated by the pedestrian; FLASH=1 if beacon was flashing during the yield event (Only applicable for Charlotte, NC site)
FOLL – Approaching vehicle has close follower; FOLL=1 if the vehicle has a follower at a short headway of approximately 2-4 seconds
G_NEAR – The observed gap/lag event has a vehicle in the near lane and no vehicle in the far lane relative to the waiting pedestrian
G_FAR – The observed gap/lag event has a vehicle in the far lane and no vehicle in the near lane relative to the waiting pedestrian

G_COMBO – The observed gap/lag event has a vehicle in both lanes (near and far) - the gap/lag size is measured relative to first vehicle arrival

HEV – Approaching vehicle is a heavy vehicle; HEV=1 if the vehicle is anything larger than the equivalent of a 15-passenger van (dump truck, TTST, bus)

MUP – There are multiple pedestrians present in the crosswalk influence area; MUP=1 if the number of pedestrians waiting at the curb is greater than 1

NEAR – Pedestrian is waiting on the near-side of the approaching vehicle; NEAR=1 if the pedestrian waits on the same side of the road that the vehicle is traveling on

PLT – Approaching vehicle is part of a platoon of vehicles; PLT=1 if the headway to the following OR the previous vehicle was short (approximately 2-4 seconds)

PREV – The previous vehicle passed without yielding; PREV=1 if the previous vehicle failed to yield to the same pedestrian waiting at the crosswalk

PXW – A pedestrian from a previous event is still present in the crosswalk; PXW=1 if the driver has to account for a pedestrian who is still in the roadway from a previous event

QUE – Vehicle is part of a queue of vehicles; QUE=1 if the queue or platoon that the vehicle is a part of is moving slowly due to some downstream congestion or incident

TRIG – The pedestrian triggered the yield by stepping into roadway; TRIG=1 if the pedestrian actively seized the roadway before the driver action indicated a yield

TRTMT – Presence of crossing treatment; TRTMT=1 if the treatment was installed and so is equivalent to the 'after' case (Only applicable for Mid-Block sites)

TTC_TAU – The time to collision threshold is satisfied; TTC_TAU=1 if the theoretical time to arrival at the crosswalk is less than 3 seconds (TTC=DIST1/SPEED_FT)

<u>Continuous Explanatory Variables</u>

DECEL – Deceleration rate necessary to come to a full stop prior to crosswalk; DECEL is calculated from measured speed and distance; DECEL=(SPEED_FT*SPEED_FT)/(2*DIST1); units are feet/sec^2

DIST1 – Vehicle position at the time of pedestrian arrival in crosswalk influence area measured in feet using a LIDAR speed measurement device

D_WAIT – The duration of pedestrian waiting time at the decision point. The waiting time is zero for all initial lag events. For all subsequent gaps, the waiting time is calculated from the duration between the initial arrival at the crosswalk and the passing of the previous vehicle in seconds.

E_GAP – Expected Gap Time between successive vehicle events at constant speed in seconds

E_LAG – Expected Lag Time b/w ped. (t1) and time vehicle would have arrived at constant speed in seconds

O_GAP – Observed Gap Time between successive vehicle events t3n and t3n+1 in seconds

O_LAG – Observed Lag Time b/w ped. arrival (t1) and vehicle arrival at the crosswalk (t3) in seconds

SPEED_FT – Vehicle speed at the time of pedestrian arrival in crosswalk influence area measured in ft/sec using a LIDAR speed measurement device in feet per second

TTC – Time until vehicle would theoretically arrive at the crosswalk; TTC is calculated from the measured speed and distance at the time pedestrian arrives in the crosswalk influence area; TTC=DIST1/SPEED_FT; units are seconds

<u>Data Collection Terms</u>

MB-CLT – Site code for data collection site: Mid-Block Crossing on Selwyn Avenue in Charlotte, NC

MB-RAL: – Site code for data collection site: Mid-Block Crossing on Sullivan Drive in Raleigh, NC

RBT-RAL – Site code for data collection site: Roundabout Crossing on Pullen Road in Raleigh, NC

LIDAR – A speed measurement device that uses laser technology used in data collection

<u>Analysis Terms</u>

CG - Critical Gap (sec.), by definition the gap time at which a minor street vehicle or pedestrian is equally likely to accept or reject the gap.

DYM – Driver Yield Model. Probabilistic model describing the likelihood of a driver yielding to pedestrians at the crosswalk.

Gap – The temporal duration between two successive vehicle arrivals at a given point of reference (front bumper to front bumper) measured in seconds

HCM – Highway Capacity Manual (TRB, 2000). A reference manual outlining traffic engineering operational analysis methodologies

Lag – The temporal duration between the pedestrian arrival at the crosswalk and the arrival of the first vehicle measured in seconds

LOGIT – Statistical model using logistic regression techniques to describe probabilities

MLE – Maximum Likelihood Estimation; a statistical methodology to estimate a model form or parameter distribution that maximizes the likelihood of observing the given sample of data points

MUTC – Manual of Uniform Traffic Control Devices (FHWA, 2002). A reference manual for traffic engineers discussion guidelines for signs, marking and signalized traffic control.

PCM – Pedestrian Crossing Model. Probabilistic model describing the likelihood of a pedestrians accepting a gap or lag in the conflicting traffic stream

P(G) – The probability of a gap occurring in the traffic stream

P(GU) – The probability of a gap being utilized by the pedestrian

P(Y) – The probability of a driver yielding

P(YU) – The probability that a yield is utilized by the pedestrian

RR – Ramsey-Routledge Method; a statistical methodology to estimate a distribution of critical gaps or lags from a sample of data

VDC – Vehicle Dynamics Constraint. The relative position to the crosswalk of the vehicle and its speed at the time of a pedestrian event is such that the necessary deceleration rate to come to a stop before the crosswalk (DECEL) is greater than the assumed comfortable deceleration rate of 10 ft/sec^2. A driver subject to VDC is considered unlikely to yield to a pedestrian.

Simulation Terms

PR – Abbreviation for “priority rules”, which is the model algorithm in the simulation model VISSIM used to describe gap acceptance and yielding behavior.

VISSIM – A microsimulation software package that models movements of individual vehicles and pedestrians from user-defined and default algorithms

1 INTRODUCTION

The field of traffic engineering has traditionally focused on the operations of motorized modes of transportation. While the analysis of vehicular traffic is most common, an increasing number of engineering projects today are including accommodations for non-motorized road users. Many cities and smaller townships have drafted master plans for pedestrian and bicycle networks, including both non-motorized trails and facilities shared with motorized traffic. The growing emphasis on the pedestrian and bicycle modes demands proper methods of analysis to determine the operational levels of service for non-motorized transportation modes as well as their interaction with vehicular traffic.

One of the most challenging components in the analysis of pedestrian facilities is the assessment of a location where the pedestrian path crosses a roadway of motorized traffic. These pedestrian crosswalks may or may not be signalized, and pedestrian delay and safety at these locations are important measures to understand. Over the past decade, pedestrian research has focused on the evaluation of *treatments* for unsignalized crossing locations that are intended to make them safer for pedestrians. The evaluation of such pedestrian crossing treatments is typically carried out through empirical before and after studies that investigate aggregated measures of effectiveness. The effectiveness of a treatment is oftentimes quantified by a decrease in vehicle speed, an increase in yielding behavior, or a reduction of crashes following installation. Alternatively, researchers sometimes use comparison sites to contrast driver and pedestrian behavior at, for instance, marked versus unmarked crosswalks (Zeeger et al, 2001). While these are adequate and statistically valid methods of analysis, their clear drawbacks are that evaluation is time-consuming and lacks microscopic detail. A macroscopic analysis of pedestrian crosswalks may be adequate for some applications, but this dissertation argues that it is insufficient for a representation of these facilities in a microsimulation environment.

Significant work has also been done on alternatives to conventional signalized pedestrian crossings. Innovative signalization schemes for pedestrian mid-block and roundabout crossings have been applied in Europe and Australia (Inman and Davis, 2007), and more recently in the United States (Tucson DOT, 2007). The general objective of these new signalization strategies is to balance the crossing safety for pedestrians with the delay experienced by motorized traffic as a result of installing the signal.

Current traffic engineering analysis tools and capacity models are of limited use for evaluating the interaction of pedestrians and vehicles at unsignalized crossing facilities. Common analysis methodologies are limited to boundary cases, which assume strictly enforced right-of-way rules (TRB, 2000). The methods typically ignore the more complex interaction of the two modes in which some drivers yield to pedestrians and some pedestrians accept gaps in traffic. Thus, while the methods may be adequate for analyzing signalized pedestrian crossings, they do not offer a way of comparing the operations of signals to unsignalized control. A true comparison of the operational impact of different unsignalized treatments is also not possible in the current framework.

The greatest challenge in the analysis of unsignalized pedestrian crossings is the interplay between pedestrian crossing and driver yielding behavior. Absent the appropriate data, pedestrian crossing behavior is oftentimes analyzed with the implication that it is generally analogous to vehicular gap acceptance. But can an unsignalized mid-block pedestrian crossing really be compared with minor street traffic operation at a two-way stop controlled intersection? In fact, yielding behavior at pedestrian crossings in the US varies greatly, which may be attributable to differences in geographic location, the type of crossing location, the time of day and a range of other factors that are not well understood in current research practice. Current research gives evidence for the variability of driver yielding behavior across geographic locations (Fitzpatrick et al., 2006) and further indicates that some pedestrian treatments are effective in increasing the rate of yielding. But an important question remains: What are the operational impacts of an increased yielding rate? In order to analyze the interaction of the pedestrian and vehicle modes it is important to gain better insight into both the yielding and the gap acceptance processes and to identify ways that these behavioral characteristics can be related back to a measurable effect on operations.

1.1 Motivation

An increasing number of cities and state agencies are placing high priority on providing adequate pedestrian facilities. Pedestrian facility improvement projects aim to create recreational pedestrian paths, to revitalize downtown areas, or to create safe walking routes to educational facilities. With increasing focus on these types of pedestrian facilities, questions about pedestrian safety and the operational interaction of pedestrians and motorized traffic need to be addressed. Especially when these pedestrian facilities intersect with streets, engineers have to decide how to control the interaction of the pedestrian and vehicle modes at the crossing.

The research presented here is inspired by two ongoing research projects investigating crossing difficulties of pedestrians with vision impairments. The first, a Bioengineering Research Partnership sponsored by the National Eye Institute (NEI) of the National Institutes of Health (NIH) quantifies differences in crossing performance of blind and sighted pedestrians at roundabouts. The second, National Cooperative Highway Research Project (NCHRP) 3-78a, is aimed at identifying and evaluating treatment solutions that may help pedestrians with vision impairments cross at roundabouts and channelized turn lanes.

The involvement in aforementioned research projects produced the need to analyze crossing performance of blind travelers and identify ways to measure the effect of treatment installation. The two projects are ultimately motivated by the American with Disabilities Act (ADA). This legislation enacted in 1990 mandates equal access to public facilities to all users of that facility, including those with mobility or vision impairments.

Especially the question of the accessibility of unsignalized roundabout crossings to blind pedestrians has triggered a lot of research in recent years. The associated US Access Board (2006) regulations oblige transportation facilities to conform to the Americans with Disabilities Act and require *equal access* for all pedestrians, including those with vision or mobility impairments regardless of the demand for crossing. More discussion on this issue will follow in later chapters.

But pedestrian safety concerns clearly extend to pedestrians without disabilities as well. The National Highway Traffic Safety Administration (NHTSA, 2006) lists a total of 4,784 pedestrian facilities in 2006 and 61,000 injuries in traffic collisions. The report further cites that the highest rate of pedestrian fatalities (almost 40%) occurred during the hours of 4pm and 8pm, suggesting a relationship between pedestrian safety and heavy PM peak hour traffic.

In a separate analysis of pedestrian and bicycle injuries based on hospital data, an FHWA Report (FHWA, 1999) found that 88% of the injuries from motor vehicle crashes occurred on the roadway. Furthermore, 38.5% of motor vehicle roadway injuries were to children under the age of 14, indicating elevated risk for young pedestrians in roadway crashes.

In efforts to improve pedestrian safety at signalized and unsignalized crossings a range of treatments or countermeasures are available. A recent NCHRP report by Fitzpatrick et al (2006) presented a thorough overview of such pedestrian crossing treatments and in many ways provided practicing engineers with helpful advice on the selection and evaluation of treatments. The pedestrian countermeasure selection system PEDSAFE (www.walkinginfo.org) has a similar objective and includes links to case studies, treatment evaluations and an image library for reference. In an effort to achieve a more comprehensive and consistent analysis of treatments, Fitzpatrick et al (2006) collected data at several sites with different treatments installed. The authors used their observations to make inferences on treatment effect on yielding behavior. However, the data collection approach in many ways was of a macroscopic nature, aggregating the results at the site level.

With the availability of different pedestrian crossing treatments, there needs to be some basis for deciding upon their installation and for analyzing their impacts. A common approach is to determine whether a signalized pedestrian crossing is *warranted*. The pedestrian signal warrant in the Manual of Uniform Traffic Control Devices (MUTCD) (FHWA, 2002) warrants the installation of a pedestrian signal when both of the following conditions are met:

A. The pedestrian volume crossing the major street at an intersection or midblock location during an average day is 100 or more for each of any 4 hours or 190 or more during any 1 hour; and

B. There are fewer than 60 gaps per hour in the traffic stream of adequate length to allow pedestrians to cross during the same period when the pedestrian volume criterion is satisfied. Where there is a divided street having a median of sufficient width for pedestrians to wait, the requirement applies separately to each direction of vehicular traffic.

{SOURCE: MUTCD, 2003 Edition, Section 4C.05 Warrant 4, Pedestrian Volume}

In the MUTCD a pedestrian signal is warranted if both the pedestrian volume is high and the conflicting vehicle flow is high, making it difficult for pedestrians to cross at a facility.

While this warrant provides decision support for engineers in areas of heavy pedestrian traffic, it does not provide guidance in other cases. Oftentimes, lower-volume crossings can prove challenging for pedestrians because of heavy vehicular traffic, poor sight distances, or high approach speeds. Such crossings with little pedestrian demand may pose safety concerns and may cause many pedestrians to avoid these types of facilities all together.

With a lack of guidance from the MUTCD, engineers may turn to the Highway Capacity Manual (HCM) (TRB, 2000) to make decisions on pedestrian treatment installations based on pedestrian delay estimation at an unsignalized pedestrian crossing. However, discussions in this document will show that the current delay calculation in the HCM effectively assumes one of two right-of-way regulations: either all drivers yield to pedestrians or none do. Clearly, both assumptions are inadequate in describing actual operations at many crosswalks and thus research insights into this problem are sorely needed.

In addition to signals, engineers and planners today have a whole range of pedestrian treatments to choose from that may or may not serve the need of a particular site. Oftentimes, unsignalized crossings can be enhanced by treatments geared at increasing driver yielding behavior, and thus forgoing signalization. Many of these treatments have been heavily researched and their effectiveness demonstrated through empirical before and after studies. Nonetheless, their true impacts on operations at a new site are difficult to predict using existing methods. Similarly, a true comparison between signalized and unsignalized operations is also challenging to conduct a priori.

The NCHRP 3-78a project places a strong emphasis on the use of microsimulation models for treatment evaluation. Motivated by the high cost of field data collection and associated risk to blind study participants, the project intends to use microsimulation to model the interaction of pedestrians and motorized traffic at signalized and unsignalized facilities. Working from calibrated base interaction models, the goal is to extrapolate treatment impacts to a wider range of geometric and operational situations.

It was through the involvement in NCHRP 3-78a that the author along with members of the research team developed the underlying concepts used in this dissertation. The planned application of microsimulation models requires that the aforementioned interaction models accurately reflect actual observations at crosswalks.

Of the few existing attempts to analyze yielding and gap acceptance through microscopic behavioral data (not through site-specific parameters), the work by Sun et al (2002) stands out. The authors investigated the use of logit and probit models to describe both components of pedestrian-vehicle interaction and demonstrated the feasibility of this approach through model validation. The authors used observational data from one crosswalk, but did not include any operational parameters in the analysis. Their work focused on binary variables such as gender and vehicle type. They did not investigate if the speed of a particular driver would allow him or her to come to a stop at the crosswalk, nor did the authors perform any evaluation of treatments.

In his doctoral dissertation, Chae (2006) performed an operational analysis of pedestrian-vehicle interaction at roundabouts using video image processing. Through sophisticated vehicle tracking technology, the author was able to obtain detailed time-sensitive data on speeds and time gaps of both modes. The author discussed a range of treatments that would affect the interaction, but did not offer any in-depth evaluation of treatment effects. Further, the Chae (2006) did not investigate midblock crossings and did not explore predictive models for behavior.

In this dissertation, the author develops and implements an event-based methodology for this type of analysis. The data used in this document were collected independently of the above projects. The author has jointly published and presented several papers including those exploring behavioral differences of blind and sighted pedestrians (Schroeder, Rouphail, and Wall Emerson, 2006), comparing pedestrian signal treatments at roundabouts (Schroeder, Rouphail and Hughes, 2008), and evaluating unsignalized pedestrian crossings in a microsimulation environment (Schroeder and Rouphail, 2007).

1.2 Contribution to Knowledge

This document builds on several of the cited research studies by evaluating the effect of treatments presented by Fitzpatrick et al (2006) and PEDSAFE using statistical modeling tools similar to the work by Sun et al (2002). The key difference is that the research in this dissertation considers operational variables as well as behavioral attributes. The modeling results can be implemented in microsimulation, much like the approach taken by Chae (2006). The research makes a contribution to the knowledge base in the field of traffic engineering in several ways:

- The research develops a data collection methodology for researchers that measures a range of discrete and continuous variables describing the interaction of pedestrians and drivers at unsignalized crosswalks. These variables describe the dynamic state of the vehicle, behavioral attributes of drivers and pedestrians, and the state of concurrent events with the interaction.

- The research adopts statistical methods to describe the probability of driver yielding and pedestrian crossing behavior from the data. The developed forecast models allow for a more realistic representation of pedestrian-vehicle interaction, overcoming the limitations of existing methodologies that only address the boundary cases of yielding behavior.

- The implementation of the probabilistic models in a microsimulation environment allows the analyst to compare the effectiveness of different types of treatments relative to a base scenario with just a zebra-striped crossing. Such quantitative comparison of the operational impact of treatments is not possible with existing methods.

- The more realistic representation of unsignalized operations allows for contrasting those crossings with signalized crosswalks in a simulation environment. In current practice it is impossible to quantify the incremental impact of a pedestrian signal on vehicle or pedestrian operations, because the evaluation of the unsignalized baseline case is overly simplistic.

1.3 Research Objectives

This research seeks to develop an analysis methodology for pedestrian-vehicle interaction that is applicable for inclusion in a microsimulation environment. The specific objectives of this research are as follows:

1. Devise a data collection methodology to evaluate the interaction of pedestrians and drivers at unsignalized pedestrian crossings at a microscopic or event level.
2. Demonstrate that pedestrian crossing and driver yielding behavior is sensitive to:
    - the dynamic characteristics of the approaching vehicle
    - behavioral characteristics of pedestrian and driver
    - concurrent events at the crosswalk
    - the installation of crosswalk treatments
3. Describe driver yielding and pedestrian crossing behavior from collected event-based data accounting for attributes of vehicle dynamics, behavior and the effect of treatments
4. Demonstrate that driver yielding and pedestrian crossing models have application to microsimulation models where they can enhance existing interaction algorithms

1.4 Research Scope

The methodology presented in this document requires significant data to properly calibrate the proposed behavioral parameters that describe pedestrian crossing and driver yielding behavior. The attributes for pedestrian and driver populations were collected at sites in Raleigh and Charlotte, NC at a sample size deemed sufficient for an illustration of the methodology.

Given the great variability of pedestrian and driver behavior, the results are clearly subject to a regional and site-specific bias and should not be generalized to other sites at this time. While the methodology is universal and thus transferable, the observed data are not. Any extension or application of this research to other sites and outside of the State of North Carolina should therefore include additional data collection and model validation efforts.

The analysis approach aimed to take full advantage of the amount of data used for model calibration. The results are contrasted with existing analysis methodologies for gap acceptance and yielding, but the models were not formerly validated with independent data not used in model development.

The data collection approach collects microscopic data on individual drivers and pedestrians, but does not track these entities in sub-second time intervals. Vehicle tracking has been demonstrated by others, but is beyond the scope of this effort.

Finally, this research focuses strictly on the *intermodal* relations of the vehicle and pedestrian modes at pedestrian crossings; it does not address the *intramodal* interaction on the approaches to the crossing, unless it has a direct effect on the interaction at the crosswalk. The intramodal processes for vehicular traffic are taken from existing models (e.g. car-following algorithms) and can be calibrated to reflect observed conditions as necessary (e.g. speed distributions). Similarly, pedestrian travel patterns, interactions between multiple pedestrians, and walking speed effects are not explicitly analyzed.

1.5 Outline of Dissertation

This document is divided into three main parts. The first part provides an overview of the problem statement and outlines the research approach and analysis methodology. This chapter presented an introduction to the research and defined the objectives in the context of existing work. Chapter 2 presents the underlying analysis framework and discusses different types of pedestrian crossings and treatments. It further reviews the behavioral process of pedestrian crossing and driver yielding behavior and summarizes existing research on the subject matter. Chapter 3 lays out a data collection methodology developed specifically for this research to obtain the necessary variables from the field. It also discusses ways of reducing and analyzing the data. Special emphasis is given on illustrating the basic concepts of logistic regression techniques.

The second part of the document presents the data and analysis results of actual field data collected for this dissertation. Data were collected at two mid-block crossing locations and one roundabout site. The data for the mid-block crossing included observations before and after the installation of two different pedestrian crossing treatments; an in-road pedestrian warning sign and an in-pavement pedestrian-actuated flashing beacon. Chapter 4 is devoted to the analysis of driver yielding behavior at the two mid-block sites and the impact of the treatments on driver behavior. Chapter 5 analyzes pedestrian crossing behavior for those same data sets and compares conventional gap acceptance analysis methods with the newly proposed logistic regression approach. Chapter 6 presents and analyzes both driver yielding and pedestrian crossing data for a single-lane roundabout crosswalk.

In the third and final part, the field observations are related back to the analysis framework presented. Chapter 7 extends the behavioral concept in the context of microsimulation. It discusses the potential for implementing of the logistic models and outlines requirements for simulation algorithms utilizing the results of this research. Chapter 8 relates the findings back to the initial research objectives and discusses areas of future research. Chapter 9 gives a list of references used in this research. Supporting documentation on data reduction, analysis methodologies and modeling outputs can be found in the Appendix.

2 ANALYSIS FRAMEWORK

The analysis framework presented in this chapter rests on the assumption that driver and pedestrian behavior can be represented through a set of descriptive parameters, that these parameters can be calibrated from field data, and that they can be used as inputs in simulation models. It is further assumed that different treatments implicitly impact the behavioral parameters of drivers and pedestrians and that these impacts are observable in the field. The research premise is as follows: if both the behavioral base condition of pedestrian and driver behavior and the treatment effect are quantifiable and observable, the resulting operational effects extracted from microsimulation are meaningful (assuming the simulation logic is valid).

The chapter presents an analysis framework for unsignalized pedestrian crossing facilities. The underlying concepts for the framework were first presented at the Annual Meeting and Exhibit of the Transportation Research Board (Schroeder and Rouphail, 2007). The chapter discusses the components of the framework and how it relates to modern microsimulation tools. It also offers a discussion of data needs in preparation for discussing the data collection methodology in the next chapter. The chapter goes on to present a brief overview of different pedestrian crossing facilities and a summary of the types of pedestrian treatments and crossing facilities. It concludes with a detailed discussion and literature review of the two main components of pedestrian-vehicle interaction: pedestrian crossing behavior and driver yielding behavior.

2.1 A Framework for Evaluating Unsignalized Crossings

This research is based on an innovative analysis framework for unsignalized pedestrian crossings that utilizes both pedestrian crossing behavior and driver yielding behavior. The framework allows for the analysis of signalized and unsignalized pedestrian crossing facilities and a comparison among the two in a microsimulation environment. A flowchart of the general analysis framework is provided in Figure 1.

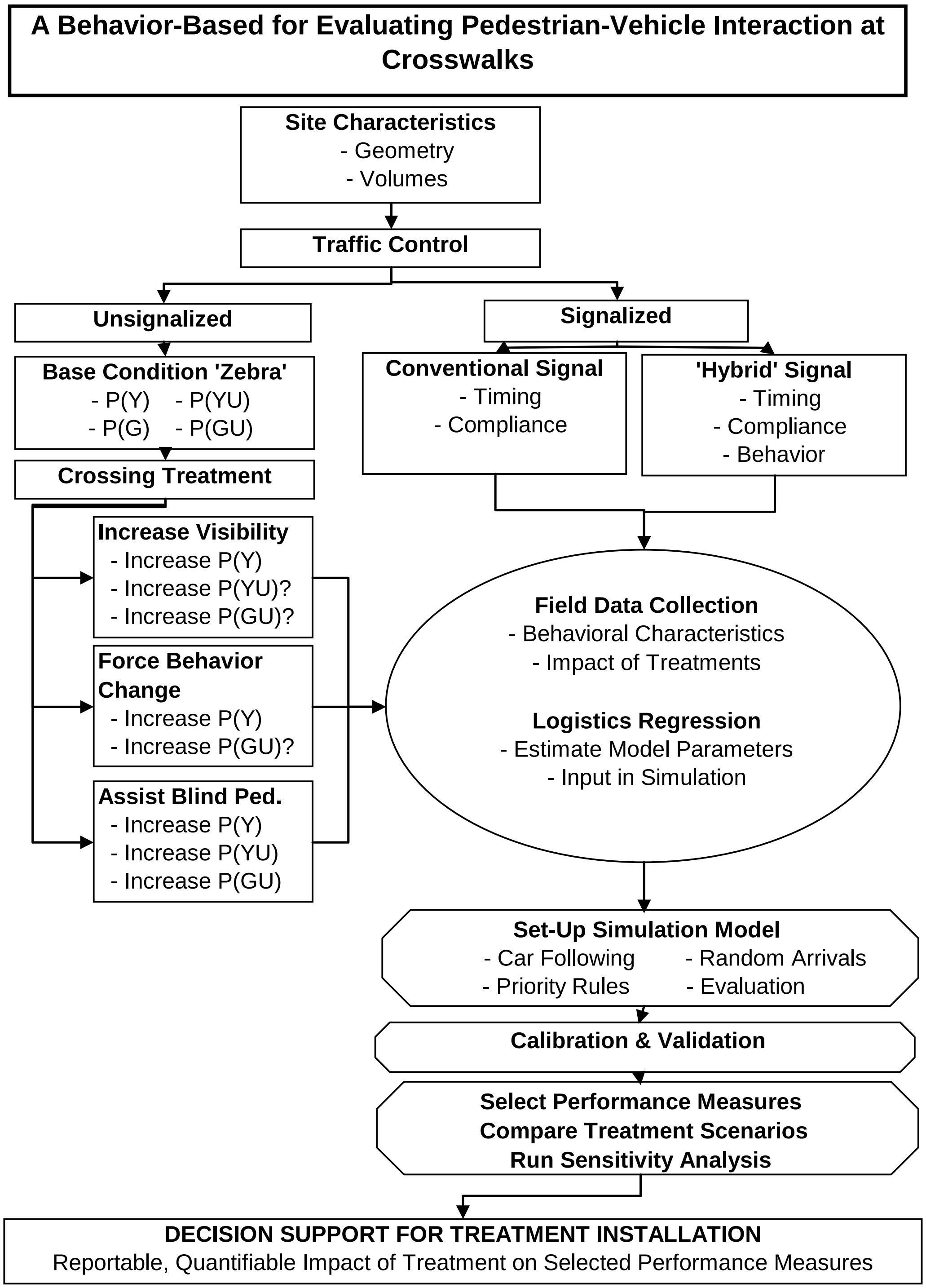


Figure 1: Analysis Framework Flowchart

The analysis methodology relies on site-specific characteristics of the crosswalk. It assumes that geometric information and traffic and pedestrian volumes are available from field visits, design drawings or forecasts. It is further assumed that the analyst is aware of the existing or proposed type of traffic control (signalized or un-signalized).

For signalized crossings a conventional signal can be described from signal timing parameters and associated analysis methodologies. Concerns about pedestrian and driver compliance to the signal indication are valid and have been explored by others (Tiwari et al., 2007). However, the analysis of these behaviors is beyond the scope of this research. The same is true for behavioral characteristics at hybrid signals including the HAWK signal (Tucson DOT, 2007 and Schroeder, Rouphail, and Hughes, 2008) and strategies such as the "Pelican" or "Toucan" signals used in Europe and Australia (Inman and Davis, 2007).

The emphasis of this dissertation is on unsignalized crossing facilities, because signalized crossings are more clearly defined in existing analysis methodologies (TRB, 2000). For a representative analysis of signalized pedestrian crossing alternatives in microsimulation, the reader is referred to Schroeder, Rouphail and Hughes (2008). That work compared the use of both conventional pedestrian-actuated signals and innovative HAWK signals at single-lane and two-lane roundabouts. It demonstrated the potential of microsimulation to evaluate signalized crossing treatments over a range of volume levels and further compared innovative and new signalization strategies prior to field implementation.

For unsignalized crossings, the author proposed a framework for evaluating the interaction of pedestrians and vehicles in a recent paper (Schroeder and Rouphail, 2007). The paper discusses modeling parameters for the interaction of pedestrian and vehicle traffic that should be included in a microscopic simulation analysis of unsignalized pedestrian crossing facilities.

Specifically, the interaction is characterized by four interaction processes that can be expressed in the form of probabilities:

P(G)	- The probability of a gap occurring in the traffic stream
P(GU)	- The probability of a gap being utilized by the pedestrian
P(Y)	- The probability of a driver yielding
P(YU)	- The probability that a yield is utilized by the pedestrian

The probability of gap occurrence, P(G), is a function of vehicle arrivals and the headway distribution in the traffic stream. The behavioral characteristics of pedestrians and drivers are generally described by the probability of crossing in a gap, P(GU), and the probability of a driver yielding to a waiting pedestrian, P(Y). The fourth parameter typically applies only to pedestrians with vision impairments or other special populations who tend to reject or miss a portion of the encountered yields. For the population of pedestrians observed in this research, the yield utilization rate, P(YU), is 100%.

The approach further hypothesizes that different treatments affect one or more of these probabilities. A later section categorizes treatments based on their intended effect: increasing visibility, forcing a behavior change, or assisting blind travelers. For example, a given treatment may be intended to increase the likelihood of yielding, but may also have an affect on pedestrian gap acceptance. In earlier work, the probabilities associated with different treatment effects were assumed for a demonstration of concept (Schroeder and Rouphail, 2007). Through the methodology put forth in this research the author will demonstrate how the probabilities can be estimated from field observations and how a treatment effect can be accounted for.

Modern microsimulation models simulate the movements of individual vehicles and pedestrians based on algorithms for car-following, lane-changing behavior and others. The models generally allow the user to simulate speed and headway distributions as random parameters and to define priority rules (PTV, 2005) to represent unsignalized points of interaction. By adopting the model algorithms to match findings from this research, microsimulation can be a viable tool for analyzing the interaction of the pedestrian and vehicle modes.

Microsimulation models minimize data collection costs compared to field evaluation and, in the case of pedestrian research, offer the potential for non-intrusive treatment evaluation, minimizing the risk to study participants. Through the analysis framework presented above, they allow the evaluation of proposed pedestrian treatments prior to installation at a new location. With proper calibration of models, simulation tools have a wide range of applications and have been used for example to model pedestrian-vehicle interaction at roundabouts (Chae, 2006).

Additional discussion on the modeling of pedestrians in microsimulation and the implementation of this research in microsimulation is provided in Chapter 7.

With models in place to describe pedestrian and driver behavior and to quantify treatment impacts, microsimulation models can be coded and calibrated from site-specific interaction parameters.

2.2 Pedestrian Crossing Facilities

Pedestrian crossings are a common feature at signalized intersections where they are typically tied to the vehicular signal phasing scheme. The analysis of these types of pedestrian crossings is outlined in the HCM. Besides these signalized crossing locations at intersections, there are three major types of unsignalized pedestrian crossings:

crossings at channelized right-turn lanes, mid-block pedestrian crossings, and crossings at the approaches to a modern roundabout.

2.2.1 Channelized Right-Turn Lanes

Channelized right-turn lanes (CTL) are commonly found at signalized intersections to create additional capacity for heavy right-turning traffic. These single-lane bypass lanes are typically free-flowing with a yield-controlled merge into downstream traffic and may be outfitted with an acceleration and/or a deceleration lane. A pedestrian crossing at the main signalized intersection inevitably requires the pedestrian movement to also cross these CTLs, which is most commonly done at an unsignalized zebra-striped crosswalk in the center of the turn lane. For a detailed discussion on CTL geometry and alternative placement for the pedestrian crosswalk refer to NCHRP Report 279 (TRB, 1985) and the NCHRP 3-72 project (TRB, 2003). While not discussed in detail in this document, a previously published paper (Schroeder, Rouphail and Wall Emerson, 2006) presents a detailed analysis comparing the crossing abilities of blind and sighted travelers at these types of facilities.

2.2.2 Mid-Block Crossings

In addition to crossings at signalized intersections, pedestrian crossings are commonly found at mid-block locations. Contrary to what is implied in the terminology, these crossings are not necessarily located in the middle of a block, but rather can be found anywhere along a roadway at locations away from an intersection crossing. The crossed roadway can range anywhere from one to four or more lanes, may have traffic in one or two directions, and may or may not be outfitted with a signal. The decision to place a signal at a mid-block location is regulated by the pedestrian signal warrant in the MUTCD (FHWA 2002).

2.2.3 Roundabout Crossings

Pedestrian crossings are also found at modern roundabouts, which are becoming an increasingly popular traffic control feature in the US. A long-term staple in Europe and Australia, an online database (Kittelson Associates, 2007) now lists more than 1,000 roundabout intersections across the United States, justifying their inclusion in this discussion. The pedestrian crossing at modern roundabouts is typically a two-stage crossing with pedestrians being able to find refuge on the splitter island as shown in Figure 2. The pedestrian crossing location is also designed to allow storage for one or more vehicles waiting to enter the roundabout downstream of the crosswalk.

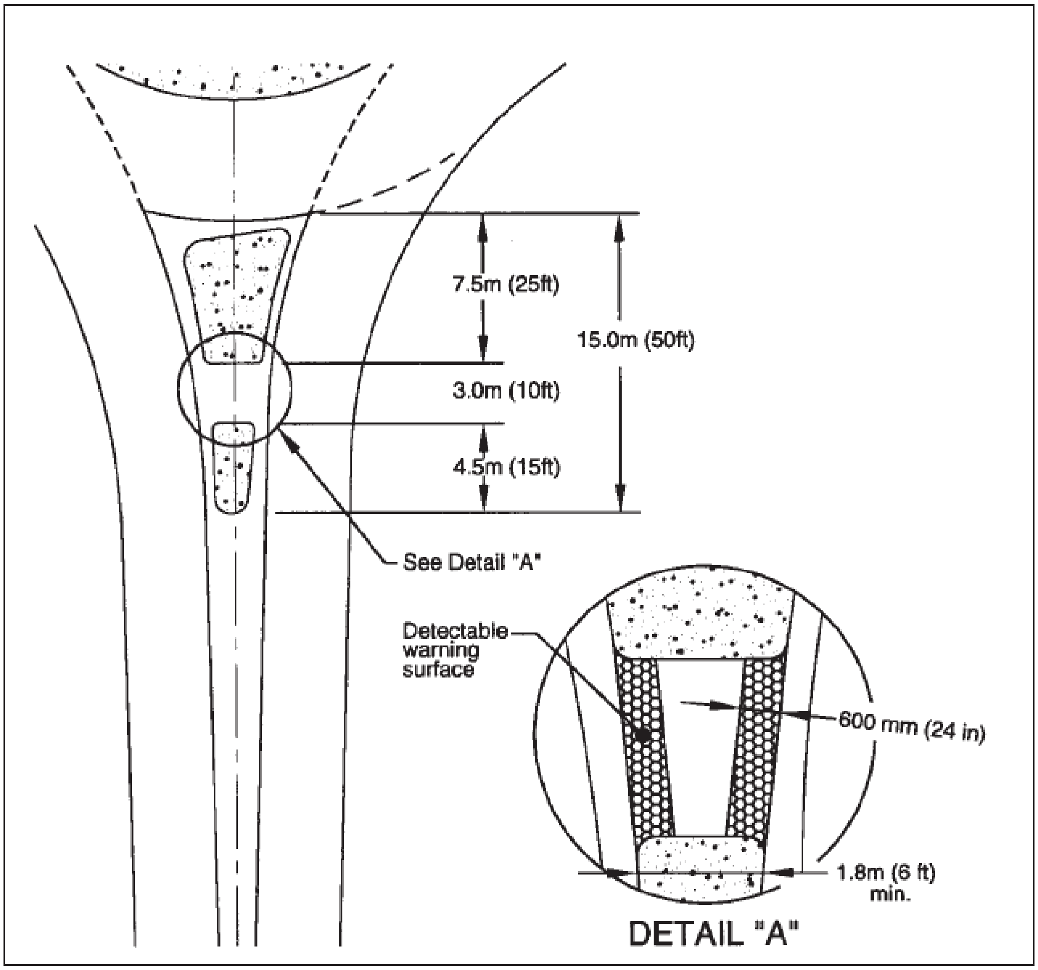


Figure 2: Roundabout Pedestrian Crossing

(SOURCE: FHWA Roundabout Guide, 2000)

For the purpose of discussion it is assumed that the base condition for pedestrian crossings at any of the three types of locations is a zebra-striped unsignalized crosswalk. At these types of crossings, legislation typically gives pedestrians in the crosswalk the right-of-way, but as later discussion shows, motorist compliance varies. To further enhance the crossing and to make it safer for pedestrians, there are several categories of pedestrian crossing treatments that aim to facilitate pedestrian crossings.

2.3 The Range of Pedestrian Treatments

A great variety of treatments are available to help traffic engineers and planners improve pedestrian facilities and to provide safe crossing opportunities for pedestrians. The PEDSAFE pedestrian countermeasure selection system is available online (www.walkinginfo.org) and lists 49 different treatments ranging from engineering solutions to education and enforcement methods. Similarly, a recent NCHRP report on "Improving Pedestrian Safety at Unsignalized Intersections" (Fitzpatrick et al, 2006) discusses a range of treatments and research findings on their safety performance.

Countermeasure selection tools such as PEDSAFE are intended to help practitioners distinguish between different treatments and make informed decisions on how to improve pedestrian facilities. Several state DOTs have developed their own decision tools or treatment matrices to support decisions. A great number of treatments have been evaluated as to their effectiveness in reducing pedestrian collisions, or in increasing the likelihood of yielding drivers. This document divides pedestrian treatments into four broad categories based on their intended functionalities:

1. Treatments that are geared at *increasing pedestrian visibility*, including static warning signs and pedestrian-actuated flashing beacons geared at increasing yielding behavior

2. Treatments that are *forcing a behavior change in drivers*, such as a raised crosswalk or chicanes geared at reducing driver speeds and creating a safer crossing environment
3. Treatments that are *interrupting traffic flow*, which includes conventional pedestrian signals and some innovative modifications of the signal phasing scheme, and
4. Special treatments intended to *help blind pedestrians*. This last category includes treatments aimed at improving gap and yield detection of blind pedestrians at unsignalized crossings.

Multiple treatments from the same or from different categories are oftentimes combined to either enhance the intended effect or supplement it. For example, the effect of a static sign could be enhanced by adding a pedestrian-actuated flashing beacon and could be supplement by additionally installing speed humps in the approach to the crosswalk. NCHRP report 562, cited above, supports this notion of a "systematic combination" (Fitzpatrick et al, 2006) of treatments to maximize the benefits to pedestrians.

2.3.1 Increasing Pedestrian Visibility

Treatments in this category have the general objective of increasing the awareness of drivers that are in the approach to a crosswalk. This category can be further divided into treatments that are a) static, b) animated, but non-responsive, and c) pedestrian-actuated.

a) *Static treatments* include conventional roadside signs and pavement marking delineating the crosswalk. This category also includes some innovative changes to conventional treatments, such as fluorescent green signs or colored pavement marking. A treatment with much promise that has been used in many municipalities is an in-road sign reminding drivers that it is a state law to yield to pedestrians within the crosswalk (Figure 3). Research showed that these signs are effective in increasing the yielding behavior of drivers (Fitzpatrick et al, 2006). All treatments in this group are fairly cost effective and easy to install.

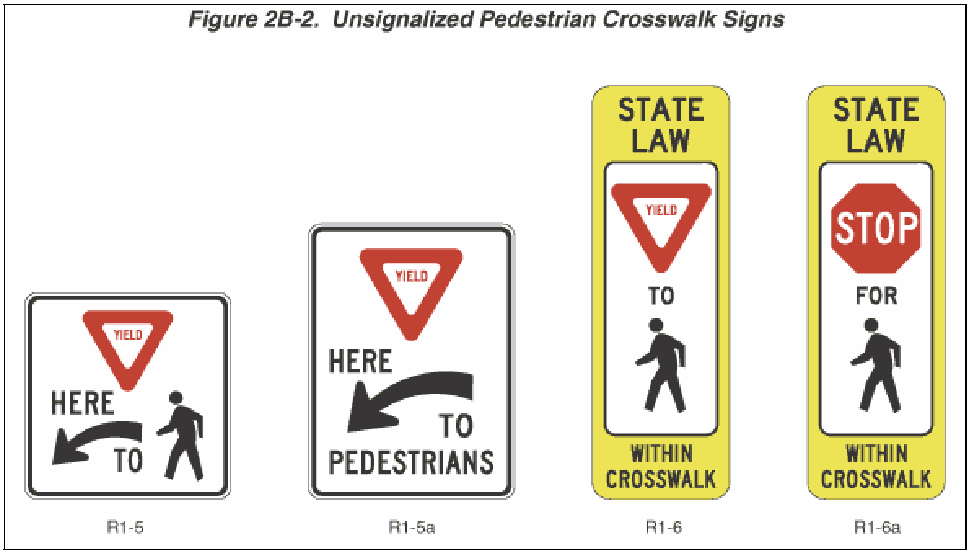


Figure 3: In-Road Pedestrian Signs

(Source: http://mutcd.fhwa.dot.gov)

b) *Animated* (but non-responsive) treatments intend to increase a driver's awareness by installing flashing beacons at the roadside, in the pavement or mounted overhead above the crosswalks. These signs increase the visibility of the crosswalk by flashing constantly. They are more expensive than group a and further require a constant power supply to operate. Figure 4 shows the example of a roadside flashing beacon.

Model R820C solar LED crosswalk flashing beacon installed at a busy intersection.

Figure 4: Roadside Pedestrian Flasher

(Source: www.walkinginfo.org/pedsafe)

c) *Pedestrian-actuated treatments* are flashing beacons similar to group b, but are only active when actuated by a pedestrian push-button. The big advantage here is that the flashing display is intuitively associated with the presence of a pedestrian. Pedestrian-actuated treatments can be mounted at the roadside, overhead or in-pavement (Figure 5). They also come at an additional cost, because of the push-button, and furthermore require communication ability (if a pedestrian on one side of the crosswalk pushes the button, flashers on both sides of the street need to start flashing).

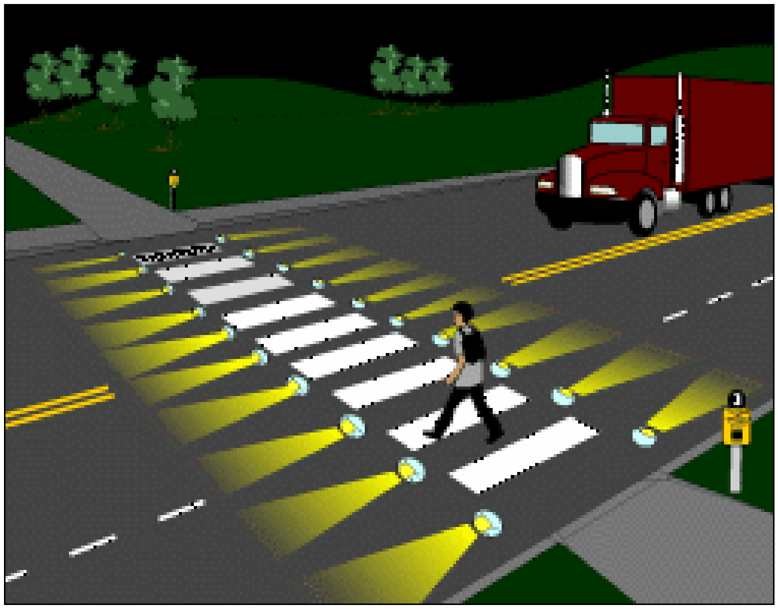


Figure 5: In-Pavement Flashing Crosswalk

(Source: www.walkinginfo.org)

The general objective of treatments in this category is to alert drivers of the presence of a pedestrian crosswalk. A by-product of increased driver attention in many cases is an increase in the yielding behavior of drivers. It is important to point out that this behavior change in drivers (more yielding) is voluntary, i.e. not enforced by physical modifications of the roadway or through legislation. The NCHRP report by Fitzpatrick et al. (2006) refers to this treatment category as "active when present" devices.

2.3.2 Forcing Behavior Change

Treatments in this category actually force drivers to modify their behavior. Examples include speed enforcement treatments (lower speed limit, enforcement) or physical modifications to the roadway aimed at reducing speeds. This could be achieved through raised crosswalks, speed humps, road diets or chicanes in the roadway (Figure 6). In general, drivers are forced to slow down, making it safer for pedestrians. Lower speeds have also been linked to increased yielding behavior (Geruschat and Hassan, 2005).

Figure 6: Raised Crosswalk, Speed Humps and Chicanes

(Source: www.walkinginfo.org/pedsafe)

There are other treatments that force a behavior change upon the pedestrian. Examples include fencing or landscape treatments delineating pedestrian paths or offset crosswalks that direct pedestrians towards oncoming traffic in a two-stage crossing (Figure 7).

Figure 7: Offset Marked Crosswalk & Signing, Offset to the right

(Source: www.walkinginfo.org/pedsafe)

2.3.3 Interrupting Traffic Flow

The most high-tech and therefore most expensive treatments are pedestrian signals, designed to interrupt traffic to create safe crossing opportunities for pedestrians. Similar to pedestrian signals at signalized intersections, these treatments can be installed at a mid-block location or roundabout pedestrian crossing to stop vehicle traffic at the approach. Signals further have the advantage that they can be outfitted with audible pedestrian signals (APS) to create equal access for pedestrians with vision disabilities.

The pedestrian clearance time at signals (flashing don't walk, FDW) is timed as a function of crossing width and pedestrian walking speed. This safety-related timing practice governs the impact of the signal on the pedestrian-induced delay to vehicle traffic through longer red phases. The effect of the signal can be mitigated through a combination of shorter crossing distance and modified timing patterns. Because the research presented here focuses on unsignalized crossings, the reader is referred to Schroeder, Rouphail, and Hughes (2008) for further discussion.

2.3.4 Assisting Blind Pedestrians

Specialized treatments under evaluation in the NCHRP 3-78a research effort aim to enhance the ability of blind pedestrians to make crossing decisions. The two broad categories here are treatments that enhance yield detection and those that target to improve gap detection abilities of the pedestrians. These treatments are beyond the scope of this work and will therefore not be discussed further here.

2.4 Pedestrian-Vehicle Interaction

This section describes the behavioral components in the interaction of pedestrians and vehicles at unsignalized crosswalks: pedestrian gap acceptance and driver yielding behavior. The analysis of this interaction is complicated by the apparent lack of a clear understanding of right-of-way legislation. While many states have legislation in place requiring vehicles to yield to pedestrians in the crosswalk, field observations on busier streets make it evident that compliance varies. More commonly, drivers and pedestrians use methods of non-verbal communication to determine crossing priority. The willingness of a driver to yield and the assertiveness with which a pedestrian seizes the crosswalk are two of many factors that may influence this interaction. Other factors may include the cross-section of the road, the type of crossing treatment or the general level of congestion at the crossing location. These behavioral processes are explored below.

2.4.1 Pedestrian Crossing Behavior

Pedestrian crossing behavior has not been explored to the same degree that vehicle gap acceptance has been investigated. While similar in concept, there are a variety of pedestrian characteristics and caveats in the interaction between the pedestrian and vehicle modes that give reason to derive separate pedestrian crossing models (PCM). The PCM terminology is introduced here, because the analysis includes both gap and lag data (defined below). This section provides an overview of general vehicle gap acceptance models. It then reviews reasons that pedestrians are believed to behave differently when making a decision to cross the roadway and summarizes existing research.

Overview of Gap Acceptance Models

Traditionally, literature on vehicle gap acceptance has used a constant value of *critical gap* (CG) that is calibrated for local conditions (Troutbeck and Brilon, 2002). It can differ depending on the type of movement and the type of vehicle. For example, the CG for left turns is likely to be larger than for right turns, and heavy vehicles tend to have longer CG because of slower acceleration profiles and longer vehicle lengths. In the following, this type of gap acceptance model will be referred to as the *deterministic model*.

By definition, the critical gap is the time between consecutive vehicles on the major road at which a vehicle waiting at the minor approach is equally likely to accept the gap or reject it. Literature on gap acceptance oftentimes assumes that drivers are both *homogeneous* and *consistent*. In a homogeneous driver population, all drivers have the same critical gap. Under consistency assumption, the same gap acceptance situation will always cause a driver to make the same (consistent) decision. Although these assumptions are not realistic, Troutbeck and Brilon (2002) justify their use because inconsistencies in driver behavior tend to increase capacity while a heterogeneous driver population will decrease capacity, thereby offsetting the previous effect.

The most common US application of deterministic gap acceptance is in the US Highway Capacity Manual (TRB, 2000). The Manual recommends using a constant critical gap from listed default parameters or locally estimating CGs from field conditions. It further recommends a reduction of its tabulated CG values for heavily populated regions (greater than 250,000), suggesting that drivers in those regions may be more likely to encounter frequent congestion and have thus lowered their CG threshold.

There are several ways for estimating CG from field data, including a graphical method (Troutbeck and Brilon, 2002), a regression method (Troutbeck and Brilon, 2002), a statistical method based on maximum likelihood estimation (Troutbeck, 2001), and the Ramsey-Routledge method (ITE, 2000). In application of these methods, the capacity of the minor street flow becomes a function of the CG on the minor approach t_c, the follow-up time on the minor approach t_f, and the conflicting major street flow q_p, as shown in HCM2000 equation 17-70 adopted below:

Equation 1: HCM Capacity Equation for Two-Way Stop Controlled Intersection (17-70)

$$Capacity = \frac{3{,}600 \times q_p \times e^{-q_p t_c}}{1 - e^{-q_p t_f}} \qquad \text{[vehicles/hour]}$$

The *follow-up time* describes the time needed for additional vehicles in a stored queue to accept the same gap. The size of t_f is typically less than t_c, because some of the decision and acceleration times for subsequent vehicles occur during the initial gap.

In addition to deterministic gap acceptance, a report compiled for the Federal Highway Administration (FHWA) Next Generation Microsimulation (NGSIM) research effort (Cambridge Systematics, 2004) discusses probabilistic gap acceptance models, for which the driver response for an identical event (same speed, same gap in conflicting traffic) can be drawn from a probabilistic distribution of possible responses. Such *probit* models assume a mean CG with a random variance term depending on the specific coefficients defined for a driver and/or situation. Conceptually, probit models could represent inconsistent driver behavior and a heterogeneous population by drawing gap acceptance decisions from random distributions.

Alternatively, probabilistic behavior can be modeled in the form of a *binary or multinomial logit* model. A logit model could describe the likelihood of gap acceptance as a function of a number of different parameters (for example assertive vs. non-assertive pedestrians, gap time, and type of the arriving vehicle). It thus introduces greater complexity in the gap acceptance model, but in turn requires a lot of data for calibration. Logit gap acceptance models have been proposed by Ben-Akiva and Lerman (1985), and

Cassidy (1995), and probit models were suggested by Mahmassani and Sheffi (1981) and Madanat (1994).

Some researchers have proposed even more complex algorithms for modeling gap acceptance. Kita (1993) used neural networks to describe the process, under the assumption that gap acceptance is not a linear sequence of events, but that multiple factors affect the decision making process. This modeling approach is capable of removing consistency assumptions, but the authors upheld the assumption of homogeneity.

Pedestrian Crossing Attributes

To assess pedestrian gap acceptance, the viewpoint needs to be shifted to the perspective of a pedestrian arriving at a crosswalk. The pedestrian population arriving at the crosswalk needs to be treated very differently from a vehicle population. Blue and Adler (2001) pointed out that pedestrians are not officially channelized, can vary their speed, can occupy any part of the walkway, can bump into each other and have almost instantaneous acceleration/deceleration profiles.

A number of researchers have attempted to predict pedestrian movement characteristics for a stream of pedestrians. The most promising research focuses on cellular automata modeling, which treats the pedestrian as an independent cell capable of movement in a defined number of directions. Research by Blue and Adler (2001) developed bi-directional cellular automata (CA) models for pedestrian movement, which in concept is similar to a car-following model that also accounts for the next following vehicle. The CA model was later improved to an octo-directional model by Holden and Cangelosi (2003) allowing for less restricted pedestrian movements that more closely resemble actual behavior. These models have application for describing the pedestrian walking behavior on the crosswalk and are frequently applied to analysis of transit and terminal facilities.

For the assessment of pedestrian behavior at road crossings, the heterogeneous nature of the pedestrian population needs to be taken into consideration. While gap acceptance for drivers is strongly linked to the acceleration capability of the vehicle, pedestrian decisions are a function of individual attributes. A typical population includes students, elderly, blind pedestrians, children, and people with baby strollers. There are drastic differences in the ability and the willingness to make crossing decisions among these sub-groups. A lot of recent research has focused on gap acceptance by blind pedestrians. Ashmead et al. (2005) found that when attempting to cross at a two-lane roundabout, blind pedestrians waited three times longer than sighted pedestrians and furthermore made about 6% ‘risky’ decisions. Sighted pedestrians didn’t make any ‘risky’ decisions. In another example, Sun et al. (2002) found from data at an unsignalized mid-block pedestrian crossing that both the minimum accepted gap time and the average accepted gap time were lower for younger than for older pedestrians.

Research at pedestrian mid-block crossings by Dunn and Petty (1984) found that pedestrians tend to exhibit more risky behavior when waiting 30 or more seconds at a crossing. Accordingly, the HCM predicts an increasing likelihood of non-compliance as pedestrian delay increases (TRB 2000). The phenomenon of non-compliance can also be interpreted in an adjustment of the critical gap to a lower threshold, raising the question whether a gap acceptance model ought to include a decay function of CG time that is a function of waiting time. On the other hand, Sun et al. (2002) actually found an increase in the average accepted gap as the waiting time of pedestrians increased. The authors explained this trend as due to pedestrians who still wait at the crosswalk after long waiting times tending to be careful in nature and therefore never accepting a short or risky gap.

When interpreting the consistency assumption, it is intuitive that pedestrians will tend to alter their gap acceptance attributes if they are in a hurry versus if they are on a leisure trip. The consistency assumption then is violated, because a similar vehicular gap and speed at a given geometry will result in different decisions by the pedestrian, depending on his/her state of mind. Pedestrian walking speeds may vary for similar reasons. For example, the HCM Chapter (TRB, 2000) on pedestrians recommends a walking speed of 4.0 ft/sec, with a lowered speed of 3.3 ft/sec if the fraction of elderly pedestrians exceeds 20% and a further reduction by 0.3ft/sec at upgrades exceeding 10%. Bennett et al. (2001) investigated pedestrian walking speeds at signalized intersections and mid-block crossings and found slower average speeds at the mid-block locations. The authors also found differences between the 15th and 85th percentile walking speeds of about 2.5 ft per second and significant variation between pedestrians with and without walking difficulty at all studied locations. Fitzpatrick et al (2006) recommended in a recent NCHRP report to lower the pedestrian walking speed used by the MUTCD to 3.5 ft/s, but further acknowledge that even lower speeds may be appropriate in some cases. The variability of walking speed is important when discussing crossing behavior, because it is directly proportional to the time required to cross a given distance.

Pedestrian Follow-Up Time

The HCM equation shown above uses the critical gap and follow-up time to calculate minor-street capacity as a function of major street flow. While a pedestrian critical gap can be observed from field data, the follow-up time concept proves challenging.

The above referenced lack of channelization for pedestrian traffic means that pedestrians are not confined to sequential queue storage like vehicles, but can occupy spaces next to each other in the waiting area. In fact, the HCM offers equations for analyzing pedestrian storage space at the crosswalk (TRB, 2000). Therefore, it is argued here that the concept of follow-up time is not applicable for pedestrians in the same fashion as for vehicles. For pedestrians, it is possible that for example, three pedestrians cross at the exact time, depending on the width of the crossing. In this case then, the classical follow-up time wouldn't apply until the 4th pedestrian, who had to wait behind the other three.

Models for Pedestrian Gap Acceptance

The discussion above suggests that pedestrian movements, pedestrian gap acceptance, and pedestrian-vehicle interaction are different enough from conventional vehicular traffic to warrant alternate models for pedestrian movements, gap acceptance, and capacity.

The deterministic gap acceptance model in the HCM2000 Pedestrian Chapter offers a method for estimating critical gap t_c as a function of crosswalk length L, Pedestrian Walking Speed S_p, and pedestrian start-up time t_s (Equation 2).

Equation 2: Pedestrian Critical Gap after HCM (Equation 18-17)

$$t_c = \frac{L}{S_p} + t_s$$

Rouphail et al (2005) described pedestrian gap acceptance as the sum of latency and actual crossing times, an approach similar to the HCM2000 method discussed above. The authors used field estimates of the median latency time in place of the HCM2000 start-up time. The authors' research compared latency times of blind and sighted pedestrians and found that blind pedestrians exhibited significantly larger latency times, resulting in longer critical gap values and presumably more delay. The increased delay to blind pedestrians is consistent with research findings presented above.

Researchers have also attempted to use advanced gap acceptance models to describe pedestrian crossings. Sun et al. (2002) calibrated probit and binary logit models to describe both pedestrian gap acceptance and driver yielding from actual field data. The authors excluded about 25% of observations for later model validation and found that binary logit models performed best in both cases, correctly predicting 85.6% of gap acceptance and 87.1% of yielding decisions. For comparison, a probit model only resulted in 68.5% correctly predicted gap acceptance decisions, and a deterministic critical gap model actually achieved a surprising 81.5% correct predictions. Regression analysis found the important factors for pedestrian gap acceptance to be gap size, number of pedestrians waiting, and age of pedestrians. Important factors for the driver yielding model were the opposite direction traffic volume, number of pedestrians waiting, and type of vehicle. The authors recommended the binary-logit model for estimation, stating that the good performance of the deterministic model was likely due to an extraordinarily homogeneous pedestrian population.

In the application of any of these methods, the analyst generally needs to distinguish between gap and lag events. A gap describes the time difference between consecutive vehicle events. A 'lag' corresponds to the time between a pedestrian's arrival at the crosswalk and the next vehicle event. Just as a gap, the lag can either result in a GO decision (ped. arrival – crossing – vehicle event) or NOGO decision (ped. arrival – vehicle event). In field estimation, it needs to be clearly distinguished which type of observation is recorded.

Field Estimates of Pedestrian Gap Acceptance

There are four traditional methods that are commonly used to estimate gap acceptance parameters from field data. The graphical method and the regression method allow the analyst to estimate the critical gap parameter only (Troutbeck and Brilon, 2002), while the maximum likelihood method (Troutbeck, 2001), and the Ramsey-Routledge method (ITE, 2000) estimate distributions of critical gaps.

The *graphical method* plots the cumulative frequency of accepted gaps and rejected gaps. The critical gap can then be obtained graphically from the intersection of the two curves, which by definition, corresponds to the gap time that is equally likely to result in a rejected or an accepted gap. This method can intuitively be adapted to the pedestrian mode and is also applicable for lag data.

In the *regression method*, the observer keeps track of how many vehicles (or pedestrians) accepted a gap of a certain size. The analyst then plots the different measured accepted gap times versus the number of vehicles that entered the intersection during that time. A linear regression is then completed on the mean gap time for each vehicle group size. The critical gap can then be calculated from the slope of the line and the intercept of the gap size. Conceptually, the critical gap represents the average gap time for one half vehicle entries. The regression method does not use rejected gap data.

For the analysis of pedestrian gap acceptance, the regression method is not applicable, because pedestrians are typically not queued in the same fashion that vehicles are. Given the lack of channelization of pedestrian movement and the potential for multiple pedestrians to wait beside each other, it is possible for more than one pedestrian to accept a relatively short gap or even for pedestrians to accept gaps out of sequence. Therefore, similar to the discussion of why the 'follow-up time' concept does not apply directly to pedestrians, it is argued here that the regression method is not applicable for pedestrian gap acceptance analysis.

For the *maximum likelihood method, MLE* according to Troutbeck (2001), the data need to be arranged in a way that only the accepted gap and the largest rejected gap are recorded for each vehicle (pedestrian). The critical gap parameter is estimated using a likelihood function and is defined as the critical gap value that maximizes the likelihood of observing the particular sample. Data for this method are difficult to obtain, because only pairs of accepted and rejected events can be used. For example, the method throws out all cases where a pedestrian crosses immediately (accepted lag only) or where a pedestrian rejects multiple gaps before a vehicle yields. In an attempt to utilize a large portion of the data, the MLE method can be applied to a sample of accepted and rejected gaps (not from the same vehicle), as long as the sample sizes are the same.

The *Ramsey-Routledge method*, similar to the graphical method, uses the frequency of accepted and rejected gaps for certain bin sizes (recommended 2 second bins) to estimate the distribution of critical gaps. Following the discussion in ITE (1994), the Ramsey-Routledge method does not require the analyst to assume a distribution as is the case in the MLE method. This brings advantages when dealing with special cases such as a multi-modal critical gap distribution, where there are two or more distinct groups within the pedestrian populations. The Ramsey-Routledge method can be applied to gap and lag data.

This section identified important differences between the pedestrian population and a population of drivers. The discussion emphasized the need for treating pedestrians as a heterogeneous and inconsistent population and further raises the question for the need of a gap acceptance decay function that reduces the critical gap as a function of waiting time. Researchers have demonstrated promising results from describing PCM through logit and potentially probit models, but also showed that the traditional gap acceptance models are fairly accurate in their prediction ability. The section presented four alternative methods, but argued that only three are applicable for pedestrian gap acceptance. The next section focuses on the second component of the interaction of the two modes: the yielding behavior of drivers approaching the crosswalk.

2.4.2 Driver Yielding Behavior

The objective of this section is to summarize existing research on driver yielding behavior and to discuss the decision-making process that leads a driver to yield to a pedestrian at the crosswalk.

Yielding Rates

When describing pedestrian-vehicle interaction, some percentage of drivers is expected to yield to a waiting pedestrian, with the actual percentage depending on factors such as the presence of a zebra-crosswalk, the vehicle speed and the local driving culture. Several studies have attempted to identify factors contributing to the yielding process.

In a study looking at driver yielding at roundabouts, Geruschat et al. (2005) found that the probability of motorists yielding to pedestrians is a function of vehicle speeds on the approach, and that they are more likely to yield at the entry than at the exit of the roundabout. Ashmead et al. (2005) found similar differences in yielding behavior between entry and exit legs of roundabouts. Harrell (1993) found that drivers are more likely to yield to pedestrians with brightly colored clothing and also yield more to an assertive pedestrian who entered the crosswalk (rather than passively remaining on the curb). Guth et al. (2005) found a great variability of yielding behavior across different roundabout geometries.

Predictive Models

In previous research Sun et al (2002) collected data on driver yielding and pedestrian gap acceptance at an unsignalized midblock pedestrian crossing and compared the fit of different statistical models. In an approach similar to what is proposed here, the authors estimated yielding probabilities based on the discrete parameters driver gender, driver age, type of vehicle, number of pedestrians, and the presence of an opposing yield. They found that drivers are more likely to yield to a group of pedestrians and that older drivers were more likely to yield than younger drivers. In the pedestrian gap acceptance model, they investigated pedestrian age, gender, waiting time, gap size and the number of pedestrians. Their results showed that a logistic modeling approach outperformed a probit model for driver yielding, as well as for pedestrian gap acceptance. The authors looked at only one crosswalk and did not analyze any pedestrian treatment effects.

The analysis proposed here expands the research approach by Sun et al (2002) in several areas. Most notably, the research by Sun et al did not look at constraints to driver yielding behavior related to vehicle dynamics. As discussed later in this chapter, there are physical limits to the ability of a driver to yield. In previous research, Geruschat and Hassan (2005) found that drivers are more likely to yield at lower speeds demonstrating the importance of dynamics variables.

Without vehicle dynamics information, the statistical model by Sun et al (2002) offers interesting insights in the yielding behavior of different driver types, but falls short of describing the true operational parameters involved in the yielding process. Nonetheless, their results strengthen the approach for the logistic regression approach proposed here and give helpful insight in sample size requirements. The authors collected 1.5 hours each of AM and PM peak data over 5 days, for a total of 15 hours of data. The resulting samples included 687 accepted gap, 938 rejected gap, and 1254 motorist yield data points, which was sufficient to allow them to estimate statistically significant probit and logit models.

The research findings above can be summarized as the decision of a driver to yield is a function of both operational and behavioral parameters. In the first category, the yield decision is triggered by both the speed of the vehicle and the assertiveness of the pedestrian. In the behavioral category, drivers are influenced by clothing and the number of pedestrians at the crosswalk. Similarly, it can be hypothesized that yielding is impacted by the presence of a conflict downstream of the crosswalk. There are also cases, where a driver may be *forced* to yield, because of a pedestrian GO decision in gap in traffic that is too short.

The HCM2000 (TRB, 2000) currently states that the procedure for unsignalized pedestrian crossings is not applicable for zebra-striped crossings, because pedestrians have the right-of-way. In other words, the method assumes that all drivers comply with legislation and yield to pedestrians in the crosswalk. In those cases, the HCM recommends using the method for two-way stop-controlled intersections. Experience shows that the compliance rate of drivers at zebra crossings is likely to vary across locations, and intuition is supported by research findings (Fitzpatrick et al., 2006) that the yielding rate is typically less than 100 %. At the same time, there is likely to be some yielding behavior, even at locations without demarcation of the pedestrian crosswalk.

2.5 Data Needs

The following discussion rests on the assumption that there are certain parameters that lead an approaching driver to the decision of whether or not to yield to a pedestrian at the crosswalk. The section presents parameters that are related to the yielding behavior of drivers and how these variables may enter into a driver yielding model.

2.5.1 The Crosswalk Interaction

The interaction of drivers and pedestrians at an unsignalized crosswalk is a very complex process. In concept, there are two *agents* involved in the interaction at pedestrian crosswalks.

From the perspective of the pedestrian arriving at the crosswalk, the decision is made whether a given gap or lag in vehicular traffic is long enough for a safe crossing or to wait for a larger gap. From the driver perspective, a similar process leads the driver to either proceed through the conflict area or to yield the right-of-way to the pedestrian. Conceptually, it can be said that the driver accepts a gap in the conflicting pedestrian stream, given that the driver has the general propensity to yield to pedestrians. In a sense, the process of pedestrian-vehicle interaction can then be described as a *dual gap acceptance process* in which the *action-reaction sequence* can be initiated by either agent.

2.5.2 Interaction Parameters

Conceptually, the probability of a driver to yield when a pedestrian is present at the crosswalk, P(Yield), can be expressed as a function of independent parameters β_i; much like it would be done in multi-linear regression analysis. Similarly, the probability of a pedestrian's decision to cross the road is a function of some variables. Through statistical modeling, these parameters can be related to the response variable as demonstrated by Sun et al. (2000) and others. Due to the discrete nature of the process (1/0 = Y/NY or

GO/NOGO) methods of categorical data analysis need to be applied. This is discussed in detail later, but regardless of the form of the dependent variable, the decision of a driver to yield or of the pedestrian to GO should be a function of the following types of variables:

- Vehicle Dynamics: A yield is only feasible if a driver can reasonably come to a complete stop (hard yield) or delay his arrival at the crosswalk enough to allow the pedestrian to cross (rolling yield). Parameters in this category include travel speeds, distance from the conflict area, and maximum (comfortable) deceleration rates for both drivers and pedestrians. These variables affect the arrival time of the vehicle and thereby also the pedestrian decision.

- Vehicle and Driver Characteristics: These attributes describe, for example the 'willingness' of drivers to yield, driver courtesy, and the type of vehicle

- Pedestrian Characteristics: Pedestrian attributes include assertiveness, the presence of multiple pedestrians, or the willingness to accept risk.

- Confounding Factors: In addition to the personal attributes above, the circumstances surrounding the interaction may impact the decision-making process. Examples include the presence of a downstream queue after the crosswalk or a yield event in the opposing direction or adjacent travel lane. Yielding behavior is also intuitively related to whether or not a vehicle is traveling in a platoon of vehicles. Similarly, pedestrians may be more willing to accept a short gap from an individual vehicle than a platoon.

Vehicle Dynamics

The category of vehicle dynamics warrants further elaboration. The following discussion analyzes this concept in relation to the *conflict point*: the hypothetical point where vehicle and pedestrian occupy the same space at the same time. To simplify the discussion, it is assumed that both vehicles and pedestrians can be represented by single points, thus ignoring the physical dimensions of each.

It will further be assumed that both agents will act to try and prevent the conflict from actually happening, by altering their travel speeds at some point. In this sense the agent with the lower *risk threshold* will react first, triggering a reaction from the other. Both action and reaction are subject to the individual driver and pedestrian behavioral parameters (*population heterogeneity*) and may further vary across situations and over time (*population inconsistency*).

Under uncongested, free-flow conditions, a driver at some point on a road and approaching a crosswalk at a speed v_d is expected to arrive at the crosswalk after a time t_d has elapsed, where $t_d=v_dx_d$ (x_d is the distance from the point to the crosswalk or conflict point, see Figure 8). At any point in time, the driver can make the decision to slow down and yield to a pedestrian, constrained by the maximum (comfortable) deceleration rate d_d. Using the dynamics relationship $0=v=v_d+dt$, the time required for driver deceleration is $t_d=(-v_d)/d_d$.

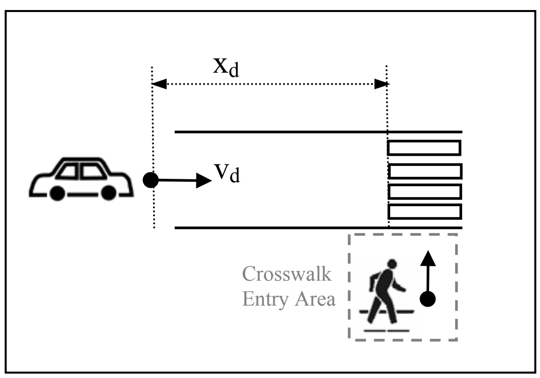


Figure 8: Time-to-Collision Concept

Assuming a comfortable deceleration rate of d_d=-10 ft/s^2 and an approach travel speed of v_d=30ft/s (about 20.5 mph), the likelihood of a driver yielding is expected to decrease rapidly if he is less than 3 seconds away from the crosswalk – because the deceleration rate to do so is more than the comfortable rate. Speaking in terms of distances and using the relationship $0=v_d^2-2d_dx_d$, this *latest decision point* (LDP) occurs at a distance of $x_d=v_0^2/2d_d=45$ feet from the conflict point. Conceptually, as travel speed increases and the deceleration rate decreases, the LDP for a driver to yield moves further away from the crosswalk.

To elaborate this relationship, Figure 9 shows the required deceleration times and distances as a function of travel speed for different comfortable deceleration rates.

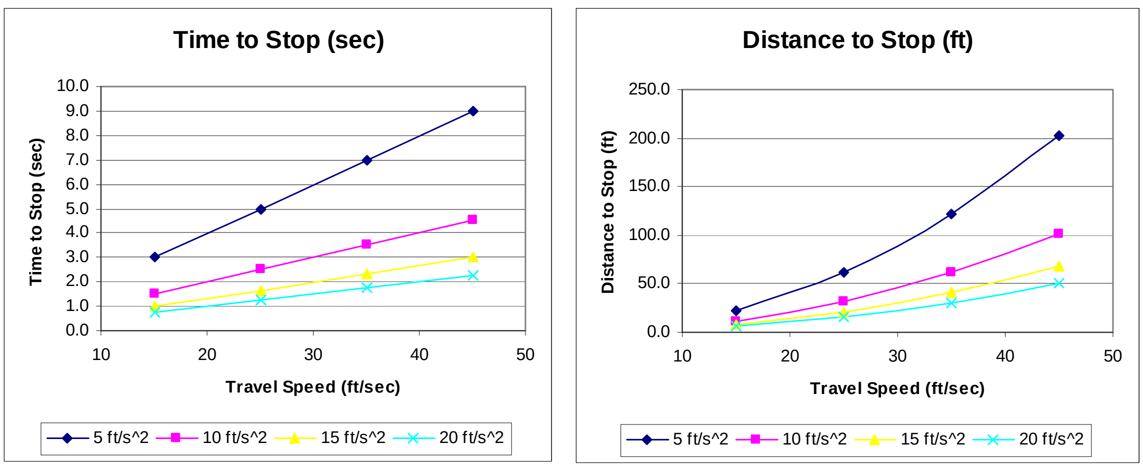


Figure 9: Time to Stop Relationships

The figures illustrate that dependent upon the given speed and deceleration profiles of a particular driver, the LDP tends to move further away from the crosswalk in the time-space domain.

To some extent, the behavior of driver yielding to pedestrians is conceptually similar to a driver reaction to the *onset of amber* at a signalized intersection. The event of a pedestrian stepping into the crosswalk influence area (CIA) is similar to the event of a signal light status changing to amber. At the time of this event, the distance of the driver from the crosswalk and the current speed will decide on whether a driver is physically capable of stopping before the crosswalk (stop bar). Just as in signal timing practice, it is therefore expected that some drivers do not have time to yield. In this case, the driver decision is subject to *vehicle dynamics constraints* (VDC) and the probability of yielding is expected to be very low.

The crosswalk yield process is different from the amber response in that drivers are not required to stop at the crosswalk (or at least don't take the law as seriously as the need to stop at a red light). So, while the VDC threshold expectedly would be well suited to describe the likelihood of a driver stopping at a light, VDC is not likely to be a perfect predictor for yielding.

The dynamic nature of the interaction is also important for the pedestrian decision. Gap acceptance theory traditionally places a strong emphasis on the temporal duration of the gap, which in turn is a function of vehicle dynamics. For VDC events, it is expected that no pedestrian GO decisions would be observed. To truly describe this interaction, it is therefore very important to capture the dimension of vehicle dynamics, VDC, and the associated duration of lags and gaps.

2.6 Chapter Summary

This chapter illustrated that pedestrian crossing and driver yielding behavior are complex processes, and that existing analysis approaches fall short of capturing this complexity. Typically, gap acceptance behavior is described by a single estimate of the critical gap, while yielding behavior is expressed by a single site-aggregated percentage.

The discussion further showed that the decision making processes for both events are a function of operational and behavioral factors. Gap acceptance theory is typically tied to the gap size, an operational measure that is a function of vehicle speed and distance. However, it ignores behavioral characteristics of the individual pedestrian by assuming population homogeneity and consistency. On the other hand, yielding behavior is aggregated into a single site estimate, thus ignoring the operational impacts of vehicle dynamics on the yield response.

These findings illustrate the need to take a closer look at both processes. With the availability of microsimulation models, it is possible to utilize more elaborate algorithms to describe these behaviors. The following chapter develops a data collection method for obtaining necessary variables in the field and presents methods of statistical analysis.

3 METHODOLOGY

The previous chapter presented a framework for analyzing unsignalized crossing facilities in a microsimulation environment. The framework proposes that the operational impact of different pedestrian treatments can be modeled implicitly through their effect on the behavioral attributes of drivers and pedestrians; predominantly driver yielding behavior and pedestrian gap acceptance.

The clear challenge for the proposed approach is that the performance measures extracted from the simulation model are only meaningful to the extent that the behavioral input parameters are reflective of the actual behavior of drivers and pedestrians. The efficacy of this approach is contingent upon the ability to develop model algorithms that are calibrated from field observations of the interaction.

This chapter presents a data collection methodology to obtain the necessary variables from field observations. It discusses data reduction and defines dependent and explanatory variables used in the analysis. It then reviews statistical methodologies to estimate probabilities of the discrete choice outcomes using logistic regression. It concludes with a description of the data collection sites studied in this research.

3.1 Data Collection

3.1.1 Interaction Characteristics

The data collection methodology needs to gather attributes of pedestrian-vehicle interaction in the field. It was argued in Chapter 2 that the dynamic characteristics of the approaching vehicle are essential for describing both driver yielding and pedestrian crossing behavior, because they directly relate to the *expected time of arrival* of the vehicle at the crosswalk. To evaluate the effect of these variables, they need to be collected accurately using reliable measurement devices. They also need to be coded at a consistent point in the interaction sequence. For the purpose of discussion, the temporal beginning of an interaction event is defined as follows:

> *A pedestrian-driver interaction event commences as a pedestrian arrives in the crosswalk influence area while a driver is in the approach of the crosswalk.*

All variables will be coded relative to this point in time (t_1). The data collection methodology assumes that the following statements are true at t_1:

- The pedestrian has indicated that she is intending to cross at the facility (rather than continuing along the sidewalk).
- The pedestrian is aware of the approaching vehicle and decides whether or not she feels comfortable to cross the road.
- The driver is aware of the pedestrian's intention and has to react (make the decision to yield or continue through the crosswalk).
- The observer knows that an event sequence (action-reaction) is about to take place (from video observation) and records the attributes of the interaction event.

The assumptions above are valid if both driver and pedestrian are consciously aware of each other's presence. It shall be noted here that there are clearly cases where that is not true, as driver or pedestrian may be distracted. In an observatory study the cognitive awareness of the involved parties is not discernable, but can only be presumed from erratic or unexpected behavior. For example, a pedestrian may step into the roadway and then retreat quickly realizing that she misjudged the position of the vehicle. Similarly, a driver may perform an emergency braking maneuver when recognizing the presence of the pedestrian too late.

From the onset of a pedestrian-driver interaction event at time t_1, there are four potential outcomes to the interaction of the two modes:

1) Pedestrian GO Decision [GO] – The pedestrian decides that there is sufficient time for a safe crossing and steps into the crosswalk at time t_2. The size of the accepted gap is defined in one of two ways:

a. The *observed lag* between the time, t_2, and the time the vehicle arrives at the crosswalk, t_3, is defined by:

$$l_{GO\_obs} = t_3 - t_2$$

Similarly, if a pedestrian rejects the initial lag for vehicle n and accepts a subsequent gap before vehicle n+1 arrives, that *observed gap* time is defined by:

$$g_{GO\_obs} = t_{3,n+1} - t_{3,n}$$

b. The *expected lag* is the difference between t_2 and the time the vehicle would have arrived at the crosswalk at zero deceleration, t_3^*. In this case, the *expected gap size* becomes a function of the vehicles speed (v_2) and distance from the crosswalk (x_2) at time t_2, such that:

$$l_{GO\_exp} = t_3^* - t_2 = (t_2 + x_2/v_2) - t_2 = x_2/v_2$$

The *expected gap* time is similarly calculated as the difference between the expected arrival times of vehicles n and n+1:

$$g_{GO\_exp} = t_{3,n+1}^* - t_{3,n}^* = x_{2,n+1}/ v_{2,n+1} - x_{2,n}/v_{2,n}$$

2) Pedestrian NO-GO Decision [NOGO]/ Driver Non-Yield Decision [NY] – The pedestrian decides that the time until the expected vehicle arrival is too short to safely cross the facility, i.e. she rejects the lag or gap. At the same time, the driver decides that it is either physically impossible to yield to the pedestrian, or he is unwilling to yield. The calculation for observed and expected NOGO lags and gaps are consistent with the discussion above.

For a NY event, the *expected* lag and gap times are equivalent to the *time to collision* of the driver, defined as the time the vehicle would have arrived at the crosswalk if it continues at speed v_1 from distance x_1 and time t_1.

3) Driver Soft Yield Decision [SY] – The decelerating vehicle creates a crossing opportunity for the pedestrian, without coming to a complete stop. The expected *time to collision* and the *necessary deceleration rate* to come to a stop for the vehicle can be calculated from its speed and position relative to the crosswalk at the time of pedestrian arrival.

4) Driver Hard Yield Decision [HY] – The driver slows down to a complete stop creating a crossing opportunity for the pedestrian. The expected arrival time and the necessary deceleration rate can be calculated from initial conditions at t_1.

Figure 10 below illustrates the different possible event outcomes for pedestrian and driver interaction in the time-space domain. In the scenario, two pedestrians A and B arrive at the crosswalk at times $t_{1,A}$ and $t_{1,B}$. The figure further shows a total of three vehicles (I, II, and III) that approach the crosswalk at a constant speed.

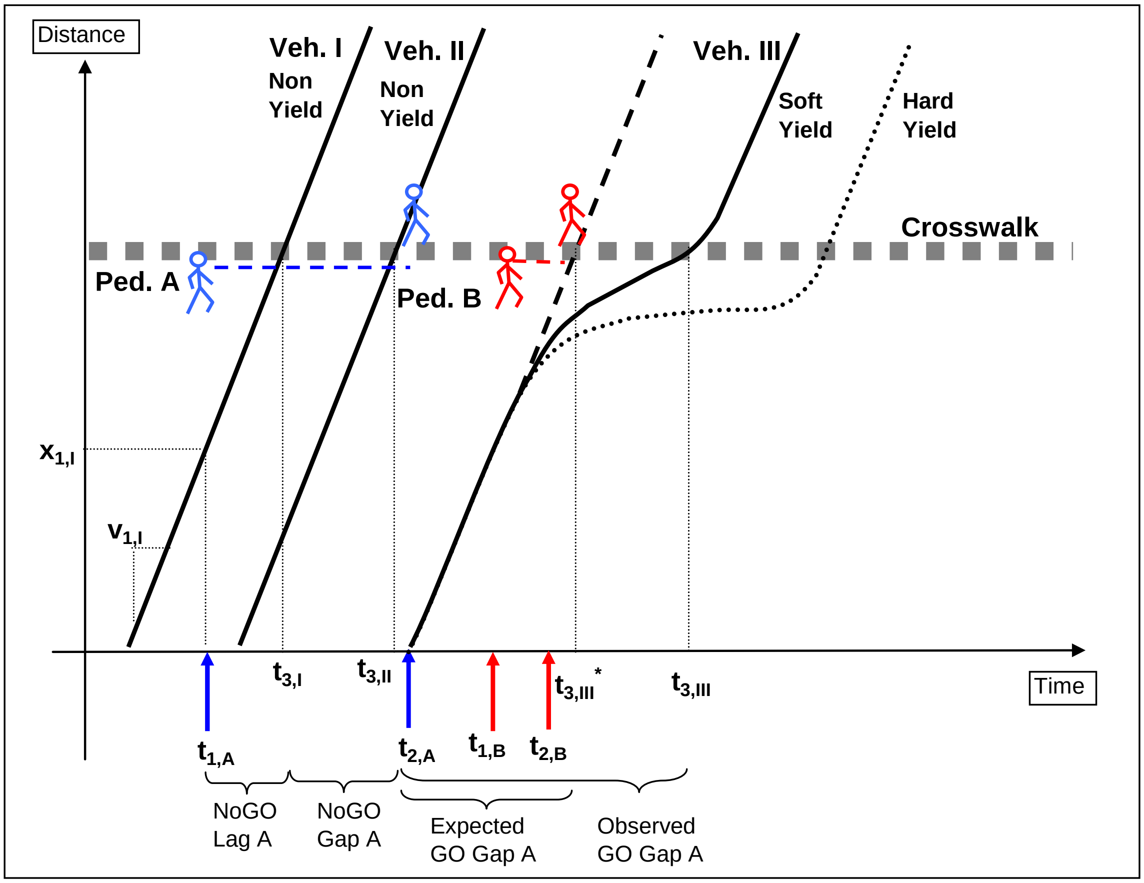


Figure 10: Pedestrian-Driver Interaction in Time-Space Domain

At the time of the first pedestrian arrival, $t_{1,A}$, vehicle I is located at a distance x_1 from the crosswalk, traveling at speed v_1. In the time-space domain, the vehicle speed is represented by the slope of the trajectory line. For this first interaction, the driver decision is NY and the pedestrian decision is NOGO for this lag event. The driver of vehicle II also decides NY and the pedestrian decides NOGO for the gap between vehicles I and II. Shortly after vehicle II passes through the crosswalk, pedestrian A begins crossing (GO decision), presumably judging the gap until vehicle III arrives to be long enough. The pedestrian bases her decision to cross on the *expected* arrival time of the vehicle, $t_{3,III}$*. As vehicle III approaches the crosswalk, pedestrian B arrives at the crosswalk and the driver decides to create a SY crossing opportunity. Pedestrian B utilizes this SY and crosses the road safely before the vehicles *observed* arrival time $t_{3,III}$. Clearly, the observed GO gap time for pedestrian A is not reflective of the state of the system at the time the pedestrian made the decision to cross. In this case, the expected GO Gap A is the better measure. The figure also show the hypothetical case, where vehicle III decides to HY resulting in an extended time of zero speed.

This interaction sequence of 2 pedestrians and 3 vehicles resulted in a total of six events that can be used in the analysis: NOGO Lag Pedestrian A, NY Vehicle I, NOGO Gap Pedestrian A, NY Vehicle II, GO Gap Pedestrian A, and SY Vehicle III. The GO decision for pedestrian B is not included in the analysis because it is merely a reaction to the yield event. For a study looking at yield utilization behavior of blind pedestrians, this event would have been considered in a model that predicts the probability of GO in a yield. This research is not concerned with the likelihood of GO in a yield, because the yield utilization rate of the observed (sighted) pedestrians was 100%.

In this context it is important to emphasize that more than one event can be associated with one pedestrian, raising questions of statistical independence of the observations. For example, pedestrian A in the above example rejected a lag and a gap before crossing in a gap. From a statistical point of view, these three events are not independent and thus violate the underlying assumptions of regression analysis. However, it is within the nature of gap acceptance studies to observe this sort of event sequence and by definition a gap GO or NOGO cannot be observed independent of a prior lag event. In the statistical analysis, all event points will therefore be included. However, to test for the effect of the event sequence a variable describing pedestrian waiting time will be introduced that controls for pedestrian delay (and therefore inherently for the number of NOGO decisions). By definition, only one event is observed for each driver.

3.1.2 Data Collection Set-Up

To effectively analyze the interaction of drivers and vehicles, it is necessary to accurately record the different variables shown in Figure 10. In general, observed time stamps at the crosswalk are easily obtained from video recordings, but the distance and speed measurements used for the expected times are more challenging. These data may be obtained through one of the following data collection approaches:

1) Vehicle tracking through ITRE-mv (Chae, 2006) or other video-image processing software that generates detailed data on vehicle trajectories on a sub-second level of analysis. This approach clearly would generate all necessary data for very precise speed and distance measurements. The clear drawback of this method is that data extraction is difficult and time-consuming, because the software has to be properly calibrated. One could also make the case that this approach would result in too much data, because the operational vehicle data are only one part of the proposed approach, and any circumstantial data would still have to be extracted in a manual fashion.
2) Manual estimation of speed and distance from video observations can be achieved by placing cones alongside the vehicle approach. This set-up is easy, only requires one data collection device (video camera), and all data can be obtained in post-processing. One drawback to this method is that the speed and distance measurements are only approximations, and are dependent on good video angles of the approach. Generally, higher elevated angles are preferable, but come at the expense of potentially losing some of the needed behavioral data. Another concern is that driver behavior might be affected by the cones. Options for an elevated camera angle are a 'natural' wall or hill, the bed of a truck or a telescoping mast pole.
3) A police speed trailer could be set up with the display pointing towards the camera (away from drivers). This way the observer gets information on the speed of vehicles, but cannot get the distance from the crosswalk. The same concern of impacting driver behavior needs to be considered.
4) A laser speed gun could be used to record the vehicle speed at each pedestrian event. Modern equipment includes a time-stamp of the observation and also

records the distance between the speed gun and the vehicle. This approach brings the need for additional data collection equipment, but otherwise balances data accuracy and processing effort. The use of a radar speed measurement device does not apply, because it only measures speeds, not distances.

For the data collection, approach 4 was selected, because it promised the best combination of data precision and time efficiency. Figure 11 shows a schematic of the data collection set-up.

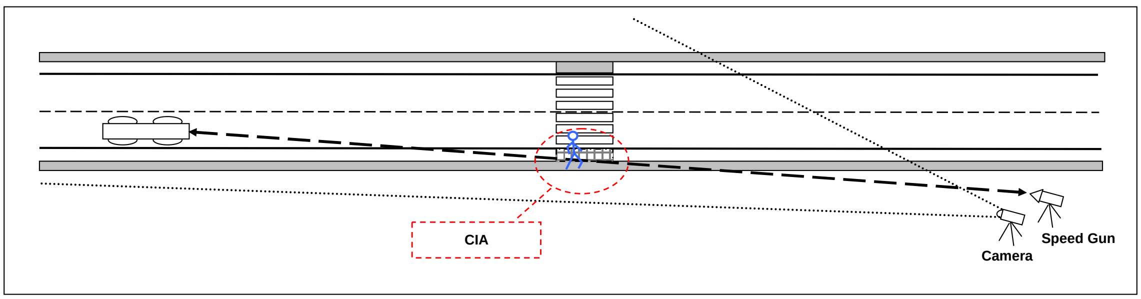


Figure 11: Data Collection Set-Up

In order to capture all relevant data, the video angle has to cover events concurrent to the interaction, such as the presence of an adjacent yield or multiple pedestrians As shown in the diagram, the video camera angle is wide enough to cover the crosswalk influence area (CIA) and the approach to the crosswalk..

Before beginning data collection, the video camera and laser speed measurement device (light detection and ranging, LIDAR) were started simultaneously to synchronize the record of speed measurements with the time stamp on the video. During the experiment, the analyst monitored the crosswalk and measured the speed and distance of the closest vehicle when a pedestrian arrived at the crosswalk. In many cases, the observer took multiple measurements of the same vehicle as the pedestrian walked towards the crosswalk. This allowed the analyst to selectively match speed observations to video events during post-processing in the lab.

The LIDAR device was able to store each speed measurement and associated distance of the vehicle from the observer. With the observer positioned at a known and constant distance from the crosswalk, it is possible to infer the distance between the vehicle and the crosswalk.

The use of additional equipment to measure vehicle speeds raises the questions of data accuracy and precision. This research used the SpeedLaser® product manufactured by Laser Atlanta (see Figure 12).

Figure 12: Picture of Laser Speed Measurement Device (Source: www.laseratlanta.com)

According to the equipment specification the speed accuracy of the laser measurements is +/- 1mph (1.6kh) (Laser Atlanta, 2008). An independent comparison of speed measurement devices (Gates, Schrock, and Bonneson, 2004) showed that LIDAR devices were the most accurate and most precise measurement option especially at higher speeds when compared to pneumatic tubes, piezoelectric sensors, tape switches, and radar. The study found that for 35 mph approach speeds the LIDAR device was 98% accurate at +/- 0.5 mph tolerance and 100% accurate for +/- 1.5 mph tolerance. If the observer is positioned at an angle to the approaching vehicle, the measurement needs to be corrected for the *cosine error* to get the vehicle speed in the travel direction. According to ITE (2000) this error is less than 1 mph if the angle of observation is less than 10 degrees. This discussion gives confidence that the measurement errors are within the human observer error, provided the measurements are made in a head-on fashion.

3.1.3 Data Extraction and Reduction

The time matched video and LIDAR observations were post-processed in the laboratory. For the speed measurements, it was assumed that the vehicle speed remained approximately constant between the time the pedestrian arrived in the CIA (t1) and the true time of the LIDAR measurement (due to the reaction time of the observer). The relative displacement of the vehicle during that time can be calculated to get an estimate at time t1. All observations were made by the same observer to assure consistency in reporting.

For each event, all parameters were extracted manually by recording time stamps for pedestrian and vehicle arrivals at the crosswalk (continuous variables) and noting the state of all binary variables. An event is recorded, if at the time a pedestrian has shown clear intentions that she plans to cross at the facility, a vehicle is approaching the crosswalk. The dynamic attributes of the interaction are coded as defined in the discussion above. In addition, the analyst recorded a range of binary indicators to describe the interaction. The following section defines these variables, which are also listed in the list of abbreviations.

3.1.4 Variable Definitions

Response Variables

The following variables describe the discrete event outcomes of the interaction:

YIELD The event results in a driver yield (Yield=1, Non-Yield=0). A yield is defined as a deliberate action on behalf of the driver that delays the vehicle arrival at the crosswalk to create a crossing opportunity for the waiting pedestrian

NY The driver decides not to yield to the pedestrian. The outcome of the vehicle event is a *non yield*

SY The outcome of the vehicle event is a *soft yield*, indicating that the driver slowed down for the pedestrian, but did not come to a full stop

HY The outcome of the vehicle event is a *hard yield*, indicating that the driver slowed down to a full stop to create a crossing opportunity for the pedestrian

Y_TYPE A variable distinguishing the type of yield outcome (HY: Y_TYPE=1, SY: Y_TYPE=0)

Y_ORDERED A categorical variable describing all three possible outcomes of the yield event. The three ordered levels of the yield outcome are non-yield (NY: Y_ORDERED=1), soft yield (SY: Y_ORDERED=2), and hard yield (HY: Y_ORDERED=3)

GO The event results in a pedestrian crossing decision. The GO variable is used to describe the binary outcome of the pedestrian event (GO=1, NOGO=0)

LAG_EVENT Pedestrian event is characterized as a lag indicating the first vehicle encounter after arriving at the crosswalk. All subsequent vehicle events are characterized as gaps

Discrete Explanatory Variables

The following variables are binary indicators describing the pedestrian-vehicle interaction. They are used as potential independent variables in the analysis.

ADY Presence of an adjacent yield in the opposite direction; ADY=1 if a vehicle in the opposite lane has already yielded for the pedestrian at the crosswalk

AST	The pedestrian is 'assertive'; AST=1 if the pedestrian exhibits assertive behavior in the approach of the crosswalk, indicated for example through fast walking pace
COM	Indication of non-verbal communication between driver and pedestrian; COM=1 if there is evidence of non-verbal interaction (waving, raising hand to say 'Thank You') between the driver and pedestrian
DECEL_TAU	The deceleration rate threshold is satisfied; DECEL_TAU=1 if the deceleration rate necessary to come to a full stop before the crosswalk is greater than 10ft/sec^2
DSC	Presence of an 'downstream conflict'; DSC=1 if a vehicle is stopped downstream of the crosswalk, or if there is heavy traffic in the circulating lane preventing immediate entry into the circle - *Only applicable for RBT-RAL site*
ENTRY	Indication of whether the event occurred at the entry or exit leg of the roundabout (Entry = 1 or Entry = 0, respectively) - *Only applicable for RBT-RAL site*
FLASH	Indication whether the flashing beacon was actuated by the pedestrian; FLASH=1 if beacon was flashing during the yield event - *Only applicable for MB-CLT site*
FOLL	Approaching vehicle has close follower; FOLL=1 if the vehicle has a follower at a short headway of approximately 2-4 seconds
G_NEAR	The observed gap/lag event has a vehicle in the near lane and no vehicle in the far lane, relative to the waiting pedestrian
G_FAR	The observed gap/lag event has a vehicle in the far lane and no vehicle in the near lane, relative to the waiting pedestrian
G_COMBO	The observed gap/lag event has a vehicle in both lanes (near and far) - the gap/lag size is measured relative to first vehicle arrival

HEV	Approaching vehicle is a heavy vehicle; HEV=1 if the vehicle is anything larger than the equivalent of a 15-passenger van (dump truck, TTST, bus)
MUP	There are multiple pedestrians present in the CIA; MUP=1 if the number of pedestrians waiting at the curb is greater than one
NEAR	Pedestrian is waiting on the near-side of the approaching vehicle; NEAR=1 if the pedestrian waits on the same side of the road that the vehicle is traveling on
PLT	Approaching vehicle is part of a platoon of vehicles; PLT=1 if the headway to the following OR the previous vehicle was short (approximately 2-4 seconds)
PREV	The previous vehicle passed without yielding; PREV=1 if the previous vehicle failed to yield to the same pedestrian waiting at the crosswalk
PXW	A pedestrian from a previous event is still present in the crosswalk; PXW=1 if the driver has to account for a pedestrian who is still in the roadway from a previous event
QUE	Vehicle is part of a queue of vehicles; QUE=1 if the queue or platoon that the vehicle is a part of is moving slowly due to some downstream congestion or incident
TRIG	The pedestrian triggered the yield by stepping into roadway; TRIG=1 if the pedestrian actively seized the roadway before the driver action indicated a yield
TRTMT	Presence of the 'in-pavement flasher' crossing treatment; TRTMT=1 if the treatment was installed and so is equivalent to the 'after' case - *Only applicable for MB-CLT and MB-RAL sites*
TTC_TAU	The time to collision threshold is satisfied; TTC_TAU=1 if the theoretical time to arrival at the crosswalk is less than 3 seconds

Continuous Explanatory Variables

The following variables describe the dynamic characteristics of the interaction of pedestrian and driver. The measures are calculated from LIDAR speed measurements and event time stamps, and are used as potential independent variables in the analysis.

DECEL Deceleration rate necessary to come to a full stop prior to crosswalk; DECEL is calculated from measured speed and distance; DECEL=(SPEED_FT*SPEED_FT)/(2*DIST1); units are feet/sec^2

DIST1 Vehicle position at the time of pedestrian arrival in crosswalk influence area, measured in feet using a LIDAR speed measurement device

D_WAIT The duration of pedestrian waiting time at the decision point. The waiting time is zero for all initial lag events. For all subsequent gaps, the waiting time is calculated from the duration between the initial arrival at the crosswalk and the passing of the previous vehicle (in seconds)

E_GAP Expected gap time between successive vehicle events at constant speed (in seconds)

E_LAG Expected lag time between pedestrian arrival (t1) and time vehicle would have arrived at constant speed (in seconds)

O_GAP Observed gap time between successive vehicle events t3n and t3n+1 (in seconds)

O_LAG Observed lag time between pedestrian (t1) and vehicle arrival at the crosswalk (t3), (in seconds)

SPEED_FT Vehicle speed at the time of pedestrian arrival in crosswalk influence area, measured in ft/sec using a LIDAR speed measurement device

TTC Time until vehicle would theoretically arrive at the crosswalk; TTC is calculated from the measured speed and distance at the time pedestrian arrives in the crosswalk influence area; TTC=DIST1/SPEED_FT; units are seconds

The variable definitions above contain the response variables for the driver yielding model (YIELD, Y_ORDERED, and Y_TYPE) and for the pedestrian crossing model (GO, NOGO, and LAG_EVENT). The actual model for pedestrian crossing behavior only utilizes the GO variable and applies it separately for gap and lag events. The NOGO and LAG_EVENT variables are included for the analysis of descriptive statistics.

Table 1: Hypothesized Impact of Independent Variables on Response

	Response Variable		
Explanatory Variables	**YIELD = 1**	**Y_TYPE = HY**	**GO = 1**
Binary Factors			
ADY	+	–	+
AST	+	+	+
COM	+	–	.
DECEL_TAU	–	+	–
DSC	+	–	+
ENTRY	+	–	+/–
FLASH	+	+/–	+
FOLL	–	–	–
HEV	–	+/–	–
MUP	+	+	–
NEAR	+	+/–	+
PLT	–	+/–	–
PREV	–	+/–	+/–
PXW	+	+	+
QUE	+	+	+
TRIG	+	+	+
TRTMT	+	–	+
TTC_TAU	–	+	–
Continous Factors			
DECEL	–	+	–
DIST1	+	–	+
O_GAP	.	.	+
T_GAP	.	.	+
O_LAG	.	.	+
T_LAG	.	.	+
SPEED_FT	–	+	–
TTC	+	–	+

Table 1 shows the hypothesized effects of the discrete and continuous explanatory variables on the dependent variables YIELD=1, Y_TYPE=HY and GO=1. A variable that is hypothesized to increase the likelihood of the response is denoted by a ‘+’. A variable that is hypothesized to decrease the likelihood of the response is denoted by a ‘-’. The sign ‘+/-‘ indicates that the effect is unclear, and a ‘.’ suggests that this variable is not applicable for the particular response.

3.2 Estimating Probability Parameters

The behavioral models introduced in the analysis framework chapter have to predict discrete decisions by pedestrian and driver. This approach is different from more common (multi-) linear regression approaches that quantify the effect of different factors on a continuous dependent variable. The behavioral responses used in this research are not continuous, but categorical.

In particular, the driver yield model predicts whether a driver yields or not. Similarly, the pedestrian crossing model predicts whether a pedestrian decides to cross or not. Conceptually, this type of discrete-choice modeling is similar to a transportation mode-choice model, predicting whether an individual takes the bus, the train or drives his/her own car to work.

3.2.1 Review of Statistical Models

The analysis of categorical data requires different statistical methodologies from interval or continuous data (Washington et al. 2003). Categorical data can either be *nominal* (age, gender) or *ordinal*, in which case something can be said about the relative ranking of values. For example, in a survey with answers from '1' to '5', it can be said that '3' is more than '2', but not necessarily that '4' is twice as much as '2'. Due to these limitations in categorical data, the mathematical operations of addition or multiplication are meaningless and the analysis requires statistical tools beyond conventional regression analysis.

A pedestrian's decision to accept or reject a gap in vehicular traffic clearly falls in the nominal category. In the case of drivers yielding to pedestrians, the decision outcome can be qualified as nominal (yield or non-yield) or could be argued to have ordinal character. In the latter case, the event outcomes could be divided into ordered responses of non-yields, soft yields, and hard yields. Depending on the characteristics of the response variable, different statistical models can be applied in categorical data analysis.

Adapting the discussion in Washington et al. (2003) to the example of drivers yielding to pedestrians, the response variable Y_{in} can describe the probability of discrete outcome i for observation n, such that:

Equation 3: General Statistical Model for Driver Yielding

$$Y_{in} = \boldsymbol{\beta}_i \mathbf{X}_{in} + \boldsymbol{\varepsilon}_{in},$$

Where $\boldsymbol{\beta}_i$ is the parameter vector for outcome i, $\mathbf{X}_{in}$ is the vector of observable covariates and $\boldsymbol{\varepsilon}_{in}$ is a vector of disturbance terms with an assumed distribution. The estimation of the parameter vector for the models can utilize either a *probit* or a *logit* approach.

Assuming a binary outcome of the yielding event Y_i and a normal distribution of the error terms ε, the probability of a driver yielding $P_n(1)$ versus the probability of a non-yield $P_n(2)$, can be expressed as a probit model:

Equation 4: Binary Probit Model for Driver Yielding

$$P_n(1) = \boldsymbol{\Phi}\{(\boldsymbol{\beta}_1 \mathbf{X}_{1n} - \boldsymbol{\beta}_2 \mathbf{X}_{2n})/\sigma\},$$

Where $\boldsymbol{\Phi}$ is the standardized cumulative normal distribution and σ is the pooled variance of all observations. The estimation of the parameter vector $\boldsymbol{\beta}$ is achieved through maximum likelihood estimation. A general problem in the use of probit models is that the outcome is not restricted to positive values between zero and one, and can therefore result in unreasonable probability estimates.

In an effort to overcome these and other restrictions of probit models, the logit approach assumes that the disturbance terms in $\boldsymbol{\varepsilon}$ follow an extreme value distribution rather than a normal distribution (Washington et al. 2003). This assumption simplifies the estimation of $P_n(1)$ above by replacing $\boldsymbol{\beta}_2 \mathbf{X}_{2n}$ with the maximum of all other outcomes $\boldsymbol{\beta}_I \mathbf{X}_{In} \neq 1$. Assuming the common Gumbel Type 1 extreme value distribution, equation 4 above becomes the standard logit function:

Equation 5: Logit Model for Driver Yielding

$$P_n(i) = \text{Exp}[\boldsymbol{\beta}_i \mathbf{X}_{in}] \,/\, \boldsymbol{\Sigma}(\text{EXP}(\boldsymbol{\beta}_I \mathbf{X}_{In}))$$

The logit model is more intuitive in that predicted probabilities will always be between zero and one. Depending on the format of the dependent variable, different logit models apply.

3.2.2 Logistic Model Forms

The most intuitive approach is to utilize the GO or YIELD response variable in a *binary logistic regression*, to predict the likelihood of a pedestrian crossing or of a driver yielding. In fact, for the pedestrian crossing model, the binary logit model is the only viable alternative. With the distinction between *hard yield* and *soft yields* more complicated model forms can be applied to the driver yield model. The categorical yield response may be described by the simple binary logit model, a multinomial logit model, a cumulative logit model for ordered responses, or a nested logit model. In the following discussion, the applicability of the driver yield model to these alternate model forms is discussed in more detail.

Binary Logistic Regression

The analysis of categorical data requires different statistical methodologies from interval or continuous data (Washington et al. 2003). The decision of a pedestrian to begin crossing has two distinct outcomes (1=GO, 0 = NOGO). Similarly, driver yielding behavior can be interpreted as a *nominal* parameter with binary outcome (1=yield, 0=non-yield). The binary logit model is the simplest logistic model form to describe this response variable. Following the discussion in Agresti (2007) the binary logistic regression model describing the log odds of response Y is given by:

Equation 6: Binary Logit Model

$$Logit[P(Y=1)] = \log\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \beta_0 + \sum_{i=1}^{m} \beta_i x_i$$

with intercept β_0 and parameters β_i describing the effects of *m* explanatory variables x_i on the yield response. Keeping all other effects fixed, a one-unit increase in the variable x_i has a multiplicative effect equal to the *odds ratio* of e^{β_i} on the likelihood of yielding. The model parameters can be obtained through maximum likelihood estimation in SAS statistical software using PROC LOGISTIC. The probability estimates for the yield response can be obtained using the exponential function as follows:

Equation 7: Estimating Probabilities from Binary Logit Model

$$P(Y=1) = \frac{e^{\alpha+\sum_{i=1}^{m}\beta_i x_i}}{1+e^{\alpha+\sum_{i=1}^{m}\beta_i x_i}} = \frac{1}{1+e^{-\left(\alpha+\sum_{i=1}^{m}\beta_i x_i\right)}}$$

For estimating the model parameters and determining significant effects, SAS PROC LOGISTIC allows the analyst to use a forward selection algorithm at a user-defined confidence level. With this algorithm, variables are added to the model in a stepwise fashion starting with the one yielding the highest Chi-Square statistic. The algorithm continues to add variables to the model, one at a time, until the significance level exceeds the desired confidence level. Alternatively, the analyst can manually add and drop variables to arrive at a satisfactory model.

Multinomial Logit Model

It can be argued from visual observations of yielding behavior that a soft yield is distinctly different from a hard yield and may be more likely to result in a risky interaction. In particular, there is a greater amount of ambiguity in interpreting a soft yield from the perspective of the pedestrian. While a hard yield is easily identified, the soft yield may require additional non-verbal communication between the involved parties. A soft yield may thus be more likely to be misinterpreted by the pedestrian and may result in a risky situation if the driver grows impatient with the lack of pedestrian response and re-accelerates.

While a binary response variable is a valid description of the event outcome of the driver yielding process, it can be argued that additional detail may be necessary in some case. For example, in the context of crossing difficulties for pedestrians with vision impairments it is evident that blind travelers have more difficulties detecting a yield in which the vehicle does not come to a complete stop (soft or rolling yield). Similarly, when deploying video detection technology to detect yielding events as is done in ongoing research at NCSU (sponsored by NIH), it is more difficult to define or detect a soft yield. The categorical yield variable with event outcomes NY, SY, and HY can be analyzed in a *multinomial logistic regression* approach. The parameter estimation and interpretation of this approach is cumbersome and ignores the relative ranking of the outcome categories.

In the multinomial logit model form the analyst has to select a base value of the response, which in this case is most intuitively the NY level. The model algorithm then estimates a separate intercept for the remaining two response levels (SY and HY). For each independent variable, the MNL model estimates separate parameters for each level, resulting in a very complicated model form. Conceptually, each variable has different effects on the log odds of SY and HY relative to the NY base. For example, a model with

3 independent variables would have 8 parameters: 2 intercepts and 2 parameters for each of the three explanatory factors.

Again, the parameter vector **β** can be estimated using maximum likelihood estimation. Assuming that the driver yielding models can be described by the three discrete outcomes HY, SY, and NY, the respective probabilities can be estimated through the following equations:

Equation 8: Probability Estimates from Multinomial Logit Model for Driver Yielding

$$P(Y=2)=\frac{e^{\beta_{0,2}+\sum_{i=1}^{m}\beta_{m,2}}}{e^{\beta_{0,2}+\sum_{i=1}^{m}\beta_{m,2}}+e^{\beta_{0,3}+\sum_{i=1}^{m}\beta_{m,3}}+1}$$

$$P(Y=3)=\frac{e^{\beta_{0,3}+\sum_{i=1}^{m}\beta_{m,3}}}{e^{\beta_{0,2}+\sum_{i=1}^{m}\beta_{m,2}}+e^{\beta_{0,3}+\sum_{i=1}^{m}\beta_{m,3}}+1}$$

$$P(Y=1)=1-\left[P(Y=2)+P(Y=3)\right]$$

Where P(Y=1), P(Y=2), and P(Y=3) are the probabilities for a driver to perform a non-yield, soft yield, and hard yield, respectively. The parameters affecting the exponential terms describe the effects of the different independent variables. After estimation of the MNL parameters, statistical significance tests can be performed using the likelihood ratio test, which is similar to the Chi-Square statistic used in simple linear regression.

Cumulative Logit Model for Ordered Responses

A cumulative logit model for ordered responses utilizes the additional information that a hard yield is in some fashion more than a soft yield, which in turn is more than a non-yield. This cumulative modeling approach typically has higher statistical power and is more intuitive in the interpretation. It is limited by the assumption of *proportional odds* on the different response levels. In other words, it assumes that the effect of a variable on SY versus NY is the same as on the difference between SY and HY. This assumption will be tested in the model development process. The model form is given below.

Equation 9: Model Form of Cumulative Logit Model for Ordered Responses

$$Logit\left[P(Y \le j)\right] = \log\left(\frac{P(Y \le j)}{1 - P(Y \le j)}\right) = \beta_{0,j} + \sum_{i=1}^{m} \beta_{i,j} x_i$$

The cumulative logit model generally results in greater statistical power than the multinomial logit model and is more easily interpreted. The likelihood of SY and HY are estimated relative to the NY baseline and separate intercepts are calculated for the two response levels. For each independent variable, the cumulative logit model only requires one parameter, assuming proportional odds on both response levels. The probabilities of any one of the three response levels are calculated from the equations below.

Equation 10: Probability Estimates from Cumulative Logit Model for Driver Yielding

$$P(Y \le 1) = \frac{e^{\beta_{0,1} + \sum_{i=1}^{m} \beta_{i,1} x_i}}{1 + e^{\beta_{0,1} + \sum_{i=1}^{m} \beta_{i,1} x_i}} = \frac{1}{1 + e^{-\left(\beta_{0,1} + \sum_{i=1}^{m} \beta_{i,1} x_i\right)}}$$

$$P(Y \le 2) = \frac{e^{\beta_{0,2} + \sum_{i=1}^{m} \beta_{i,2} x_i}}{1 + e^{\beta_{0,2} + \sum_{i=1}^{m} \beta_{i,2} x_i}} = \frac{1}{1 + e^{-\left(\beta_{0,2} + \sum_{i=1}^{m} \beta_{i,2} x_i\right)}}$$

$$P(Y = 1) = P(Y \le 1)$$

$$P(Y = 2) = P(Y \le 2) - P(Y \le 1)$$

$$P(Y = 3) = 1 - P(Y \le 2)$$

The cumulative logit model for ordered responses estimates the probability that the response is less than or equal to level j. The probability of Y equal level j is obtained by subtraction as shown above. In the interpretation of this model form, each probability parameter increases or decreases the log odds of the categorical response in the direction from NY to HY.

Nested Logit Model

A final possibility is to apply a *nested logit* model that predicts the likelihood of a hard yield given that a yield occurred. Conceptually, this represents a two-stage binary logit model with the first stage consistent to the initial binary logit discussed above. Given that the first level of the nested logit predicts a yield, the second level predicts the likelihood that the driver performs a hard yield (versus the baseline soft yield). The flowchart in Figure 13 illustrates the model form.

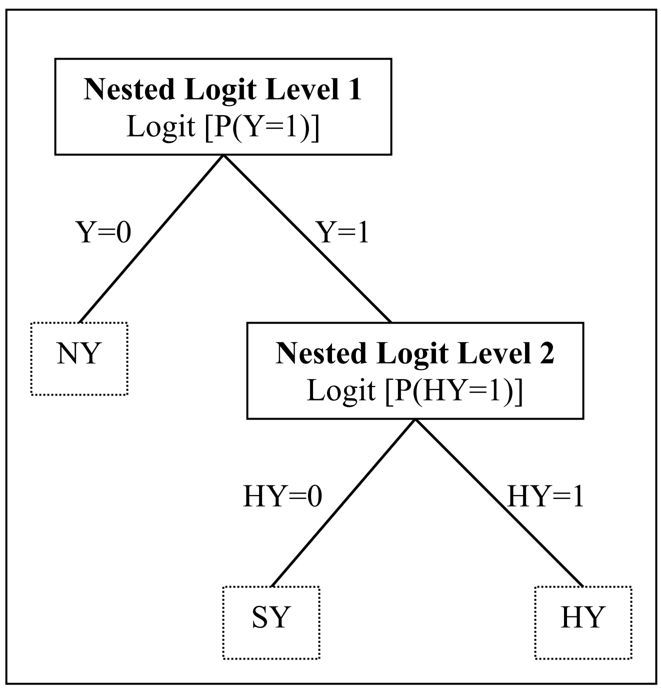


Figure 13: Nested Binary Logit Flowchart

The model form is consistent with equations 6 and 7, only that the estimation of the second level is performed on only a subset of the observations (those with YIELD=1).

The response is the binary variable Y_TYPE, which takes the value 0 for SY and 1 for HY outcomes.

3.2.3 Statistical Inference for Logit

The output of logistic regression models is interpreted differently from multilinear regression. This section discusses inference statistics for logit regression and how different models are compared in their relative fit.

In the PROC LOGISTIC output, statistics for individual variables include the parameter estimates β_i, the standard error of the estimate and a Wald Chi-Square test for the null hypothesis $\beta_i=0$. The Wald test statistic calculates the z-statistic by dividing the parameter estimate by its standard error. Similar to significance tests for linear regression models, the probability test can be interpreted with regard to a user-selected confidence interval by getting a p-value for z from a standard normal table ($p<0.05$ indicates a 95% confidence level). The Wald test is adequate for large samples (Agresti, 2007).

The interpretation of the individual model parameters is more difficult than for linear regression due to the exponential form of the logit equation. Following the discussion in Agresti (2007), the odds of a response 1 for a binary logit model are given by:

Equation 11: Odds of Response 1 for Binary Logit Model

$$\frac{P(x)}{1-P(x)} = e^{\beta_0+\beta_i x_i} = e^{\beta_0}\left(e^{\beta_i}\right)^x$$

The slope parameters β_i in the exponential relationship in equation 11 can be interpreted through the *odds ratio* of the parameter. For a continuous variable, a one-unit increase in the variable results in an e^{β} increase in the odds of the response variable. For a binary explanatory variable the odds ratio is interpreted as an increase in the odds of the response from when the variable increases from levels 0 to 1. The odds ratio is the increase in the likelihood of the response for a variable assuming that all other variables are fixed.

Continuing the parallel to linear regression, the commonly used R-square test statistic describes the amount of variability in the data that is explained by the model. In general, a higher R^2 value indicates a better model fit, but the statistic is inflated with the addition of more variables. The adjusted R^2 penalizes the model for inclusion of additional variables and is a better measure for models with many independent variables.

In the estimation of logistic regression models in PROC LOGISTIC, SAS uses a generalization of the usual R^2 statistic to mimic the analysis of linear regression. According to the SAS user manual (SAS Institute, 1999) the likelihood-based *pseudo R^2* is calculated by:

Equation 12: Pseudo R-Square for Logit Model

$$R^2 = 1 - \left\{ \frac{L(0)}{L(\hat{\beta})} \right\}^{\frac{2}{n}}$$

where n is the sample size and L(0) and $L(\hat{\beta})$ are the likelihood of the intercept-only model and the specified model, respectively. However, even this generalization does not cover the complete range from 0 to 1. Alternatively, the *max-rescaled R-Square* divides the generalized R-square by the upper bound of the R^2 estimate to achieve a statistic that ranges all the way from 0 to 1.

The max-rescaled R^2 statistic provides a sense of the overall model fit, but is not well suited to compare different models. The overall model fit is also tested using three different statistics testing the hypothesis that the overall parameter vector $\boldsymbol{\beta}$ is zero: likelihood ratio test, score test, and Wald test. However, these statistics are also not well suited in comparing different models, because they generally show high significance even if only one parameter has a significant effect on the response (Agresti, 2007).

A better method of model comparison is given by three information criteria that are included in the PROC LOGISTIC output: -2 Log Likelihood Criterion, Akaike Information Criterion (AIC), and Schwarz Criterion (SC). The -2 Log Likelihood criterion tests the null hypothesis that all effects in the model are zero and approximately follows a chi-square null distribution. The difference in the -2 Log Likelihood statistics of two models is significant if it exceeds the corresponding Chi-square value at the difference in degrees of freedom between the two models.

The AIC and SC criteria both are adjustments to the -2 Log Likelihood criterion to account for the number of terms in the model and the sample size. According to SAS Institute (1999) these latter criteria are best suited for comparing different model forms that use the same data set, but a different number of parameters. According to Agresti (2007), the AIC is calculated by:

Equation 13: Akaike Information Criterion (AIC) for Logit Model Estimation

$$\text{AIC} = -2(\text{log likelihood} - \text{number of parameters in model})$$

For the AIC or SC criteria a smaller statistic signifies an improvement in model fit to the data. While the AIC and SC statistics are a better estimate of overall model fit than the -2 Log Likelihood statistic, they cannot be used in the same fashion to test statistical difference by subtraction.

Besides these statistics, the comparison of different models should also consider their practical significance. Agresti (2007) argues that:

> *It is sensible to include a variable that is important for the purposes of the study and report its estimated effect even if it is not statistically significant. ... Likewise,*

with a very large sample size sometimes a term might be statistically significant but not practically significant.

This notion is very important in the context of analyzing pedestrian-vehicle interaction in this research, because practical application is clearly important in the field of civil engineering. Therefore, while statistical model fit is important, and the evaluation of all significant parameters is intriguing, there are practical limitations that need to be considered as well. Especially in light of the proposed application to a microsimulation environment, the selected models need to be implementable in software.

3.2.4 Analysis Approach

In the data analysis chapters, all four logistic model forms are applied to the driver yielding models (binary logit, multinomial logit, cumulative logit, and nested logit). For the pedestrian crossing models, only the binary logit model is applicable because the GO response only has two distinct levels.

For both sets of models, the analysis begins with a general analysis of descriptive statistics of the different variables using SAS PROC MEANS. This allows the analyst to develop a feel for the data. In each category, the MEANS procedure will be applied to the entire data set as well as to the before and after conditions (for mid-block), the entry and exit leg (for roundabout), and the different levels of the response variables.

In the next step, a correlation analysis is performed using SAS PROC CORR to identify significant correlations between independent variables and response variables. This step also helps screen issues with multicollinearity between independent variables. Additionally, binary explanatory variables are related to the dependent variables with SAS PROC FREQ, which generates 2x2 contingency tables for the variable pairs and performs Chi-square statistical tests.

Before moving into the logistic regression analysis, the author first applied multilinear regression models (MLR) to all data sets. The categorical nature of the response violates the underlying assumptions of these models and the result will likely exhibit irrational estimates (predicting probabilities less than zero or greater than 1). Nonetheless, these models are a helpful tool for an initial assessment of the feasibility of regression analysis for the given data set.

For the logistic regression analysis, several different modeling approaches are applied that differ in the number and type of parameters that are considered. Initially, the analysis focused on the *full model* that includes all eligible parameters and was intended to get a general feel for which parameters show strong association with the dependent variable in the logistic regression. Next, an *unrestricted model* is evaluated, which is strictly guided by statistical model fit. After arriving at a model with ideal statistical fit, the logistic analysis was repeated but limited to variables that have application to microsimulation. In this *restricted model* approach only factors that could feasibly be implemented in microsimulation models were considered.

The Unrestricted Model

Using a user-specified confidence level of 0.05, the PROC LOGISTIC modeling algorithm can apply a forward selection algorithm and add variables to the model one at a time until they no longer satisfy the threshold. Variables are added starting with the highest Chi-Square statistic. This approach is motivated by the objective to achieve the best possible model fit for the data, ignoring practical applicability of the final model.

The Restricted Model

It was argued previously that practical significance can be equally if not more important than statistical significance in the model selection process. With large data sets, statistical significance of parameters can be coincidental and may not have a meaningful interpretation. A central assumption of this research is that the resulting models can be implemented in a microsimulation environment to quantify the impact of behavioral variables. This model selection approach is therefore restricted to practically significant parameters that can be implemented in microsimulation. However, the approach still considers statistical significance as a secondary selection criterion.

The question of implementability requires some knowledge of the way microsimulation models work, which is discussed in more detail in Chapter 7. Conceptually, the decision algorithms to yield or cross the road are updated every simulation time step (typically at 0.1 second intervals), based on the state of the explanatory variables. The data collection approach made the key assumption that driver and pedestrian make these decision at the time a pedestrian arrives at the crosswalk (t_1). With this assumption, only variables that can be observed or measured at this point in time are allowed to enter in the restricted model.

Following this assumption, several of the collected variables are left out of the restricted model development approach. For example, the variable TRIG is measured after the defined onset of the event. A driver can observe a brisk pedestrian walking pace on the approach (AST) and base his yielding decision on the presumption that this pedestrian might step into the roadway. However, if the pedestrian actually does so is unknown at t_1. Similarly, the presence of an adjacent yield (ADY) is not evident at t_1, because that yield has yet to occur. In the observational data it was not discerned when the adjacent yield took place, so it cannot be deduced when and if the driver in the opposite lane was aware of it.

For the temporal parameters used in the pedestrian crossing models, the restricted models are limited to the *expected* gap and lag times, because those are quantified from the state of the system at t_1 (both in the field and in the simulation model). The observed times may be influenced by other events, as discussed above.

Following this reasoning, several variables were not allowed to enter the restricted model: ADY, COM, FOLL, PREV, PXW, TRIG, O_GAP, and O_LAG. From the entire list of explanatory variables the following list was included in the development of the restricted models: AST, DSC, ENTRY, FLASH, HEV, MUP, NEAR, PLT, QUE, TRTMT, DECEL, DIST1, E_GAP, E_LAG, SPEED_FT, and TTC.

The usefulness of the variables in both unrestricted and restricted models may further be limited by low sample sizes. The maximum likelihood estimation of the predictor parameters in logistic regression is problematic with *sparse data* (Agresti, 2007). This occurs if a contingency table of the response and an explanatory variable has a cell with few observations. If a cell has a count of 0 (an *empty cell*) the independent variable is virtually a perfect predictor of a specific response level. The consequence is that the maximum likelihood procedure may not converge at an estimate. The concern with sparse data is especially evident for variables that are observed less frequently, including ADY, DSC, HEV, MUP, QUE, and potentially others, depending on the particular data set. To achieve a finite model estimate from the maximum likelihood estimation, the marginal counts in the contingency table have to be greater than 0 (Agresti, 2007).

3.3 Site Description

The methodology was applied to two unsignalized midblock crosswalks in Raleigh and Charlotte, North Carolina and a single-lane roundabout also in Raleigh, NC. Both mid-block sites have two-lane cross-sections and were selected because of heavy pedestrian activity and vehicle flows and because of the already planned installation of a new pedestrian crossing treatment. The roundabout site also sees heavy pedestrian and vehicle traffic, but no treatment effect was studied.

The first crosswalk, on Selwyn Avenue in Charlotte, NC (MB-CLT), is adjacent to the campus of Queens University. The two-lane site has unusually wide 20-foot (6.1 meters)lanes with a posted speed limit of 35 mph. The roadway has on-street parking starting approximately 100 feet to the north of the crosswalk. The crosswalk is used by students, faculty and residents in the communities adjacent to the university. The road functions primarily as a north-south arterial. Because of concerns for pedestrian crossing safety, the City of Charlotte decided to install pedestrian-actuated, in-pavement flashing beacons at the crosswalk. Figure 14 shows photos of the data collection site, and a close-up view of the treatment after installation.

The second crosswalk, on Sullivan Drive in Raleigh, NC (MB-RAL), is on the campus of North Carolina State University. The facility has standard 12-foot lanes and a speed limit of 25 mph. The crosswalk is used primarily by students walking to class from adjacent surface parking lots. The road functions as access to the parking facility, but is also used by through traffic avoiding heavier-traveled arterial roads to the north and south. The NCSU Department of Transportation decided to install an in-road pedestrian warning sign at the crosswalk to increase driver yielding behavior. Figure 15 shows photos of the data collection site and a close-up view of the treatment.

The single-lane roundabout is located at the intersection of Pullen Road and Stinson Drive in Raleigh, NC (RBT-RAL). Pullen Road is a heavily traveled 2-lane minor arterial street just east of the NCSU campus. Stinson Drive serves as the visitor's entrance to the university's main campus. The intersection sees heavy north-south through traffic, as well as some traffic entering and leaving the university. With several campus bus routes going through the roundabout, and with delivery trucks accessing the university, there is also a significant amount of heavy vehicles. This research utilized the southern crosswalk because it sees the heaviest activity of pedestrians. Figure 16 shows photos of the roundabout from a near-by rooftop, and a composite view of two time-synchronized cameras. This view allows the analyst to record observations from a ground level view of the crosswalk, consistent with the other sites, while simultaneously monitoring the vehicle operations for the entire site.

The “before” data collection for the mid-block sites both took place in early spring 2007, when the sites were marked with zebra striped crosswalks and outfitted with standard pedestrian signage. The author allowed a six-week driver acclimation period for drivers and pedestrians before collecting the “after” data. This was deemed a sufficient amount of time because the populations of university-affiliated pedestrians and commuter traffic were expected to travel the sites daily, and would thus get sufficient exposure to the new measure. The roundabout data were collected during the fall 2007 semester. All data collection took place during good weather conditions (no rain or ice) and while the semester at the respective universities were in session (no breaks or holidays).

a) View of Data Collection Site looking South

b) Close-up view of in-pavement flashing crosswalk

Figure 14: Photos of Data Collection Site MB-CLT

a) View of Data Collection Site looking East

b) Close-up view of in-road pedestrian warning sign

Figure 15: Photos Data Collection Site MB-RAL


a) Overhead-View of Data Collection Site looking North

b) Composite Two-Camera View used for data collection

Figure 16: Photos of Data Collection Site RBT-RAL

For all three sites, the author performed multiple hours of observations. During data collection, a video camera was positioned to record events at the crosswalk while the author monitored pedestrian activity. Whenever a pedestrian was in the approach to the crosswalk, the author measured the speed and distance of the closest vehicle with a LIDAR speed measurement device. The start of the video camera and the LIDAR device were time-synchronized to allow for post-processing in the lab. Additionally, the LIDAR device generated a beep sound, audible on the video, every time a measurement was performed. This allowed the author to precisely match up the speed and distance time-stamp with the video observations.

All data sets required significant post-processing in the lab. The original video observations were time-stamped and copied to DVD. The time-stamps in the LIDAR device output files were matched up with the beginning of the video and the distance measurements converted to distances relative to the crosswalk. The device measures the distance to the vehicles, which can be converted by knowing the distance between the observer and the crosswalk.

Once the data were cleaned up for analysis, the analyst replayed each video looking for pedestrian events. All time-stamps were entered manually into an Excel spreadsheet and the video was paused and rewound, as necessary, to capture all variables. This very time-consuming process resulted in a data extraction time of about 10 hours per hour of video, depending on the number of events per hour. This estimate does not include time requirements for actual data collection, data preparation or any analysis of the data. A total of 17 hours of video were used for this research.

Depending on the volume of pedestrians and vehicles, each hour of video resulted in up to 200 separate events for driver yielding or pedestrian crossing behavior. The analysis only used video events that could be matched up with a LIDAR measurement. The final sample sizes for the MB-CLT, MB-RAL and RBT-RAL sites included 604 yielding and

551 crossing events, 470 yielding and 768 crossing events, and 100 yielding and 88 crossing events, respectively. Overall, 2581 interaction events were used in the analysis, corresponding to an average of approximately 150 events per hour of video.

3.4 Chapter Summary

This chapter proposed a data collection methodology to measure event-based interaction data of both the pedestrian and vehicle mode in the field. The methodology uses time-synchronized LIDAR vehicle dynamics measurements and video observations to extract a range of continuous and discrete interaction variables.

Statistical analysis techniques that can estimate the likelihood of driver yielding and the likelihood of a pedestrian crossing decision as a function of both binary and continuous explanatory variables were reviewed. The response variables themselves are of a categorical nature, requiring the use of logistic regression techniques. While a binary response can be described by a relatively simple binary logit model, the three-level yield response may require more complicated modeling approaches. The multinomial, cumulative, and nested logit model forms all have promise for this analysis.

With the availability of statistical analysis procedures, the author developed an analysis approach to evaluate the field data. The analysis includes the evaluation of unrestricted models that maximize statistical fit and restricted models that are limited to variables implementable in microsimulation.

Using the time-synchronized video observations and vehicle dynamics measurements, the author was able to analyze 17 hours of video observations for three different data collection sites. The three sites include two unsignalized mid-block crossings and one crossing at a single-lane roundabout. The mid-block sites were each visited twice and evaluated in conditions ‘before’ and ‘after’ the installation of treatments intended to improve pedestrian operations.

4 DRIVER YIELDING MODELS AT MID-BLOCK CROSSINGS

This chapter discusses the development and analysis of statistical models describing the likelihood of drivers yielding to pedestrians at unsignalized mid-block crosswalks. Initially, the author examined descriptive statistics of the individual parameters to acquire a general sense of the trends and variability in the data. Next, the interaction of different parameters was investigated with special attention to the operational parameters associated with vehicle dynamic constraints. In the final analysis logistic regression models were developed to describe driver yielding behavior.

Data were collected on the dynamics of the approaching vehicles, behavioral characteristics of drivers and pedestrians, and the circumstances surrounding the pedestrian-vehicle interaction event.

Three different response variables were evaluated. The first, YIELD, is a binary indicator describing whether the driver yielded or not. The categorical variable Y_ORDERED, distinguishes between non-yield (NY), soft yields (SY) and hard yields (HY) events. Y_TYPE is a binary variable that only considers the two types of yield events.

In the following, the results from the two mid-block test sites are presented separately. First, the crosswalk on Selwyn Avenue in Charlotte, NC (MB-CLT) is analyzed including the treatment effect of the pedestrian-actuated in-pavement flashing beacons. Second, the crosswalk on Sullivan Drive in Raleigh, NC (MB-RAL) is analyzed including the treatment effect of the in-road pedestrian warning sign.

Due to the size of some tables, the results of correlation analyses and all regression models are relegated to Appendix A. For the logistic regression model, the chapter repeats pertinent statistics and gives equations for the selected predictive models in different categories.

4.1 Event-Based Analysis for MB-CLT

4.1.1 Descriptive Statistics

The author used SAS PROC MEANS to obtain descriptive statistics on the modeling parameters. The results in Table 2 show the mean and standard deviation for all 604 data points, for the before (361) and after (243) treatment conditions, and for yield (105) and non-yield (499) events.

Table 2: Descriptive Statistics, MB-CLT

	ALL DATA		BEFORE		AFTER		YIELDS		NON-YIELDS	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Sample Size	604	.	361	.	243	.	105	.	499	.
Response Variables										
YIELD	0.174	0.379	0.150	0.357	0.209	0.407	1.000	0.000	0.000	0.000
Y_ORDERED	1.289	0.662	1.266	0.655	1.324	0.671	2.667	0.474	1.000	0.000
Y_TYPE*	0.667	0.474	0.778	0.420	0.549	0.503	0.667	0.474	.	.
Binary Factors										
ADY	0.084	0.278	0.086	0.281	0.082	0.275	0.229	0.422	0.054	0.226
AST	0.142	0.349	0.141	0.349	0.143	0.351	0.371	0.486	0.094	0.292
COM	0.050	0.217	0.058	0.234	0.037	0.189	0.286	0.454	0.000	0.000
DECEL_TAU	0.106	0.308	0.069	0.254	0.160	0.367	0.000	0.000	0.128	0.334
FLASH	0.131	0.337	0.000	0.000	0.324	0.469	0.276	0.449	0.100	0.300
FOLL	0.489	0.500	0.476	0.500	0.508	0.501	0.429	0.497	0.502	0.500
HEV	0.015	0.121	0.011	0.105	0.021	0.142	0.019	0.137	0.014	0.118
MUP	0.321	0.467	0.302	0.460	0.348	0.477	0.410	0.494	0.302	0.460
NEAR	0.511	0.500	0.501	0.501	0.525	0.500	0.448	0.500	0.524	0.500
PLT	0.671	0.470	0.681	0.467	0.656	0.476	0.505	0.502	0.706	0.456
PREV	0.678	0.468	0.701	0.459	0.643	0.480	0.648	0.480	0.684	0.465
PXW	0.132	0.339	0.150	0.357	0.107	0.309	0.390	0.490	0.078	0.268
QUE	0.007	0.081	0.011	0.105	0.000	0.000	0.019	0.137	0.004	0.063
TRIG	0.079	0.270	0.044	0.206	0.131	0.338	0.305	0.463	0.032	0.176
TRTMT	0.403	0.491	0.000	0.000	1.000	0.000	0.486	0.502	0.386	0.487
TTC_TAU	0.175	0.380	0.116	0.321	0.262	0.441	0.019	0.137	0.208	0.406
Continous Factors										
DECEL	4.787	5.928	3.959	4.540	6.013	7.368	2.266	1.630	5.316	6.353
DIST1	335.433	256.526	381.892	273.154	266.697	212.314	406.698	254.921	320.467	254.588
SPEED_FT	40.341	9.419	40.897	9.488	39.518	9.274	36.754	10.738	41.094	8.949
TTC	8.376	6.002	9.468	6.369	6.753	4.999	11.027	5.934	7.818	5.871

* The Sample Size for Y_TYPE is only 105 observations, because it only considers HY and SY events

The response variable, YIELD, is a binary variable, so its mean is equivalent to the overall observed yielding rate. The overall yielding rate at the site is 17.4%, with 15.0% yielding in the 'before' case and 20.9% yielding after treatment implementation. Though small, this difference is significant at the 90% level. The ordered variable Y_ORDERED shows a similar trend, and Y_TYPE suggests that 66.7% of yields were classified as hard yields.

Table 2 also begins to shed light on why the observed yielding rates may be so low at the site. The average observed speed (SPEED_FT) at the site is 40.34 ft/sec (27.5mph or 44.26 km/h) and is significantly higher for non-yield events ($p<0.0001$). The installation of the treatment had no significant effect on speed. There is also a large variation in the relative distance from the crosswalk at the time of a pedestrian arrival (DIST1) and at least some vehicles were probably too close to be able to stop. The vehicle dynamics constraint factors TTC and DECEL also show high standard deviations. By examining the VDC factors in terms of thresholds (TTC_TAU and DECEL_TAU), it becomes evident that no yields were observed at deceleration rates above 10 ft/sec^2 and only 1.9% of yields occurred at TTC times below 3 seconds.

The low yielding rate may also be associated with the frequent occurrence of vehicle platoons and drivers avoiding sudden yields in fear of a rear-end collision. Overall, 67.1% of vehicles traveled in platoons (PLT), 48.9% had a close follower (FOLL) and 67.8% were preceded by a non-yielding vehicle (PREV). Furthermore, only few events are associated with 'non-verbal communication, COM, (5.0%), or an adjacent yield, ADY (8.4%) and vehicle queuing, QUE was negligible (0.7%).

The data further show that 51.1% of pedestrians were at the NEAR side of the vehicle, 32.1% traveled in a group (MUP) and 14.2% exhibited assertive behavior (AST) indicated by brisk walking during their approach to the crosswalk. About 7.9% of pedestrians were observed to actually 'trigger' a yield (TRIG) by stepping onto the roadway. In 13.2% of the events, a previous pedestrian was still in the crosswalk (PXW). Only 1.5% of events were associated with a heavy vehicle presence (HEV).

Comparing the data for yield and non-yield events, almost 3 times as many yields were associated with the actuated flasher (FLASH). Interestingly, the treatment was only activated in 32.4% of the events captured in the 'after' case. Yield events also showed a higher likelihood of pedestrian assertiveness, ‘trigger’ behavior, and the presence of a previous pedestrian still in the crosswalk. Non-yield events were associated with significantly higher speeds and lower distances from the crosswalk (both $p<0.0001$). Consequently, non-yield events are associated with lower time-to-collision (TTC) and higher necessary deceleration rates (DECEL) with p-values of <0.0001 and 0.0017, respectively.

4.1.2 Variable Interactions

Table A-23 in Appendix A shows the correlation matrix for all variables. The results suggest that many of the variables exhibit significant correlations with the dependent variable, as indicated by low p-values. The correlation coefficients are relatively low, suggesting that no single variable is a consistent predictor of yielding. The strongest correlations are evident for COM, AST, TRIG, and PXW, pointing to the major importance of the behavior of the pedestrian in influencing the yielding process.

The correlation for platoons (PLT) is stronger than FOLL and PREV, which is surprising, because the three factors are clearly closely related. This suggests that the mere fact that a driver is traveling in a platoon may be more important than the relative position in the platoon. The three variables are expectedly well correlated amongst each other.

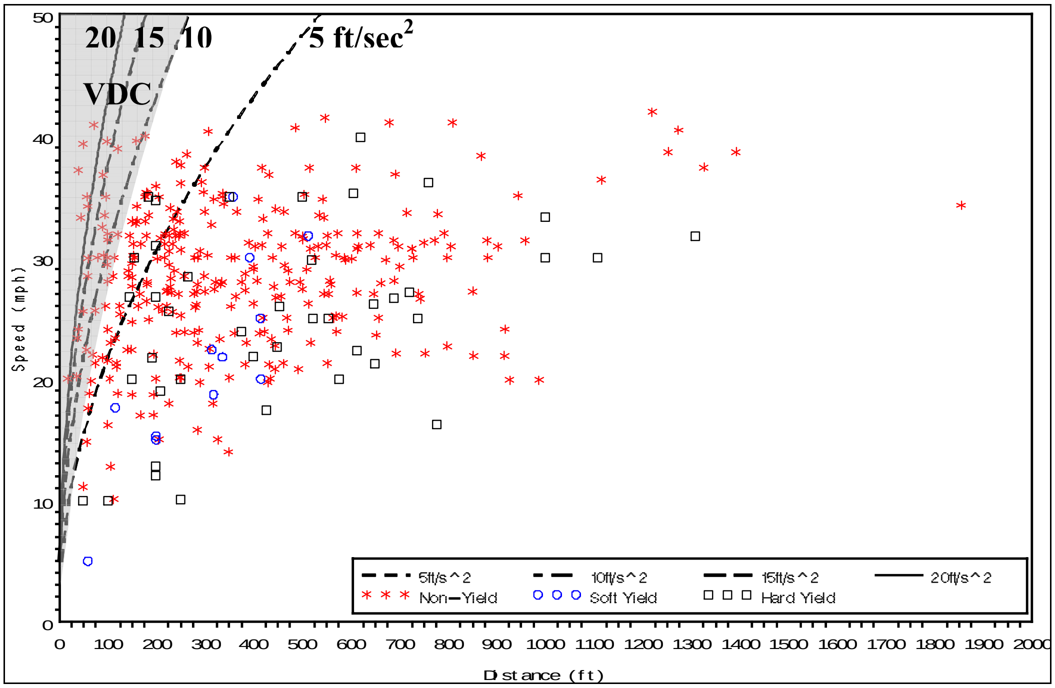
Several of the continuous variables show significant correlation with the response variable, however at low correlation coefficients. The level YIELD=1 is associated with greater DIST1 and TTC, but is inversely correlated with SPEED and DECEL. These trends point towards the importance of vehicle dynamics on yielding behavior.

Only few of the explanatory variables show high correlations with each other. Relatively strong associations are evident between TRIG, AST and PXW, suggesting that assertive pedestrians are more likely to also trigger a yield and that pedestrian behavior may be more assertive if a previous pedestrian is still in the crosswalk.

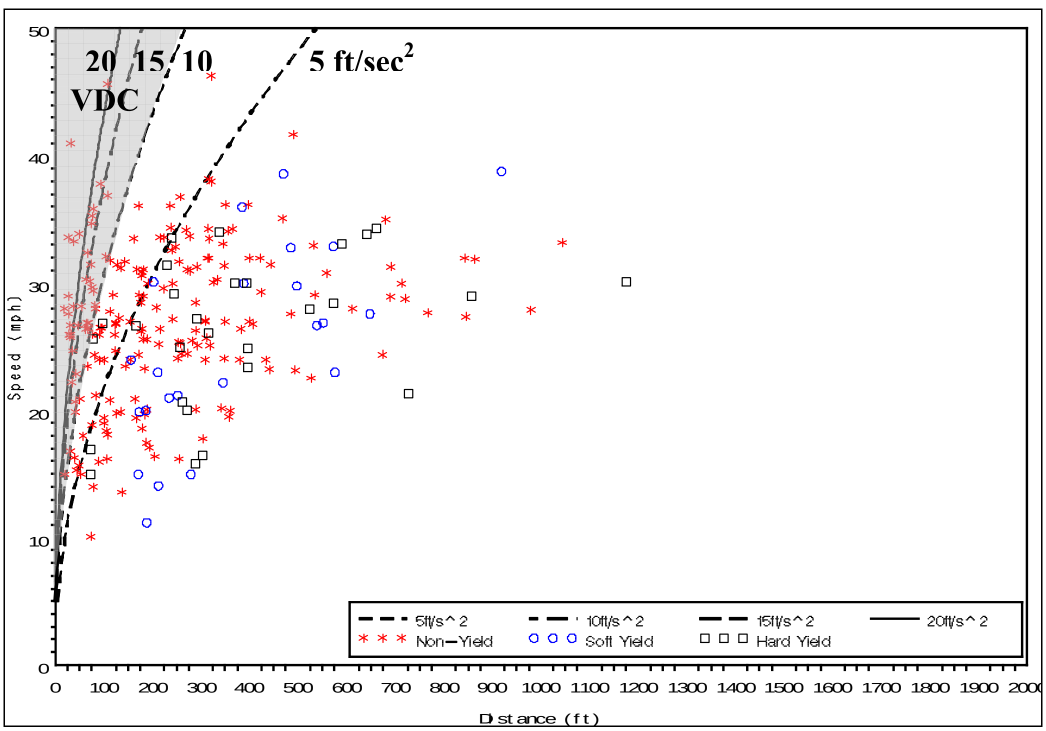
Another weak, but significant correlation is evident between TRTMT/FLASH and TRIG, suggesting that pedestrian behavior may have been affected by the presence and activation of the treatment. Future analysis of the associated pedestrian gap acceptance data may provide further insight into this relationship.

4.1.3 Vehicle Dynamics Constraints

In the discussion in Chapter 2, the author made the point that drivers may be subject to 'vehicle dynamics constraints' (VDC) in their decision to yield to a pedestrian. Figure 17 shows a plot of the relationship between vehicle speed and distance by yield outcome for the before and after cases. The figure shows non-yield events as stars, soft yields as circles and hard yields as squares. Curves of constant deceleration rates for 5, 10, 15, and 20 ft/sec^2 have been superimposed on the graphs (1 ft/sec^2 = 0.3048 m/sec^2).



a) 'Before' Case*



b) 'After' Case*

* Shaded Area is region of 'Vehicle Dynamics Constraints' (VDC) with DECEL>10ft/sec^2

Figure 17: Speed-Distance Relationship including Deceleration Thresholds, MB-CLT

The deceleration rate of $10ft/sec^2$ is also used in traditional signal timing applications (ITE, 1982) when calculating the length of the clearance phase for drivers, although more recent documents use a rate of $11.2\ ft/sec^2$ (TRB, 2000). That phase is timed long enough so that drivers that are too close and too fast to stop can proceed through the intersection without running the red light while others can decelerate at this acceptable deceleration rate or below.

The relationship in Figure 17 supports the notion of VDC affecting the likelihood of drivers to yield. From over 600 observations, no yield events were observed above the $10\ ft/sec^2$ and only a total of 7 yield events (5 before, 2 after) were observed above $5\ ft/sec^2$. The figure further shows that a large number of non-yields are observed below the theoretical yield threshold. This is because this particular site may have an overall low propensity to yield, independent of VDC. It is also important to keep in mind that non-yielding vehicles that were far from the crosswalk may have been part of a fast-moving vehicle platoon, or simply were drivers that had no interest in yielding.

From the relationships shown, the author hypothesized that for a 'high-yield' site, characterized by low speeds, narrow lanes, a courteous driver population, and assertive pedestrians, the VDC threshold could be a fairly accurate predictor for yield and non-yield events.

4.2 Yield Model Development for MB-CLT

4.2.1 Variable Selection

Given the strong indication of the impact of VDC, the author decided to exclude all observations with a deceleration rate in excess of $10\ ft/sec^2$ from further analysis. The reasoning for excluding these data is that they would introduce a bias in classifying these as 'non-yield events' in the logistic model. These particular drivers may very well have yielded, had they only been a little further away from the crosswalk at the time of the pedestrian arrival. The goal of the analysis then is to assess what other factors may explain the yielding behavior of drivers, when they actually had a choice. The remaining data set for MB-CLT contained 540 observations.

Additionally, the author decided to exclude the parameter COM from further analysis, because 2x2 contingency tables with the YIELD response showed that all COM=1 events were associated with YIELD =1. This phenomenon may be evidence for bias, as it is unlikely to observe non-verbal communication (waving, raising hand to say 'thank you') in a non-yield event. Similarly, interaction tables for HEV by YIELD showed cells with less than 5 observations in both data sets. The contingency tables showed no significant interaction between the variables from Chi-Square Tests and Fisher's Exact Tests. The latter is a better test for small samples, because it doesn't use large-sample approximations of the Chi-Square distribution. Consequently, the data suggest that the yielding patterns of heavy vehicles are not different from that of passenger cars and they will therefore be treated as one population in this analysis. Future research with a larger sample size of HEV observations is necessary to investigate the interaction of HEV with other variables (for example platoons).

Furthermore, the MB_CLT data has only four observations of vehicle queues (QUE), which is too small of a sample to include in the analysis. The remaining explanatory variables considered in the models are ADY, AST, FLASH, FOLL, NEAR, PLT, PREV, PXW, TRIG, TRTMT, DECEL, DIST1, SPEED_FT, and TTC.

4.2.2 Multilinear Regression Analysis

It is considered good practice in categorical data analysis to first attempt a simpler multi-linear regression approach. While this approach ignores the categorical nature of the response variable and may violate certain practical constraints (yield probability less than zero or greater than one), it is a good benchmark for model comparison.

Table A-24 shows the results of multi-linear regression using SAS PROC GLM. The full model in Table A-24-a shows significant parameters for ADY, FLASH, NEAR, PLT, PREV, PXW, TRIG, and TTC. The highest parameters and thus strongest effects are observed for TRIG, FLASH, and PLT suggesting the likelihood of yielding is increased for ‘triggered’ events and if the pedestrian activates the flashing beacons, while the presence of a vehicle platoon decreases the yield probability. The signs of most parameters are as hypothesized, except for FOLL and DIST1 which are not significant. The overall model fit is significant ($p<.0001$) and has an overall adjusted R^2 value of 0.27.

In the restricted model, the yield response is predicted by PLT, NEAR, AST, SPEED_FT, DECEL, TRTMT, and FLASH with all variables except for TRTMT being significant. These variables are considered to have practical application with feasibility of implementation in microsimulation. The overall model fit is less than the full model with an adjusted R^2 of 0.18. Figure 18 shows a plot of varying a subset of parameters for the restricted model.

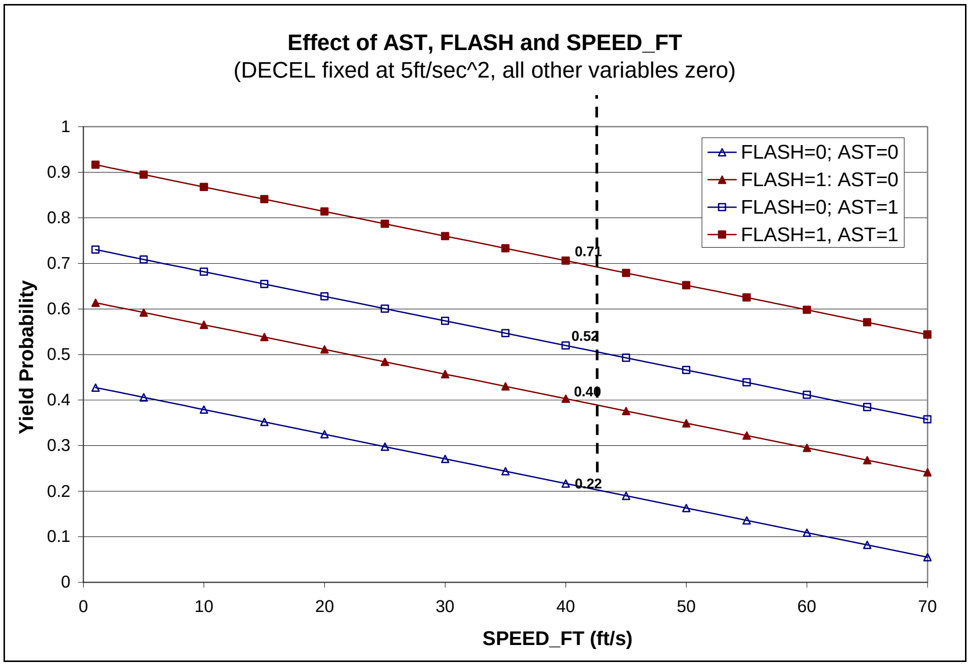


Figure 18: Model Probability Plots – Multi-Linear Regression, Restricted Model, MB-CLT

The plot suggests the limitation of the linear model for this type of analysis, because the indicated effects of FLASH and AST are constant over the entire range of speeds. The vertical line shows the predicted probabilities of yielding at a speed of 40 ft/sec.

Various forms of logistic regression were applied to the data sets. Starting with different binary logit models for a 1/0 yield response (YIELD) the analysis then considers more complex model forms for the response variables Y_ORDERED and Y_TYPE by distinguishing hard from soft yields.

4.2.3 Binary Logit Models – MB-CLT

Full Model

The initial modeling approach considers all feasible variables, ignoring statistical significance or the practical applicability of the emerging model. The full model is intended to show general associations between the explanatory variables and the YIELD response.

The results in Table A-25-a show that significant estimates were obtained for ADY, FLASH, NEAR, PLT, PREV, PXW, TRIG, and DECEL ($p<0.10$). The variable AST is just above that threshold with $p=0.11$, while the remaining variables have low chi-square test associations with the response. The overall model R-Square value for this model is 0.2408 and the Max.-Rescaled R^2 is 0.3843.

Unrestricted Model

The modeling algorithm in SAS/STAT PROC LOGISTIC includes a 'forward selection' algorithm that sequentially adds variables to the model starting with the one with the highest Chi-Square statistic. The algorithm continues until the Chi-Square value of the next parameter falls below the user-specified significance threshold of 0.05. The final model uses eight explanatory variables and has an R^2 value 0.2286 (max. rescaled R^2 is 0.3648).

The 'unrestricted' model in Table A-25-b suggests that drivers are more likely to yield if an adjacent yield is present (ADY), if the pedestrian is waiting at the nearside of the road (NEAR), if the pedestrian triggers a yield by stepping onto the roadway (TRIG), if a previous pedestrian is still in the crosswalk (PXW), and if the in-pavement pedestrian flasher is activated (FLASH). Similarly, the likelihood of yielding is decreased if the driver is traveling in a platoon (PLT), if the previous vehicle failed to yield (PREV), and if yielding would require greater deceleration rates (DECEL). This last effect is particular interesting, considering that vehicles subject to vehicle dynamics constraints (DECEL>10ft/s^2) have been removed from the analysis. Note that the DECEL parameter is essentially an interaction term of DIST1 and SPEED_FT, neither of which is significant at the selected confidence level. The use of the interaction term without the individual effects is justified, because the term has scientific meaning (the deceleration rate) and is therefore not a conventional interaction term.

When all other parameters are kept constant, the model results show the multiplicative effects of each variable x_i on the odds of yielding, given by the term e^{β_i}. This is also called the *odds ratio* of the effect (Agresti, 2007). For example, the estimated odds of a yield occurring if there is an adjacent yield is 2.63 times the odds for a non-ADY event. If the vehicle travels in a platoon, the odds for a yield are reduced 0.47 times and are also reduced 0.36 times if the previous vehicle did not yield. The strongest effect is evident from TRIG, followed by PXW, FLASH and ADY. Note that the mere presence of the treatment (TRTMT) is not significant in the model, but that pedestrians actually have to actuate the flashers in order to influence driver behavior. The flasher actuation increased the odds of yielding 2.79 times compared to a non-actuation. The odds in yielding are further reduced 0.65 times for each additional 1ft/sec^2 in necessary deceleration rate.

Restricted Model

One difficulty in the above approach is that some of the parameters may be observable in the field, but are difficult to predict or assume for a future site. For example, the presence of an adjacent yield is merely a function of random pedestrian and vehicle arrivals. The following restricted model therefore focuses on variables that have the potential for implementation in microsimulation as was discussed in Chapter 3.

Table A-25 also shows the binary logistic regression results for the *restricted models*. Of the variables listed above, HEV and MUP were excluded because of very high p-values. In restricted model 1 all other variables were left in the model, even if the effects are not significant at the given sample size. The final model R^2 value in the seven-variable model is 0.1800 (max. rescaled R^2 is 0.2874).

The odds of yielding are increased by AST, NEAR, FLASH, and TRTMT and decreased by PLT, SPEED_FT, and DECEL. The strongest effect is evident from the pedestrian assertiveness, which increases the odds of yielding 6.57 times. Again, the effect of FLASH is stronger than TRTMT, which is not significant. The effect of NEAR is strong, but also not significant in this model. Vehicle platoons continue to show a significant reduction in yielding. Both continuous variables are significant with comparable effects for a unit increase in SPEED_FT and DECEL.

Restricted Model 2 removes the non-significant parameters in the previous model resulting in a 5-variable model with all effects significant. The likelihood of yielding is increased by AST and FLASH and decreased by PLT, DECEL, and SPEED_FT. Finally, restricted model 3 further reduces the number of variables to a 4-variable model by eliminating SPEED_FT. The two variables DECEL and SPEED are clearly similar, which is supported by correlation coefficients in table A-24. The variable DECEL is kept in the model because it had a higher chi-square value in the previous model and is furthermore more meaningful by accounting for both speed and distance. The model in A-26-e is therefore considered the best model with practically meaningful variables to predict the likelihood of yielding at site MB-CLT.

Model Comparison

Statistical tests for the overall model (likelihood ratio, Wald, and Score tests) are significant at $p<0.0001$ for all models. The model fit of different models is best compared using the AIC and SC criteria, where a lower value generally indicates better overall model fit. The results indicate that all models are fairly comparable in these model fit statistics. In this case, the practical significance for model selection weighs more heavily than minor differences in statistical model fit.

The pseudo R-square and max-rescaled R^2 values for all models are fairly low. While these measures are not as easily interpreted as the R^2 statistics for linear regression model, they do provide a general feel of model fit. In this sense, the low statistics for the yield models are not surprising, because of the complexity of the interaction of the two modes. Additional data collection at high-yield sites may result in a better model fit, but likely never to very high levels.

In the comparison of the two models the effects of assertiveness and the yield trigger are interesting. While the unrestricted model selects TRIG with an odds ratio of 6.04, the restricted model 3 was limited to AST, because of its practical significance. However, AST still resulted in a similar odds ratio of 5.59 and high significance. So why didn't AST show up in the unrestricted model? This is explained by the correlation of these two variables shown in table A-25 (correlation coefficient of 0.56 at $p<0.0001$). Conceptually, the two variables seem to 'explain' similar yield events, but TRIG (corr.=0.38) shows a slightly higher correlation with YIELD then AST (corr.=0.30). In the unrestricted model, TRIG therefore enters the model first with a higher Chi-square value and then leaves little additional yield variability that would be explained by AST.

Figure 19 shows graphical representations produced by varying some effects in the model, while keeping other factors fixed. The unrestricted model shows a decreasing trend of the predicted probability of yielding with increasing deceleration rate. It further suggests that the likelihood of yielding is higher for 'trigger' events and higher for pedestrians who activate the treatment (FLASH=1). As suggested by the coefficients in Table A-25-d, the effect of TRIG is stronger than that of the flasher being activated. The comparative probabilities for a fixed deceleration of 5ft/sec^2 (1.5m/s^2) are shown in the figure. The corresponding equation is given below.

Equation 14: DYM – Mid-Block Yield – Unrestricted Model, MB-CLT

$$\text{logit}[P(Y=1)] = -0.1240 + 0.9669ADY - 0.7543PLT - 1.0156PREV + 0.5902NEAR + 1.7988TRIG + 1.1498PXW - 0.4349DECEL + 1.0264FLASH$$

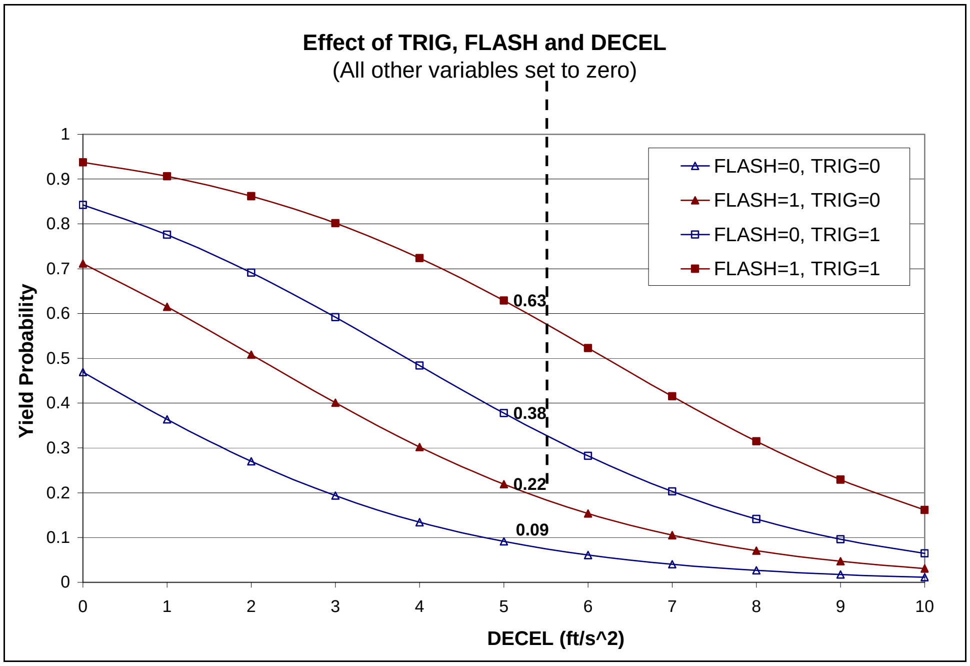


Figure 19: Model Probability Plots – Binary Logit, Unrestricted, MB-CLT

For the restricted model, Figure 20 shows a similar relationship between the yield probability, FLASH and AST as a function of the necessary deceleration rate to yield (PLT is fixed at zero). The likelihood of yielding decreases with an increasing rate of deceleration that would be necessary to stop at the crosswalk. Because events with DECEL > 10 ft/sec^2 were removed from model development, the equation is not defined in that region and the resulting probability of yield is zero. The resulting equation is given below.

Equation 15:DYM – Mid-Block Yield – Restricted Model 3, MB-CLT

logit[P(Y=1)] = -0.3776 + 1.7206*AST + 1.1891*FLASH - 0.9551*PLT - 0.3818 * DECEL

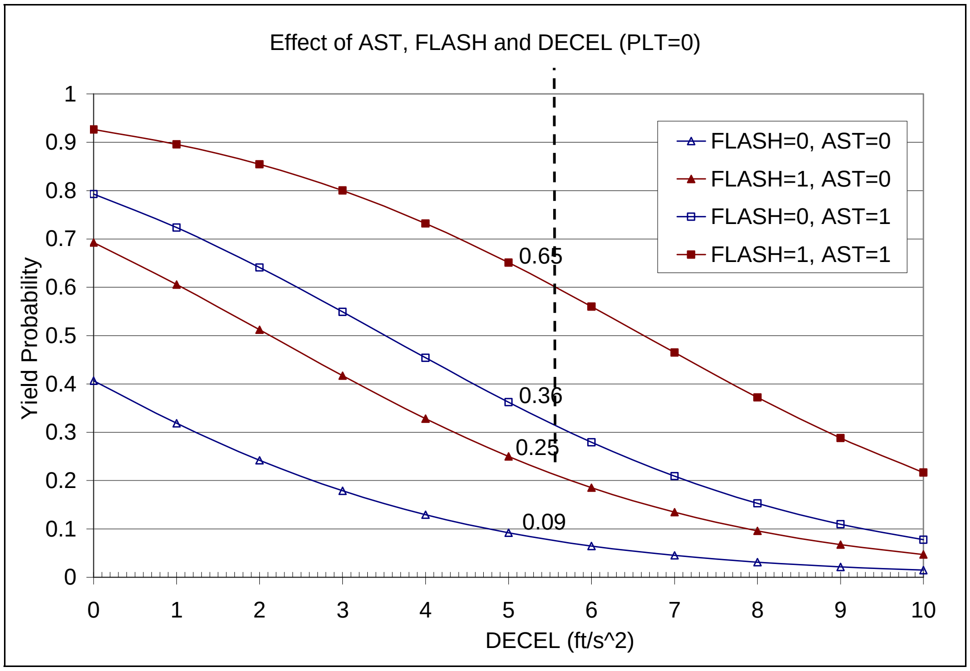


Figure 20: Model Probability Plots – Binary Logit, Restricted Model 3, MB-CLT

Figure 20 shows a base yielding rate of about 40% for non-assertive pedestrians that do not activate the flasher. At a deceleration rate of zero seconds, this is equivalent to a vehicle that is very far away from the crosswalk at the time of pedestrian arrival. If the variables AST and FLASH take the value '1' the odds of yielding increase by a multiplicative factor equal to the odds ratio (5.59 for AST and 3.28 for FLASH).

Looking at a constant deceleration rate of 5 feet/sec^2 the base yield rate at the MB-CLT site is drops to 9%. By activating the flasher, the likelihood of yielding increases to 25%. An assertive pedestrian will encounter a yield from 36% or 65% of vehicles, depending on whether she activates the treatment or not. The effect of PLT is not shown in the figure, but the odds ratio of 0.39 suggests that the likelihood of yielding is reduced by that factor if the vehicle is traveling in a platoon.

In the comparison of the unrestricted model and restricted model 3, the AIC estimates are 430.43 and 443.42, respectively. Similarly, the -2 log likelihood statistics for the two models are 391.86 and 433.42, respectively. The -2 log likelihood statistic approximately follows a Chi-Square distribution and the difference is tested at the difference in degrees of freedom between the two models. Consequently, the difference of 41.56 is statistically significant at 8-4=4 degrees of freedom ($p<0.0001$). By excluding some variables in the restricted model, the analyst thus sacrifices some explanatory power. This is also evident by the max-rescaled R^2 statistics for the unrestricted model (0.3648) and restricted model 2 (0.2671). Both models use variables FLASH, PLT, DECEL and a variable describing pedestrian behavior (either AST or TRIG). The difference in model fit seems to originate primarily from variables ADY, PREV, and PXW.

4.2.4 Cumulative Logit Model

As discussed above, the yield response can also be interpreted as an *ordered categorical* variable. It is assumed that a 'soft yield' is in some sense more than a non-yield and that a 'hard yield' is more than a soft yield. If this assumption holds true, the *cumulative logit model for ordered responses* results in a model with additional information about the response variable and relatively high statistical power.

Table A-26 shows the resulting models for the MB-CLT site. The tables show that the *unrestricted* cumulative logit models contain largely the same variables that were significant in the binary logit approach, giving additional confidence to these earlier results. Yielding behavior is described by variables ADY, FLASH, PLT, PREV, PXW, TRIG and DECEL. By restricting the variables to those with practical significance, restricted model 2 uses variables AST, FLASH, PLT, and DECEL.

Despite the overall model significance, the cumulative models were rejected, because the *proportional odds assumption* was consistently violated. The cumulative logit approach generally assumes that the effect of a variable is constant across all different response categories and thus uses only one parameter for each variable. In other words the relative odds of a variable on the response interval 'non-yield' to 'soft yield' is proportional to the 'soft yield' to 'hard yield' distinction. The significance tests for the proportional odds assumption are highly significant for all models ($p<0.0001$), suggesting that the assumption that the proportional odds model is valid is rejected. Therefore, while the model results (variables, effect size, and sign of effect) are generally reasonable and intuitive the cumulative logit model is probably not a good model for these data.

4.2.5 Multinomial Logit Model

With the cumulative logit model rejected due to a violation of the proportional odds assumption, it is possible to fit a multinomial logit model to the data. This model form still uses all three response categories, but no longer assumes that the responses are ordered. The resulting models for MB-CLT are shown in table A-27.

Using the SAS forward selection algorithm at the 95% confidence level (unrestricted model), the resulting model predicts the likelihood of SY and HY, relative to the NY benchmark from variables ADY, AST, FLASH, PLT, PREV, TRIG, DECEL and TTC. The restricted model 2 again uses AST, FLASH, PLT, and DECEL.

Because the multinomial does not assume proportional odds, it uses two intercepts (one for SY and one for HY) and further estimates individual parameters for SY and HY for each variable (labeled as -2 and -3 in the tables), making the interpretation of this model more cumbersome. It results in two equations, one for each level of the yield response relative to the NY baseline.

The parameter estimates in this multinomial logit form give further insight in why the proportional odds assumption was rejected for the cumulative logit model. For example, the two slope parameters for the AST variable in restricted model 2 are 2.501 and 1.365 for the Y_ORDERED levels 2 and 3, respectively. The variable thus has a much larger effect on the odds of a soft yield then a hard yield. The cumulative logit model would have assumed the same effect for both levels. The parameter estimates for levels 2 and 3 are also different for the remaining variables in restricted model 2.

4.2.6 Nested Logit Model

The more complex model forms presented above indicated that there is merit in distinguishing between soft and hard yields in the models. An alternative approach to interpreting the data is to utilize a nested logit model that first predicts the likelihood of a yield occurring (same as binary logit above) and then predicts the yield type, given that the event was a yield.

In the model development of the second level of the nested logit models, the variable COM was considered as a valid factor. It was determined earlier that the variable was biased in distinguishing yield and non-yield evens, but this concern does not apply in distinguishing between yield types.

Table A-28 shows this second component of nested logit models for the MB-CLT site. The unrestricted model predicts the likelihood of a HY, given Y from variables AST, COM, TRTMT, and SPEED_FT. The coefficients for the AST, COM, and TRTMT parameters are negative, indicating that a 'true' value for these variables decreases the likelihood of a 'hard yield'. Similarly, the likelihood of a HY is increased with faster approach vehicle speeds. The odds ratios indicate that the strongest effect is evident for TRMT, which decreases the log likelihood of a HY by a factor of 0.105, followed by COM and AST.

The initial restricted model has a variety of parameters that are not significant. The modified restricted model 2 was further limited to variables AST, TRTMT, and SPEED_FT. The effects are consistent with the unrestricted model discussed above, with AST and TRTMT decreasing the likelihood of a 'hard yield' and SPEED_FT increasing it. Alternatively, restricted model 3 uses DECEL instead of SPEED for two reasons. First, the variable use is consistent with the first level of the nested logit, and second, the DECEL variable combines vehicle speed and distance making it more useful in its application to microsimulation. Figure 21 and Equation 16 show the resulting predictive model for the second stage nest.

Equation 16: DYM – Mid-Block Yield – Nested Logit, Restricted Model 3, MB-CLT

$$\text{logit}[P(HY=1)] = 1.5249 - 1.4754AST - 1.5803TRTMT + 0.2873DECEL$$

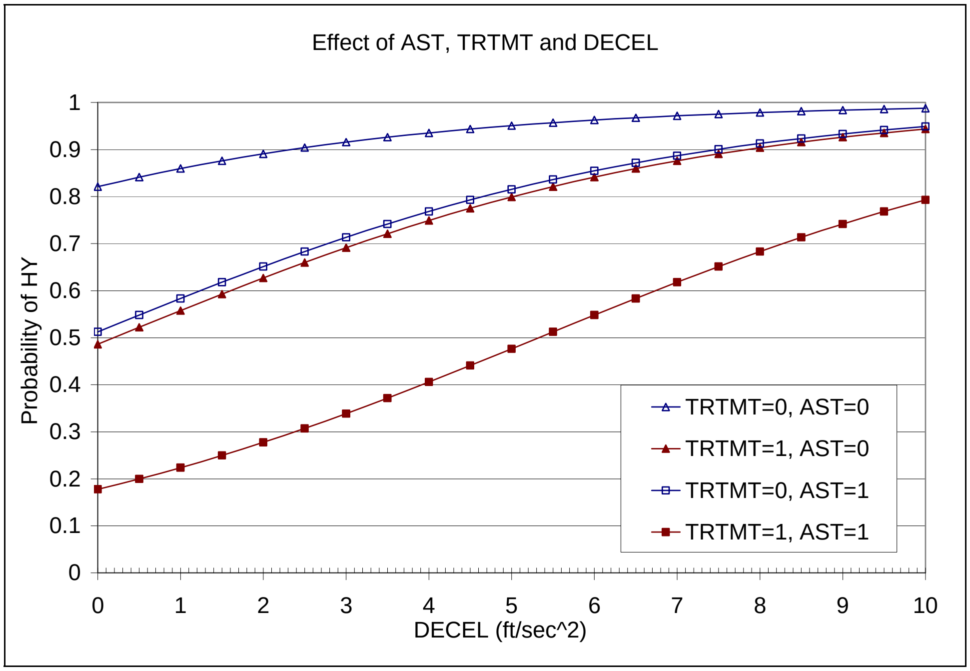


Figure 21: Model Probability Plots – Nested Logit, Restricted Model 3, MB-CLT

The figure suggests that the likelihood of a hard yield increases with required deceleration rate. This is intuitive because at higher rates the driver has less of a choice to simply slow down to a roll. The likelihood of a HY is furthermore greater for a non-assertive pedestrian, which suggest that drivers react to assertiveness by slowing down earlier. A HY is also more likely in the 'before' case, suggesting that with installation of the in-pavement flashing beacon drivers are more likely to yield in a rolling fashion.

The AIC statistics for the unrestricted model and restricted model 3 are 113.84 and 122.67, respectively. The difference in -2 log likelihood for the unrestricted model (103.84) and restricted model 3 (114.67) is statistically significant at 4-3=1 degree of freedom (p=0.0001). The adjusted R^2 statistics of the two models are 0.3435 and 0.2299, respectively. By limiting the model to restricted variables the analyst gives up some statistical fit.

4.2.7 MB-CLT Site Summary

The analysis of the MB-CLT site demonstrated the benefits of the event-based analysis approach and logistic regression to analyze driver yielding behavior. A simplistic before and after evaluation of the in-pavement flashing beacon treatment would have concluded that the treatment results in a 39% increase in the yield rate from 15.0% to 20.9%. The generally low yielding behavior would then be attributed to 67% vehicle platooning and relatively fast approach speeds at a two lane facility with unusually wide lanes.

A closer look at the dynamic characteristics of yielding behavior revealed that not a single yield was observed if the deceleration rate necessary to come to a stop at the crosswalk exceeded 10 ft/sec^2 measured from the time a pedestrian arrived at the crosswalk. The author reasoned that these drivers were subject to vehicle dynamics constraints, similar to drivers passing through a signalized intersection during the 'amber' intersection. In the predictive models for driver yielding these events were excluded.

When investigating the probability of yielding behavior for non-VDC drivers, the most promising model form is a two-level nested binary logit model. The first level predicts an increased probability of yielding for assertive pedestrians and for those that activate the 'flasher' treatment. The yield probability is decreased if the vehicle is traveling in a platoon and further reduces with an increase in the necessary deceleration rate. In the second level of the model, another binary logit model predicts an increasing likelihood of a ‘hard yield’ with increasing DECEL rate. The likelihood of HY is decreased for assertive pedestrians and is less after treatment installation.

The overall probability of a HY can be calculated by multiplying the two probability functions. The likelihood of SY correspondingly is the likelihood of a yield multiplied by one minus the probability of a hard yield. Because the two levels of the model contain different variables, it is difficult to visualize the combined models. In an effort to do so, Figure 22 shows the probability of HY and SY for variables AST, FLASH and DECEL in the ‘post treatment’ case (the variable TRTMT is fixed at 1 in the second-level nest).

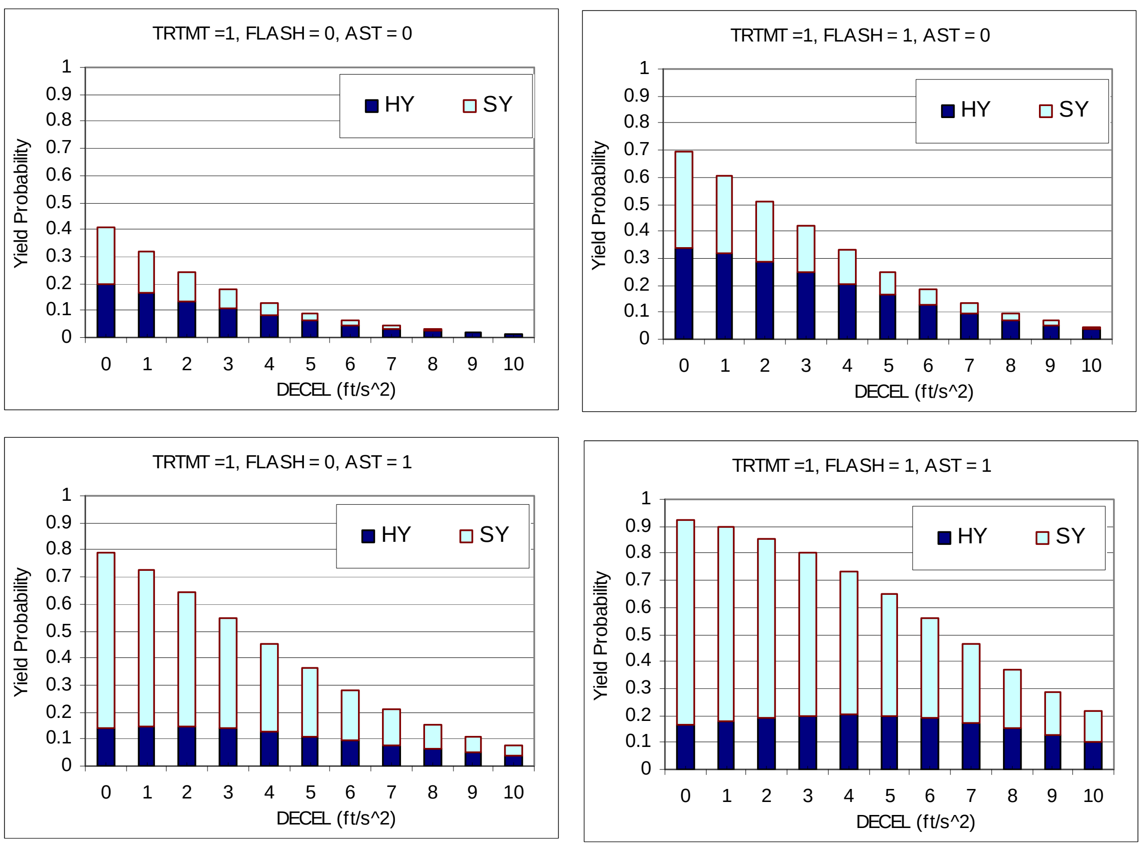


Figure 22: Combined Yield Probability for MB-CLT <u>after</u> Treatment Installation

The relationship between pedestrian assertiveness, treatment activation, and necessary deceleration rate in figure 22 is an intuitive way to visualize the predictions from the yielding algorithms developed in this research. While the models do not explain all variability in yielding behavior, they follow initial hypotheses and can be implemented in a simulation environment. They therefore allow a more accurate representation of the yielding process in microsimulation than the state of the practice, accounting for variations in pedestrian behavior, the effect of vehicle dynamics, and the impact of a pedestrian crossing treatment.

4.3 Event-Based Analysis for MB-RAL

4.3.1 Descriptive Statistics

The results in Table 3 are for a total sample size of 470 data points with 265 'before' and 205 in the 'after' condition. Overall, 158 yields and 312 non-yields were observed, suggesting a yielding rate of 33.6%. The yielding percentage increased significantly after installation of the treatment from 26.8% to 42.4%, corresponding to a 58% increase in yielding (p=0.0004).

Table 3: Descriptive Statistics, MB-RAL

Variable	ALL DATA Mean	ALL DATA StdDev	BEFORE Mean	BEFORE StdDev	AFTER Mean	AFTER StdDev	YIELDS Mean	YIELDS StdDev	NON-YIELDS Mean	NON-YIELDS StdDev
Sample Size	470	.	265	.	205	.	158	.	312	.
Response Variables										
YIELD	0.336	0.473	0.268	0.444	0.424	0.495	1.000	0.000	0.000	0.000
Y_ORDERED	1.513	0.777	1.411	0.729	1.644	0.820	2.525	0.501	1.000	0.000
Y_TYPE*	0.525	0.501	0.535	0.502	0.517	0.503	0.525	0.501	.	.
Binary Factors										
ADY	0.066	0.248	0.060	0.239	0.073	0.261	0.120	0.326	0.038	0.193
AST	0.091	0.289	0.072	0.258	0.117	0.322	0.209	0.408	0.032	0.176
COM	0.091	0.289	0.072	0.258	0.117	0.322	0.272	0.446	0.000	0.000
DECEL_TAU	0.085	0.279	0.109	0.313	0.054	0.226	0.013	0.112	0.122	0.328
FOLL	0.245	0.430	0.223	0.417	0.273	0.447	0.253	0.436	0.240	0.428
HEV	0.021	0.144	0.026	0.161	0.015	0.120	0.019	0.137	0.022	0.148
MUP	0.351	0.478	0.347	0.477	0.356	0.480	0.443	0.498	0.304	0.461
NEAR	0.626	0.485	0.619	0.487	0.634	0.483	0.665	0.474	0.606	0.489
PLT	0.383	0.487	0.366	0.483	0.405	0.492	0.342	0.476	0.404	0.491
PREV	0.294	0.456	0.343	0.476	0.229	0.421	0.247	0.433	0.317	0.466
PXW	0.213	0.410	0.189	0.392	0.244	0.430	0.348	0.478	0.144	0.352
QUE	0.051	0.220	0.042	0.200	0.063	0.244	0.076	0.266	0.038	0.193
TRIG	0.051	0.220	0.042	0.200	0.063	0.244	0.139	0.347	0.006	0.080
TRTMT	0.436	0.496	0.000	0.000	1.000	0.000	0.551	0.499	0.378	0.486
TTC_TAU	0.221	0.416	0.226	0.419	0.215	0.412	0.101	0.303	0.282	0.451
Continous Factors										
DECEL	4.601	4.145	4.890	4.554	4.227	3.523	3.138	1.929	5.341	4.732
DIST1	202.624	134.729	216.215	148.238	185.055	112.888	224.699	126.678	191.445	137.476
LDECEL	1.267	0.699	1.311	0.731	1.210	0.654	0.987	0.577	1.407	0.714
LDIST1	5.085	0.723	5.135	0.752	5.019	0.681	5.231	0.679	5.011	0.735
SPEED_FT	35.147	8.998	36.584	8.586	33.289	9.197	33.418	10.011	36.023	8.320
TTC	5.783	3.577	5.963	3.951	5.553	3.020	6.727	3.412	5.308	3.569

* The Sample Size for Y_TYPE is only 158 observations, because it only considers HY and SY events

The facility statistics show a mean speed of 36.6 ft/s (24.9mph) in the before condition and 33.3 ft/s (22.70mph) in the after period ($p<0.0001$). Note that these values are for all vehicles, so that the free-flow speed may be significantly higher. The overall observed standard deviation of speeds was 9.0 ft/s and the maximum observed speed at the site was 66.6 ft/s (45.4 mph).

Most other variables are consistent in the before and after data sets, with any variability explained by random variation ($p>0.1$). The variable PREV had a significantly lower mean in the 'after' data set, which needs to be considered in the model development.

Several variables exhibit significant differences when comparing the 'yield' and 'non-yield' data sets. Yielding events appear to be associated with ADY, AST, COM, DECEL_TAU, PXW, TRIG, TRTMT, TTC_TAU and all continuous variables. Surprisingly, the effect of platoons (PLT) is not significant at this site ($p=0.187$). With an overall percentage of 38.3%, platoons are less common here than at the MB-CLT site. More importantly, the lower speed of vehicles (and thus platoons) may decrease a driver's perceived risk of a rear-end collision when yielding. Consistent with the other site, driver yielding behavior seems to be associated mostly with vehicle dynamics and the behavior of the pedestrian.

4.3.2 Variable Interactions

The correlation matrix in Table A-29 supports the association of the above-mentioned explanatory variables with the YIELD response. Several correlation coefficients are significant, but small, supporting the notion that the yielding process is a complex combination of factors, rather than the result of any single variable. The strongest correlation is evident with COM, but experience from the MB-CLT site suggests a potential bias in the collection of this variable. This notion is supported by the 2x2 contingency table of COM by Yield, which again shows that no YIELD=0 events were observed with evidence for non-verbal communication.

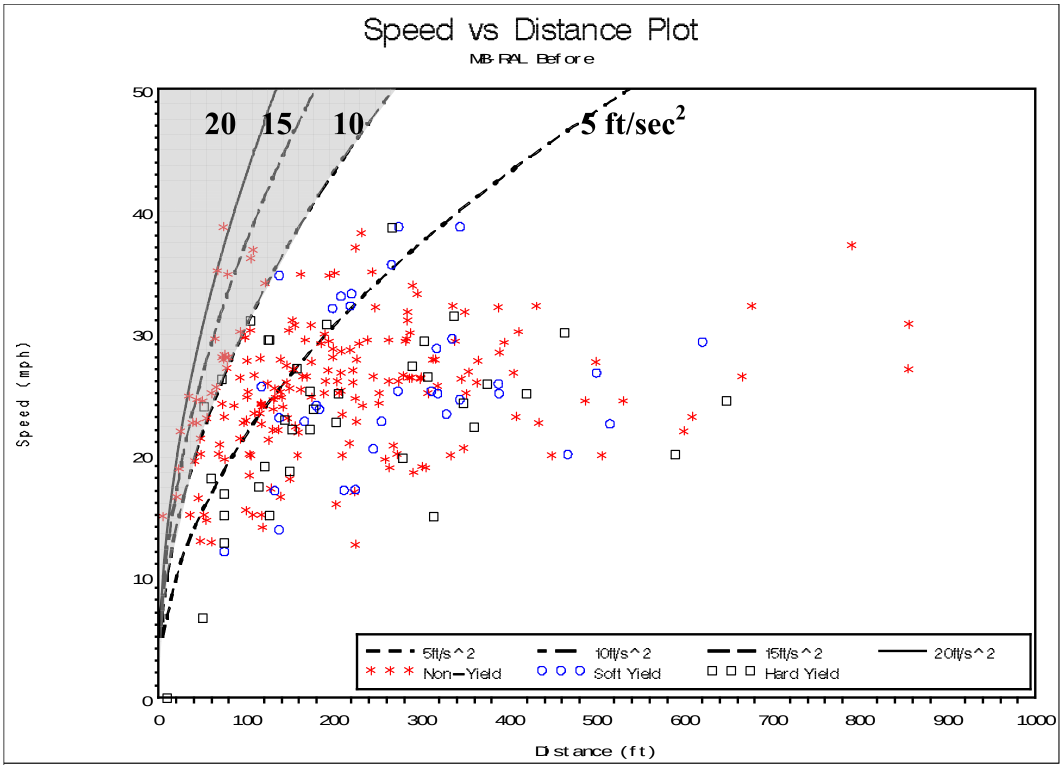
The correlation coefficients among explanatory variables show a strong interaction between AST and TRIG, urging caution in the use of these variables in model development. Expectedly strong correlations exist between PLT and FOLL, and between the two threshold parameters DECEL_TAU and TTC_TAU. Interactions between other binary variables are negligible.

A surprising find is that of 24 TRIG=1 observations only two were associated with a non-yield. So, while the variable was distributed across event types for the MB-CLT site (of 48 TRIG=1 events, 16 were associated with non-yields), the pedestrian 'trigger' behavior more consistently resulted in yields at the MB-RAL site. This may be explained by the site characteristics of MB-RAL. With lower speed limit, narrower lanes and a more campus-like appeal, drivers may be more reactive to the pedestrian behavior and less likely to swerve around a pedestrian who has stepped into the roadway. This behavior was observed quite frequently at MB-CLT.

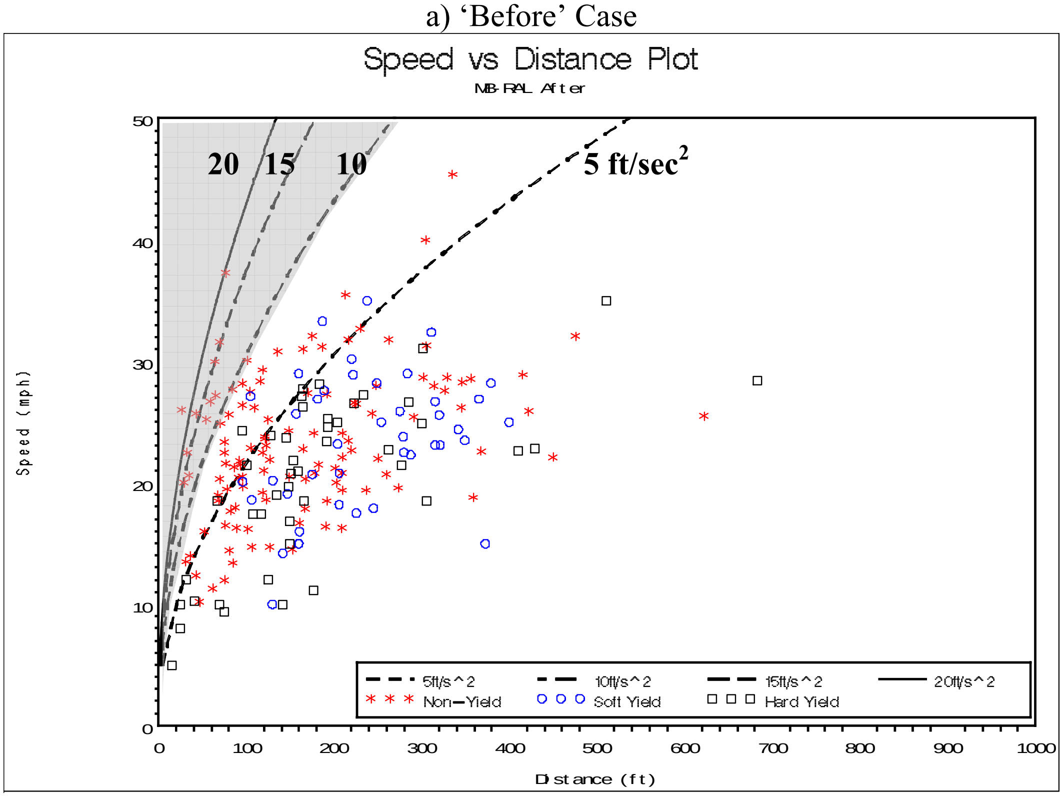
While the distribution of the TRIG variable is consistent with driver behavior observed in the videos, it is still problematic in the model development process. In general it is good practice to have at least 5 observations in each cell of the 2x2 matrix, but it is more important that the predicted frequency is greater than 5 (Agresti 2007). The marginal row and column totals are also sufficiently large and the variable will therefore be considered in the model development process.

4.3.3 Vehicle Dynamics Constraints

Figure 23 shows the speed-distance relationships for the MB-RAL site for the before and after cases with the same superimposed deceleration curves.



a) 'Before' Case



b) 'After' Case

Figure 23: Speed-Distance Relationship including Deceleration Thresholds, MB-RAL

Similar to the trends observed at the other site, the VDC threshold of 10 ft/sec^2 appears to give an upper boundary of the deceleration rate that is 'acceptable' to drivers in the approach of the crosswalk. During the 'before' observation, there were in fact two events in which yielding drivers applied deceleration rates in excess of 10ft/sec^2. These events were from individual vehicles (non-platoon), which were 52 and 72 feet from the crosswalk at the time of the pedestrian arrival, traveling at 35.0 and 38.4 ft/s, respectively. The first event was 'triggered' by the pedestrian. The corresponding TTC times are calculated at 1.5 and 1.9 seconds, suggesting that these situations could be categorized as 'risky' events. To be consistent with the analysis of the MB-CLT site, these two yield events will be excluded from the modeling analysis, along with all 'non-yield' events that fall above the VDC threshold.

4.4 Yield Model Development for MB-RAL

4.4.1 Variable Selection

After removing the VDC observations, the remaining MB-RAL data set contained 430 observations. Consistent with the other site, the variable COM is removed from the further analysis, because 2x2 contingency tables with the YIELD response showed that all COM=1 events were associated with YIELD =1. Similarly, interaction tables for HEV by YIELD showed cells with less than 5 observations and Fisher's Exact test showed no significant effect of these variables on the YIELD response. The MB-RAL site did exhibit significant queuing resulting in 24 QUE=1 observations. The variable will therefore be considered in the model development.

The remaining explanatory variables to be considered in the regression model are ADY, AST, FOLL, NEAR, PLT, PREV, PXW, QUE, TRIG, TRTMT, DECEL, DIST1, SPEED_FT, and TTC. Due to the nature of the treatment at this site, the variable FLASH is not applicable.

4.4.2 Multilinear Regression Analysis

The multilinear regression analysis allows the analyst to explore the regression fit of the data with a simpler model form. Table A-30 shows the models for the MB-RAL data set with significant parameters ADY, AST, NEAR, PXW, QUE, TRIG, TRTMT, and DECEL in the ‘full model’. The largest effects are observed for ADY, AST, QUE, and TRIG. Parameter signs are largely as hypothesized. Parameters for FOLL, SPEED and DIST1 violate the initial hypotheses but are generally small and non-significant. The overall model fit is significant ($p<.0001$) and has a relatively poor overall R^2 value of 0.2518.

Narrowing the field of variables in the ‘restricted model’ predicts an expected increase in the likelihood of yielding with AST, NEAR, and TRTMT, and a decrease with PLT, DECEL, and SPEED. The limitations of the multilinear approach are evident when looking at a graphical representation of this model (Figure 24). For example, the graph predicts yield probabilities greater than 1.0 for an assertive pedestrian after treatment installation (AST=1, TRMT=1).

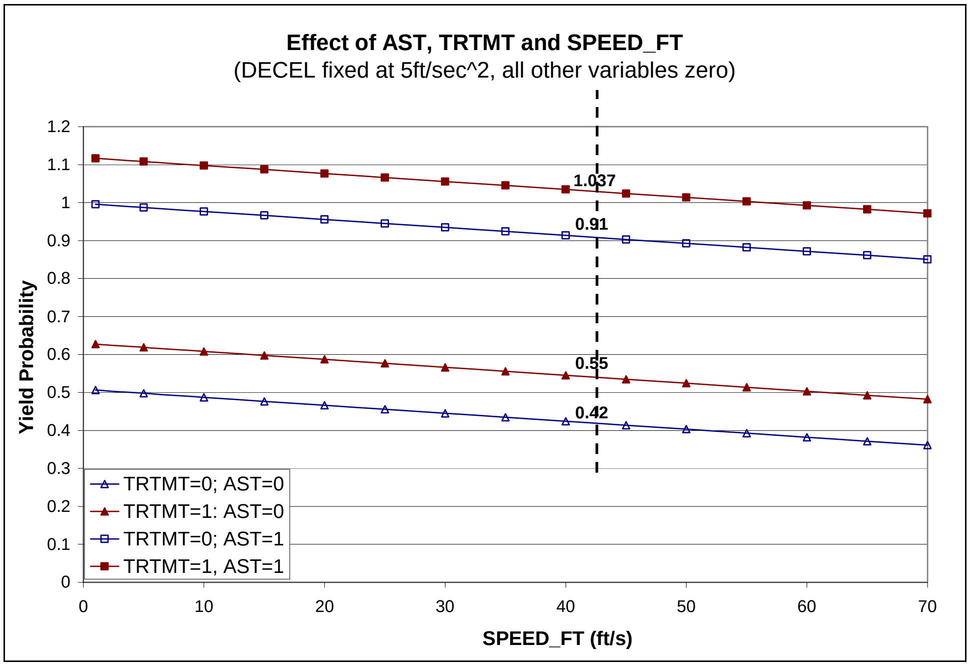


Figure 24: Model Probability Plots – Multi-Linear Regression, Restricted Model, MB-RAL

In the following, various forms of logistic regression will be applied to the data sets. Starting with different binary logit models for a 1/0 yield response (YIELD) the analysis will then consider more complicated model forms for the ordered response Y_ORDERED and on the distinction of 'hard' and 'soft' yields with Y_TYPE.

4.4.3 Binary Logit Models – MB-RAL

Full Model

The Full model for MB-RAL in Table A-31 shows significant logistic regression parameters for ADY, AST, NEAR, PXW, QUE, TRIG, TRTMT and DECEL at the 90% confidence level.

Unrestricted Model

Applying the forward selection algorithm with a p=0.05 threshold, SAS produces an eight-variable unrestricted model for MB-RAL. The model includes parameters ADY, AST, NEAR, PREV, PXW, TRIG, TRTMT, and DECEL, which are largely the same as the significant parameters in the full model. The variable QUE did not make it into the model, but PREV met the probability threshold.

The largest odds ratios are present for AST and TRIG, which increase the log odds of a yield occurring by factors 6.1 and 5.3, respectively. Effects of ADY, NEAR, and PXW are also high with odds ratios greater than 2. The treatment effect still increases the yield probability 1.7 times. There is further evidence that the necessary deceleration rate (DECEL) has a strong effect. Despite the fact the VDC was applied, an increase of 1 ft/sec^2 in necessary deceleration rate still decreases the log odds of yielding 0.69 times.

Restricted Model

Just as for the other data set, the restricted model is limited to variables that can be implemented in microsimulation. The resulting six-variable restricted model 1 has a comparable model fit to previous models. With the exception of the speed effect, all parameters in the model are significant. With an odds ratio close to 1.0, the effect of speed is very minor, resulting in a model that is most sensitive to the binary states surrounding the interaction at the crosswalk and the deceleration rate.

When eliminating the speed effect, restricted model 2 predicts an increasing likelihood of yielding from AST, NEAR and TRTMT. PLT and DECEL decrease the likelihood of yielding. The strongest effect is evident from pedestrian assertiveness, which in the absence of the TRIG variable now has an odds ratio of 12.02. Keeping everything else constant, the assertiveness of a pedestrian therefore has a major impact on yielding behavior at this site.

Model Comparison

The tests statistics for the overall model fit are significant for both the unrestricted and restricted models at $p<0.0001$. The pseudo R-Square values of the models are comparable to the model fit resulting from the MB-CLT crosswalk data. Neither model comes close to fully describing the yielding process, but both provide valuable and significant insight into parameters related to driver yielding behavior.

Figure 25 graphs the unrestricted model as a function of DECEL, TRTMT and AST and keeping all other variables fixed based on equation 17. The figure shows that with an increase in necessary deceleration rate, the yield probability of driver decreases sharply. At a constant deceleration rate of 5 ft/sec^2 the base yielding rate is 0.10, which increases to 0.16 after the treatment has been installed. An assertive pedestrian faces yielding probabilities of 0.40 and 0.54 before and after treatment installation, respectively. The relationship emphasizes that the collected data suggest a strong influence of the pedestrian behavior on yielding behavior.

Equation 17: DYM – Mid-Block Yield – Binary Logit, Unrestricted Model, MB-RAL

$$\text{logit}[P(Y=1) = -0.3229 + .1.0963ADY + 1.8089AST + 0.7021NEAR - 0.5755PREV + 0.9257PXW + 1.6642TRIG + 0.5399TRTMT - 0.3758DECEL$$

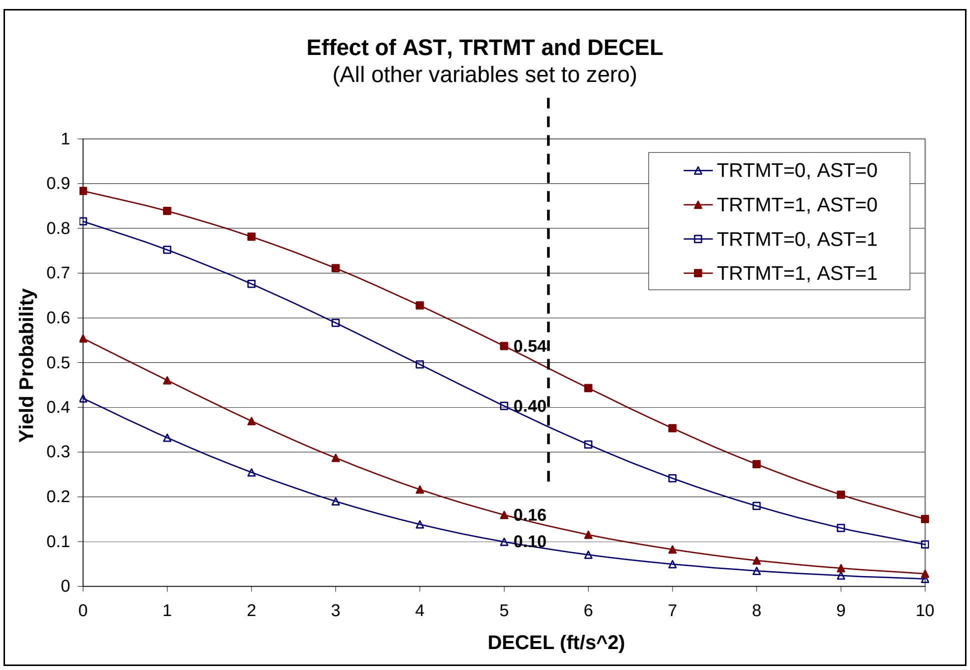


Figure 25: Model Probability Plots – Binary Logit, Unrestricted Model, MB-RAL

The graph for the restricted model in Figure 26 and corresponding equation 18 shows a similar trend to the unrestricted model. Again, the impact of the crossing treatment and pedestrian assertiveness play a major role in yielding.

Equation 18: DYM – Mid-Block Yield – Binary Logit, Restricted Model 2, MB-RAL

logit[P(Y=1) = -0.1240 + 2.4865 AST + 0.6165 NEAR - 0.4907 PLT + 0.6477 TRTMT - 0.3441 DECEL

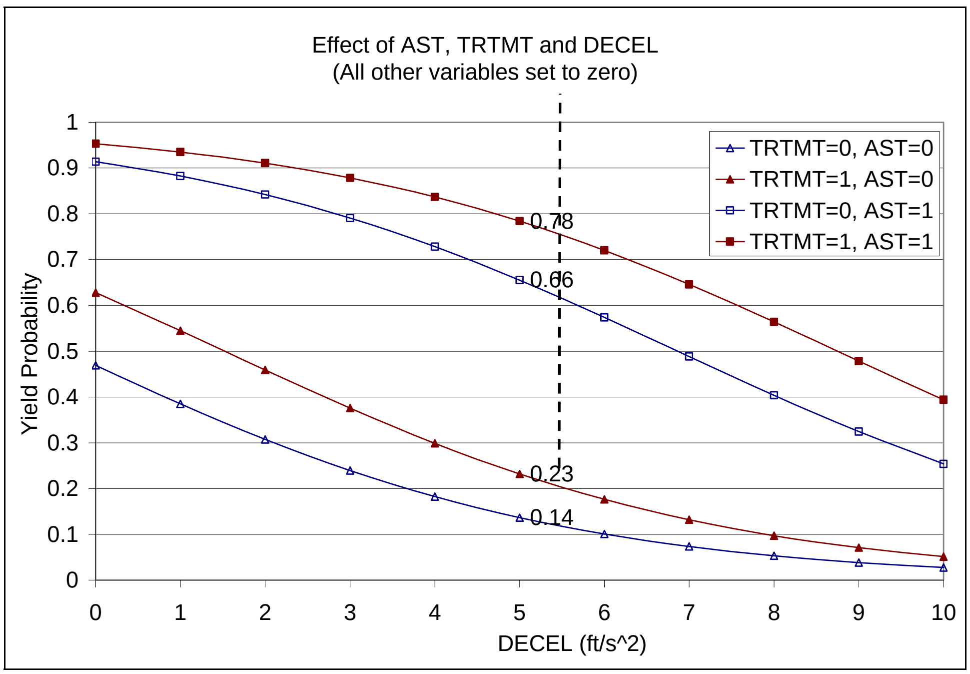


Figure 26: Model Probability Plots – Binary Logit, Restricted Model 2, MB-RAL

At a necessary deceleration rate of 5 ft/sec^2 a driver yields with a likelihood of 0.14 in the base case. This increases to 0.23 with treatment installation. The likelihood of a driver yielding to an assertive pedestrian in the same condition is 66% without the treatment and 78% with the presence of the in-roadway pedestrian sign. The effects of NEAR and PLT are not shown, but their effects in yielding can be interpreted from the odds ratios. If the pedestrian is at the near-side of the vehicle, the log odds of yielding are increased by a factor of 1.85. If the vehicle is traveling in a platoon, the odds of yielding are decreased by a factor 0.61. Conceptually, the condition NEAR=1 raises all curves in Figure 26 while PLT=1 lowers them.

The AIC statistics for unrestricted and restricted model 2 are 465.02 and 491.62, respectively. The difference in -2 log likelihood between unrestricted (447.02) and restricted model 2 (479.62) is statistically significant at 8-5=3 degrees of freedom ($p<0.0001$) in a chi-square test comparison. Similarly, the max-rescaled R^2 statistic for the unrestricted model (0.3204) is larger than for restricted model 2 (0.2442). The additional descriptive power of the unrestricted model seems to be attributable to variables ADY and PXW. Both models use variables AST, NEAR, TRTMT, DECEL, variables describing vehicle headways (PREV or PLT) and those describing pedestrian behavior (AST or TRIG).

4.4.4 Cumulative Logit Model

The cumulative logit model for ordered responses uses the categorical response variable Y_ORDERED with three levels: NY, SY, and HY. All cumulative models for the MB-RAL violate the proportional odds assumption, consistent with the findings at MB-CLT. This indicates that the parameter effects are not the same for the difference between levels SY and HY as they are for levels NY and SY.

Estimating the models despite this violation, the resulting models are shown in Table A-32. The unrestricted model predicts effects in the direction of HY through AST, NEAR, PXW, and TRTMT. An increase in DECEL affects the log odds in the direction of NY, thus decreasing the odds of yielding. Restricted Model 2 shows similar variable effects. AST, NEAR, and TRTMT shift the odds towards HY, while PLT and DECEL work in the opposite direction.

Because all models violate the proportional odds assumption, the cumulative logit model is not adequate for the MB-RAL yield data set and was not explored further.

4.4.5 Multinomial Logit Model

The results for the multinomial logit models for MB-RAL are shown in table A-33. Using the SAS forward selection algorithm at the 95% confidence level the unrestricted models for the MB-RAL predicts the SY and HY outcomes from variables ADY, AST, NEAR, PREV, PXW, TRIG, DECEL and SPEED_FT at a max-rescaled R-square of 0.3702. The restricted model 2 uses AST, NEAR, PLT, TRTMT, and DECEL and has a max-rescaled R-square of 0.2301. The better statistical fit of the unrestricted model is also evident in the AIC with a value of 653.088 compared to 703.391 for the restricted model. The difference is significant at $p<0.0001$.

For restricted model 2, the parameter estimates for response levels 2 and 3 again show differences. For example AST-2 and AST-3 have parameters 3.1928 and 1.3702, respectively, indicating that the assertiveness has a stronger effect on the likelihood of a soft yield than a hard yield. For this model, the two levels of TRTMT and DECEL are relatively close with the treatment increasing the likelihood of both yield types and an increase in DECEL generally decreasing the odds of yielding. Relating these findings back to the cumulative logit model, it is likely that the prime reason that the proportional odds assumption was rejected is due to the assertiveness variable.

4.4.6 Nested Logit

Given the promising results of the multinomial logit model in separating variable effects on the SY and HY responses, the nested logit approach offers an alternative way to do so while keeping the overall model form simple. Using the binary logit model described above as the first level nest, the second level predicts the likelihood of a 'hard yield' given that the first level resulted in a yield.

The second level of the unrestricted nested logit model for MB-RAL (Table A-34). uses variables ADY, AST, COM, QUE, and TRIG. Interestingly, the treatment effect is not significant for this site. The log likelihood of a hard yield is decreased by ADY, AST, COM, and TRIG and increased by QUE. The odds ratios suggest the strongest effects from QUE, followed by TRIG, AST, ADY and COM.

Restricting the model to selected parameters and eliminating those with poor significance results in a three-variable model (restricted model 2) with effects AST, DECEL and SPEED_FT. Given the correlation between the two continuous variables, it is preferable to eliminate one of them from the model. Restricted model 3 using AST and SPEED_FT has a slightly better model fit than restricted model 4 (with AST and DECEL) and the parameter estimate for DECEL is not significant at the given sample size in the latter model. However, restricted model 4 is considered to have greater practical significance, accounting for both vehicle speed and distance through the DECEL variable. It is therefore selected as the preferred model for the second-stage nest for MB-RAL and is also consistent with earlier model forms. It predicts a decreased likelihood of HY with pedestrian assertiveness and an increased odds of HY with greater DECEL rate as shown in equation 19 and Figure 27.

Equation 19: DYM – Mid-Block Yield, Nested Logit, Restricted Model 4, MB-RAL

$$\text{logit}[P(HY=1) = 0.0965 - 1.8219\ AST + 0.1109\ DECEL$$

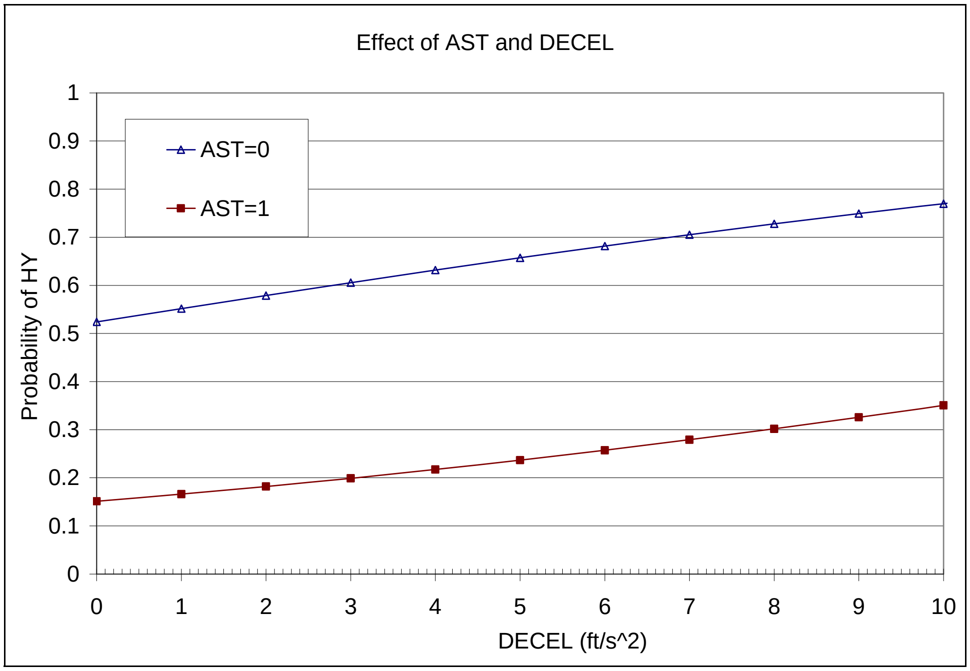


Figure 27: Model Probability Plots – Nested Logit Level 2, Restricted Model 4, MB-RAL

The figure illustrates that the likelihood of a HY decreases with increasing speed of the vehicle. Furthermore, an assertive pedestrian in all cases is less likely to encounter a hard yield. Restricted model 4 again has a higher AIC statistic (204.325) than the unrestricted model (176.978), thus sacrificing some model fit for the sake of applicability to microsimulation.

4.4.7 MB-RAL Site Summary

A simplistic analysis of driver yielding behavior at the MB-RAL site indicated that the in-road pedestrian warning sign resulted in an increase in the yield rate from 26.8% to 42.4%, a significant increase of 58%. On an aggregated level, drivers at this site exhibit a greater willingness to yield and a very effective low-cost treatment.

Taking into consideration the position of the vehicles in the time-space domain at the time of pedestrian arrival again suggests that drivers constrained by VDC will not yield.

Excluding these events with DECEL greater than $10ft/sec^2$ allows the event-based logistic analysis to be applied only to drivers who in fact have a choice to yield.

The two-level nested binary-logit model is preferred to describe the probability of driver yielding. The first level predicts an increase in the log odds of yielding for assertive pedestrians, for pedestrians waiting at the near-side of the crossing relative to the vehicle, and shows a positive impact of the treatment. The odds of yielding are reduced for drivers traveling in a platoon and are diminished for an increase in the necessary deceleration rate. Given that the first level predicts a yield, the likelihood of a HY increases with increasing necessary deceleration rate and is generally lower for assertive pedestrians.

The two models can be combined into an overall model that predicts the likelihood of HY by multiplying the probability predictions from the individual models. The probability of SY correspondingly is the likelihood of yield multiplied by [1-P(HY)]. Naturally, the sum of the two probabilities equals the overall yield probability shown in Figure 26. Frequency plots for the resulting model for the four combinations of AST and TRTMT variables are given in Figure 28 as a function of the necessary deceleration rate.

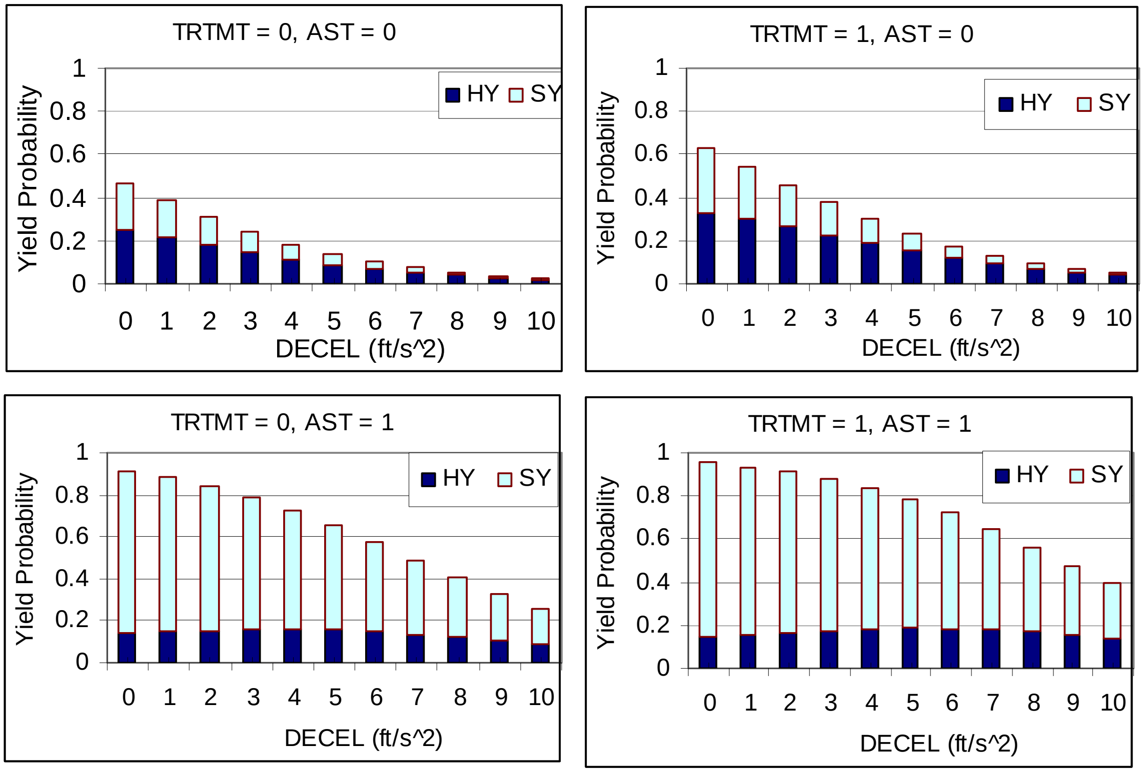


Figure 28: Combined Yield Probability for MB-RAL Site

An interesting trend in figure 28 is that the probability of hard yields for assertive pedestrians seems to be constant and thus independent of the deceleration rate. For non-assertive pedestrians, the likelihood of a hard yield drops proportional to the overall yield rate with greater deceleration rate.

4.5 Chapter Summary

The findings presented in this document shed light on the complex interaction of pedestrians and vehicles at unsignalized crosswalks. The data showed clear evidence that it is important to account for vehicle dynamics constraints on the evaluation of crosswalks. The yield threshold in this study was set at a deceleration rate of 10ft/sec^2, which coincides with signal timing practice for the amber phase at signalized intersections. Variables describing these vehicle dynamics are a function of the vehicle speed and distance from the crosswalk and proved important even below the 10ft/sec^2 threshold.

Vehicle yields also showed a strong correlation with the behavior of the pedestrian. An assertive pedestrian or one who tries to trigger a yield would oftentimes elicit a response from the driver. The data further suggest that this assertiveness may be related to prior events, such as the presence of a previous pedestrian in the crosswalk. This relationship, as well as the effect of pedestrian waiting time (number of rejected gaps) will be explored in future research.

Additionally, the data gave evidence to a strong effect of vehicle platoons in reducing the likelihood of yielding. In fact, the frequent occurrence of platoons may explain the low overall yielding rate at the MB-CTL site, and to a lesser extent at the MB-RAL site.

The analysis of the treatments showed a significant effect on yielding at both sites. The analysis of the in-pavement flashing beacon at MB-CLT showed a significant effect on yielding, especially when the treatment is activated. Higher actuation rates, or the use of 'passive' pedestrian detection technology, therefore have potential for further increasing the effect of the treatment on yielding.

In the comparison of the unrestricted and restricted modeling approaches it is important to highlight that the unrestricted models for both sites found variables ADY and PXW to be significant descriptors of yielding. These variables were not included in the restricted models because they were not necessarily measured at the time of pedestrian arrival at the crosswalk. For an interaction event, the variables for an adjacent yield and the presence of a pedestrian in the crosswalk were coded as "true" if observed at any point in time during the interaction. Because of this data collection bias, they were excluded from the restricted analysis. Through more detailed data collection, relating the time of an adjacent yield to the yield response, the inclusion of these variables in a restricted yield model may be possible.

The research demonstrated that the data collection approach and analysis methodology can be combined with logistic regression techniques to develop predictive models for driver yielding behavior. The implications of such predictive models for driver yielding behavior is especially important in combination with modern microsimulation tools, which may eventually be used to predict performance of a future site. This will be explored further in Chapter 7.

5 PEDESTRIAN CROSSING MODELS AT MID-BLOCK

This chapter discusses the development and analysis of statistical models describing pedestrian gap acceptance behavior at the two unsignalized mid-block crosswalks. The chapter initially reviews methods that are commonly used for analyzing gap acceptance behavior for vehicles as presented in Chapter 2. These methods are then applied to the collected pedestrian data to provide a benchmark for the logistic regression analysis. The author examines descriptive statistics and correlations of individual parameters to explore trends and variability in the data. Ultimately, using the results of this analysis, logistic regression techniques are applied to develop predictive models for pedestrian crossings from the behavioral data sets.

5.1 Characterizing Pedestrian Gap Acceptance

The gap acceptance concept is commonly applied in the analysis of driver behavior at yield- or stop-controlled intersections. For example, a driver waiting to enter a modern roundabout screens the circulating traffic for a large-enough gap between successive vehicles. Similarly, a driver waiting at the minor approach of a two-way stop controlled intersection looks for gaps in traffic on the major road. At an unsignalized pedestrian mid-block crossing, pedestrians have to make a similar decision before crossing the road: Is the gap in the traffic stream large enough to allow for a safe crossing?

The pedestrian's decision is similar to that of drivers in that she has to judge the arrival time of the next vehicle and how long it would take to cross the road at a comfortable walking speed. It is conceptually similar to minor-street through traffic at a two-way stop-controlled intersection with a two-directional conflicting traffic stream.

However, the pedestrian gap acceptance process is different than that for drivers, for two main reasons: a lack of channelization and the potential of driver yielding. Vehicles waiting at a single-lane approach at a yield or stop-controlled junction have to enter the intersection in a “first-in-first-out” prioritization scheme (FIFO). Pedestrians typically wait beside each other and can decide to cross the road even if they are not first in line. For this reason, chapter 2 discussed that the commonly used concept of follow-up time doesn’t apply to pedestrians.

With the potential of drivers yielding to pedestrians, the gap acceptance process is further complicated because there are now two alternative types of crossing opportunities: crossing in a gap or crossing in a yield. The models for driver yielding in Chapter 4 predicted the likelihood of a yield, defined as:

> *… an obvious driver action that delayed the vehicle arrival at the crosswalk and thus creates a crossing opportunity for the pedestrian. The driver action can be deliberate or can be triggered by the pedestrian by stepping into the roadway.*

In the yield analysis the inclusion of the triggered or forced yields was justified, because the logistic regression approach accounted for this category with a binary explanatory variable. The likelihood of a driver yielding was thus predicted both with and without a triggering behavior on the part of the pedestrian.

The models for pedestrian crossing decisions discussed in this chapter similarly predict the likelihood of a GO Decision, defined as:

> *… a deliberate action by the pedestrian evident by stepping off the sidewalk and into the roadway with intent to cross. This pedestrian action can further be characterized as being a function of the lag time to the next vehicle, or by the gap time between successive vehicles in the conflicting traffic stream. By definition, these events do not include crossings that occurred because of a vehicle yield event.*

Theoretically, the analysis framework allows for the inclusion of both gap and yield crossings in the prediction of pedestrian GO decision by introducing a binary indicator variable for yield presence. This type of general crossing model therefore could feasibly predict the likelihood of a pedestrian GO decision for both yield and gap conditions.

In reality, it is expected that most (if not all) sighted pedestrians will in fact accept a yield crossing opportunity. In ongoing research on the crossing behavior of pedestrians with vision impairments (NCHRP 3-78a), it is evident that the yield detection capabilities of blind travelers are less than 100%. However, for the sighted pedestrians observed in this research a perfect detection results in a perfect correlation between yield=1 and GO=1, thus making the yield variable useless as a predictor. In the maximum likelihood estimation of the predictor parameters in logistic regression, this results in sparse data (Agresti, 2007), meaning that a 2x2 contingency table of YIELD by GO has an empty cell for the yield=1/GO=0 pair. In the parameter estimation the result is a model that doesn't converge at an estimate.

Consequently, the analysis in this chapter does not include GO decisions that are the direct result of a yield (these events were analyzed in the previous chapter). However, the analysis does include crossing decisions that take place with an adjacent yield. Even with a yield in one lane, the decision to cross the other lane remains a gap selection process (of course this decision is influenced by the yielding vehicle). The following section discusses the difference between gap and lag events, and defines other parameters pertinent to the model.

5.1.1 Definitions

It is important to first distinguish between decisions that are made with respect to gaps versus lags. A gap is typically defined as the time headway between two successive vehicles at a fixed point; in this research that point is the beginning of the striped crosswalk. Gaps then are typically observed while a pedestrian is waiting at the curb under steady traffic conditions.

On the other hand, a lag is defined as the time interval elapsed until the first vehicle arrival measured from the time the pedestrian arrives at the crosswalk. For this first encounter the gap between successive vehicles is irrelevant, because the pedestrian can arrive at the crosswalk any time during a gap passage. The elapsed lead time since the last vehicle is ignored and the pedestrian makes his/her crossing decision based on the lag time remaining to the next vehicle.

The two mid-block crosswalks analyzed in this chapter are both at facilities with a two-lane cross-section, with one lane of traffic per direction. In this context, it is important to distinguish whether the gap or lag the pedestrian encounters is in the near lane or the far lane relative to her own position. Presumably, the pedestrian decision to cross is not the same in both cases. In fact, it is hypothesized that for a single-vehicle arrival, the near-side critical gap is lower than the far side critical gap, because it enables the pedestrian to more quickly clear the area of conflict (assuming the other lane is empty). The decision is likely to be yet again different for events that are characterized by vehicles in both lanes. A further discussion of these gap acceptance concepts is given in Fitzpatrick et al. (2006).

An additional challenge in defining gaps and lags presents itself as a consequence of the data collection methodology. The author recorded time-stamps for the actual vehicle arrivals at the crosswalks and thus can derive the temporal duration of gaps and lags from the time stamps in the form of observed gaps/lags. However, it can be reasoned that in some cases the observed vehicle arrivals at the crosswalks may have been influenced by a pedestrian action. Specifically, an assertive pedestrian may have elicited a driver reaction thereby delaying the arrival time at the crosswalk. In this case the observed gap/lag will be less than the expected gap/lag that assumes that the driver continues at the original speed. The data collection methodology discussed in chapter 3 records the vehicle speed and distance from the crosswalk at the time the pedestrian arrives. This makes it possible to calculate the expected arrival time and thus the expected gap or lag time.

The distinction between observed and expected gap is also important in the model application to microsimulation. A model algorithm would predict a pedestrian GO or NOGO decision based on the instantaneous state of the system, i.e., the expected arrival time. Any predictive model with application to microsimulation therefore should be based on expected arrival times. As a driver decelerates the expected time to arrival increases from one time step to the next and may thus still result in an eventual crossing by the pedestrian.

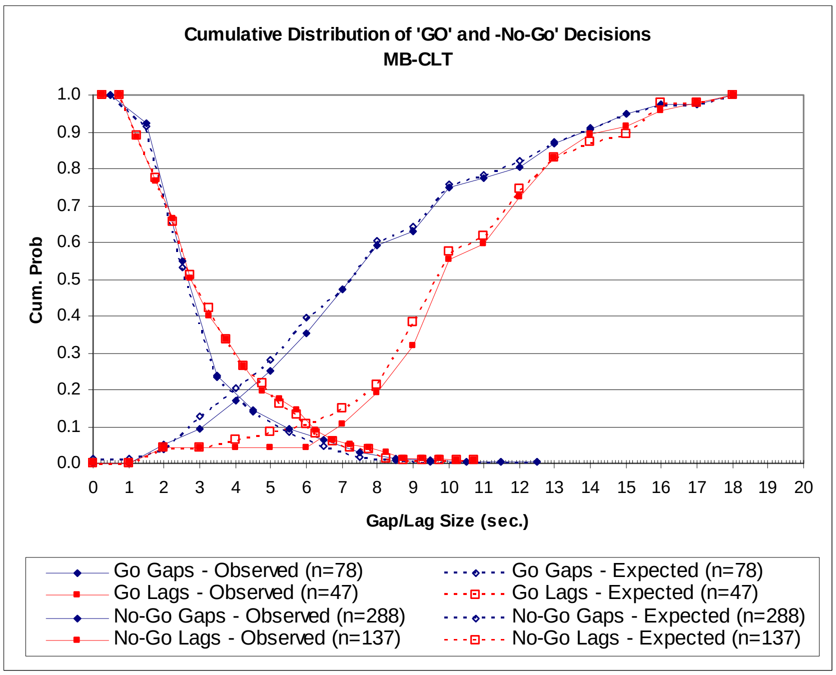
5.2 Traditional Gap Acceptance Approaches

The discussion in Chapter 2 identified four traditional methods for quantifying gap acceptance parameters: graphical method, regression method, Ramsey-Routledge method, and maximum likelihood estimation. The chapter further stated that the regression method assumes a FIFO prioritization scheme and sequential discharge from the standing queue (of vehicles) in which the first driver accepts a gap greater or equal to the critical gap. Additional vehicles in theory will accept the same gap if the residual time between the actual gap size and the initial critical gap is greater than their follow-up time. Because the pedestrian stream is not channelized in the same fashion, multiple pedestrians can in fact accept the same gap (independent of follow-up time) thus violating the assumptions underlying the graphical method. In the following section, the remaining three methods will be applied to data collected at the two mid-block crossing sites.

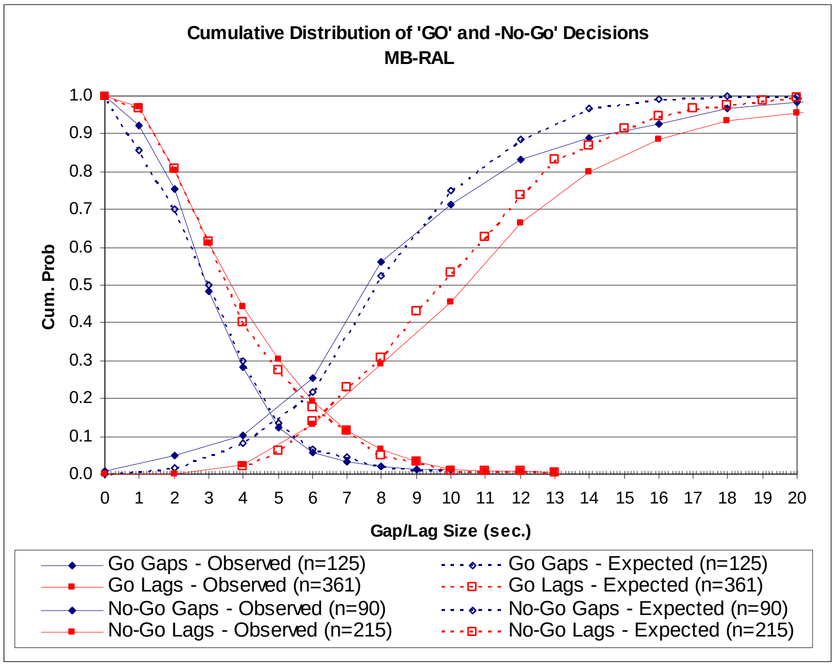
5.2.1 Graphical Method

The graphical method plots the cumulative distributions of gaps (or lags) that resulted in a GO and those that resulted in a NOGO decision as a function of gap size. By definition, the resulting critical gap (or lag) is the intersection of the two probability plots or the gap size at which the likelihood of GO and NOGO is the same. The underlying frequency distributions were extracted from the data sets using the PROC FREQ procedure in SAS. Binary indicators in the data set allowed for a separate analysis of gaps and lags and of events in the before and after periods.

Figure 29-a shows the resulting cumulative probability plots for gaps and lags at the MB-CLT site. Figure 29-b shows corresponding plots for MB-RAL. Both figures further distinguish the observed and expected gaps and lags.



a) MB-CLT



b) MB-RAL

Figure 29: Cumulative Probability Plots for Pedestrian Gap Acceptance

Table 4 below shows the critical gap and lag times obtained for the two sites.

Table 4: Critical Gap/Lag Results - All Data

	Critical Gap (sec.)		Critical Lag (sec.)	
SITE	**Observed**	**Expected**	**Observed**	**Expected**
MB-CLT	4.1	3.9	6.5	6
MB-RAL	4.8	4.9	6.4	6.2

The table shows that the critical lag times are higher than the critical gap times for both sites. This is explained by the pedestrian behavior. Upon initial arrival at the crosswalk (lag) the pedestrian has to screen the conflicting traffic stream, a cognitive process that requires time. Conceptually, the pedestrian needs this time to make the decision on whether or not it is safe to cross. For the subsequent crossings in gaps, this screening process presumably takes place before the temporal onset of the gap (i.e. while the vehicle passes in front of the pedestrian). The crossing then is initiated as soon as the vehicle clears the conflict area, maximizing the efficiency with which the gap is utilized.

In comparing the two sites, it is surprising that the critical gap appears to be lower for the MB-CLT site while the actual crossing distance is longer than at the MB-RAL site (40 feet compared to 24 feet). At an assumed walking speed of 3.5 feet per second, the expected crossing times at the MB-CLT and MB-RAL sites are 11.4 and 6.9 seconds, respectively. The substantially lower critical gap times indicate that one or both of the following are true: the pedestrians walk substantially faster than the 3.5 feet/sec assumed in the upcoming release of the MUTCD and/or the pedestrian's decision to GO is based on a distance shorter than the true crossing distance. The software package SIDRA INTERSECTION (SIDRA SOLUTIONS, 2007) recognizes the latter behavior pattern and allows the analyst to code an "effective crosswalk width" that is less than the actual crossing distance. Presumably, pedestrians at the MB-CLT site feel safe before completing the entire crossing, which is reflected in their decision making.

Figure B-55 in the Appendix shows the cumulative distributions of observed gaps and lags in the before and after categories for the MB-CLT site; Figure B-56 is the equivalent figure for MB-RAL. Table 5 presents a summary of the critical gaps and lags obtained from the plots.

Table 5: Critical Gap/Lag Results – Before and After

		Critical Gap (sec.)		Critical Lag (sec.)	
Site	**Category**	**Observed**	**Expected**	**Observed**	**Expected**
MB-CLT	Before	3.6	3.4	7.4	7.8
	After	3.2	3.0	4.9	4.3
MB-RAL	Before	5.1	5.1	6.7	6.3
	After	4.8	5.0	6.5	5.4

The table suggests that the treatment installation may have an effect on pedestrian gap acceptance. The critical gaps appear to be lower in the after condition, although with the graphical method it cannot be tested if this difference is statistically significant because no standard deviation is given. The impact appears largest for the expected lags, suggesting that the treatments have the largest impact on the initial decision process. The suggestion that the treatment installation would affect pedestrian decision-making is intriguing, because both treatments clearly target driver behavior.

5.2.2 Maximum Likelihood Estimation

While the graphical method presented above provides an intuitive estimate of critical gap and lag times, a clear disadvantage is that it fails to account for the stochastic nature of the gap acceptance process. The single estimator for critical gap decisions is useful only for some methods that rely on the concept, such as the Highway Capacity Manual methodology, for evaluating the delay of vehicles at the minor approach to a two-way stop controlled intersection; or more appropriately here, to estimate the delay for pedestrians crossing at a mid-block location (assuming no yields).

However, as analysis methodologies move towards stochastic microsimulation models, it becomes important to account for the variability of the gap selection process in the pedestrian population. The method for gap acceptance estimation described by Troutbeck (1992) uses maximum likelihood estimation (MLE) to predict the critical gap mean and standard deviation assuming that the population of critical gaps is log-normally distributed. The MLE procedure predicts the distribution parameters (in this case mean and standard deviation) that maximize the likelihood of observing the given sample of critical gaps.

The MLE gap procedure by Troutbeck (1992) uses within-subject paired gap acceptance data for estimation. For each driver (pedestrian) observed, the analyst records the longest rejected gap and the actual accepted gap, with the latter being expectedly the larger of the two. By using the longest rejected gap (as opposed to a random NOGO decision) the difference between the two observations is presumably minimized making it statistically easier (i.e. using a smaller sample size) to arrive at an estimate.

The nature of the estimation procedure makes it inapplicable for estimating the distribution of critical lags. By definition, the lag corresponds to the first event in the pedestrian-vehicle interaction process and it is therefore not possible to observe more than one for the same pedestrian (other than in the case of a controlled experiment with repeated crossings). Furthermore, the method naturally works best in conditions of heavy conflicting traffic, where each subject is likely forced to reject multiple gaps prior to the actual crossings.

The MLE procedure for gap estimation is implemented in a spreadsheet that Troutbeck developed as a supplement to the referenced paper. The following tables give the estimation results obtained by using that spreadsheet. Table 6 shows the results including the number of iterations it took to arrive at an estimate, the sample size, the mean and standard deviation of the critical gap, and two-sided t-test results on the difference in critical gap in the before and after cases where applicable.

Table 6: MLE Results - Paired Data - Gaps

	Charlotte, NC			Raleigh, NC		
	B&A (n=45)	Before (n=21)	After (n=24)	B&A (n=25)	Before (n=17)	After* (n=8)
Number of Iterations	35	25	57	31	34	.
Mean Critical Gap	5.7	5.6	6.0	6.6	6.3	.
SD of the Critical Gap	1.864	1.997	1.530	2.303	2.374	.
Difference B - A		-0.39				
p-value		0.4732				

* MLE Estimation did not converge - Macro Error

Table 6 shows a mean critical gap of 5.7 seconds at the MB-CLT site and 6.6 seconds at MB-RAL. Consistent with the previous method, the site with the wide crosswalk surprisingly has the shorter critical gap time.

A before and after comparison shows no significant impact of the treatment installation on critical gaps at the MB-CLT site. For the after condition at MB-RAL, the MLE method did not converge at an estimate, presumably due to low sample size. These findings illustrate the limitations of the MLE method, because the need for within-subject paired observations severely reduces the number of useable observations for this application.

5.2.3 Ramsey-Routledge Method

The Ramsey-Routledge (RR) method for gap acceptance analysis is described in the ITE Manual for Transportation Engineering Studies (ITE, 1994) and is based on Ramsey and Routledge, 1973. Similar to the MLE method, the RR approach also estimates a distribution of critical gaps/lags. It is different from MLE because no assumptions about the shape of that distribution are made. The RR approach estimates a frequency distribution of critical gaps in 2 second bins, independent of a theoretical distribution (1 second bins are possible, but require a larger sample size). The following analysis is based on the procedure outlined in ITE (1994) applied to both gaps and lags.

Figure 30 shows the resulting distributions of critical gaps and critical lags for both the MB-CLT and MB-RAL sites. Table 7 gives a summary of the mean, standard deviation and sample size of these distributions.

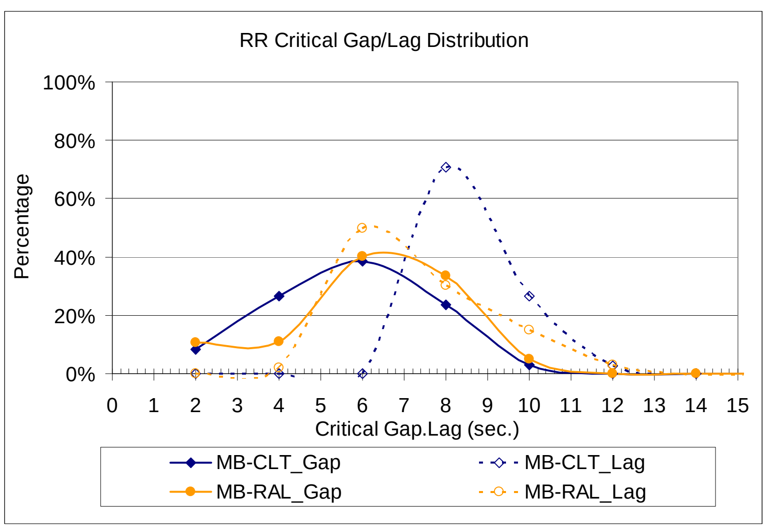


Figure 30: Gap/Lag Distributions from Ramsey-Routledge Methodology

Table 7: Critical Gap/Lag Results from RR Method

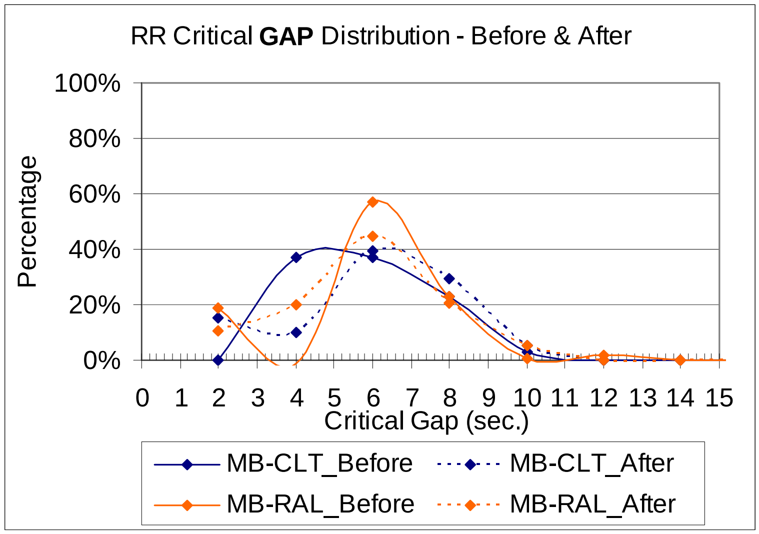
	MB-CLT			MB-RAL		
	Mean	SD	n	Mean	SD	n
Critical Gap (sec.)	5.74*	2.53	341	6.22*	2.63	325
Critical Lag (sec.)	8.64	2.96	185	7.36	2.79	527

* Some large Go and NoGO decisions were removed to meet assumptions

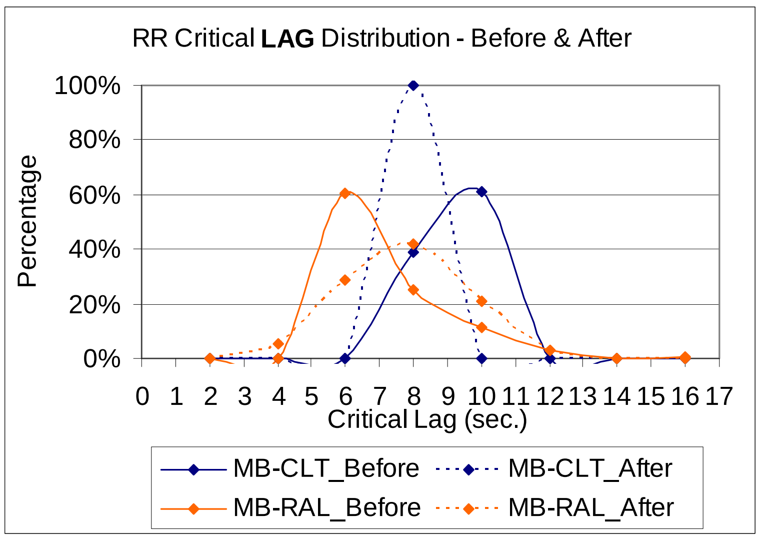
Consistent with the previous two estimation approaches, the RR method predicts larger mean critical lags than gaps. To produce a valid estimate from this method, some large GO and NOGO decisions had to be removed from the analysis for some categories (*). The RR method assumes an increasing percentage of GO decisions with greater bin size relative to the total number of observations in the bin. If this assumption was violated at large gap sizes (clearly above the critical gap) all events in those larger bins were excluded from the analysis.

Consistent with the other two methods, the RR analysis suggests that the critical gap is lower at the MB-CLT site than at the MB-RAL site. This difference is significant at $p<0.0001$ in a two-sided t-test. The critical lag distributions suggest the opposite trend, with a significantly higher estimate at the MB-CLT site ($p<0.0001$).

Figure 31 and Table 8 show the results separately in the before and after conditions.



a) Gaps



b) Lags

Figure 31: Before & After Distributions from Ramsey-Routledge Methodology

Table 8: Critical Gap/Lag Results from RR Method - Before & After

	MB-CLT			MB-RAL		
GAPS	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**
Before	5.85	2.52	185	5.85	2.58	143
After	5.99*	2.61	165	5.8	2.55	66
p-value		0.6110			0.8957	
	MB-CLT			**MB-RAL**		
LAGS	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**
Before	9.22	3.05	93	7.15	2.75	336
After	8.00	2.83	91	7.76	2.86	191
p-value		0.0054			0.0174	

* Some large Go and NoGO decisions were removed to meet assumptions

The table shows that the two treatments did not have a significant effect on the critical gap at either crossing. The mean critical gaps are nearly identical at both sites for the before and after conditions. The lag distributions for MB-CLT show a statistically significant decrease in the mean critical lag from 9.22 to 8.00 seconds. The lag data set for the MB-RAL site actually suggests a statistically significant increase in the critical lag size from 7.15 to 7.76 seconds with treatment installation.

5.2.4 Result Synthesis from Traditional Gap Acceptance Approaches

This section applied three common methods for gap acceptance to the data collected at the two midblock crosswalks MB-RAL and MB-CLT. The analysis presents an important benchmark against which to measure the following logistic regression analysis of pedestrian crossing behavior. Table 9 presents summary statistics of the results from all three methods.

Table 9: Summary Comparison of Traditional Gap Acceptance Approaches

		MB-CLT			MB-RAL		
		All	Before	After	All	Before	After
Mean Gap (sec.)	**Graphical Method**	4.1	3.6	3.2	4.8	5.1	4.8
	MLE Method	5.7	5.6	6.0	6.6	6.3	.
	RR Method	5.7	5.9	6.0	6.2	5.9	5.8
Mean Lag (sec.)	**Graphical Method**	6.5	7.4	4.9	6.4	6.7	6.5
	MLE Method	.	.	.	.	.	.
	RR Method	8.6	9.2	8.0	7.4	7.1	7.8

The summary table shows that the MLE and RR are relatively close in their estimation of the mean pedestrian critical gap times, where applicable. The graphical method predicts lower critical values in all cases. The methods are inconsistent in their prediction of how the treatments affect gap acceptance behavior.

The methods described above are useful in evaluating average pedestrian behavior and are sufficient to determine inputs for deterministic delay models that are based on the gap acceptance concept. Further, the RR and MLE methods account for heterogeneity in the pedestrian population by estimating a distribution of critical gaps. In a microsimulation application, gap acceptance algorithms can ideally utilize these distributions directly. Alternatively, at least some currently available microsimulation tools allow the modeler to code multiple "types" of pedestrians (PTV, 2003). Given the distribution of critical gaps, the overall population can be subdivided into multiple groups, whose gap acceptance behavior and relative frequency match the calculated distributions.

However, all the above methods fail to identify underlying contributions to the variability in gap acceptance behavior. The analyst may assume that variability can be attributed to population heterogeneity, with some pedestrians having inherently but consistently different gap selection attributes. Using the event-based approach suggested in this research, the gap selection process can account for many factors that contribute to the observed variability.

5.3 <u>Event Based Analysis for MB-CLT</u>

Data were collected describing driver characteristics, pedestrian characteristics, the dynamics of the closest approaching vehicle, and the conditions associated with the pedestrian-vehicle interaction event. Due to the complexity of the data, the following sections will discuss each site separately. A comparison of the results from both locations is provided in the chapter summary.

5.3.1 Descriptive Statistics

Consistent with the event-based analysis of driver yielding behavior in the previous chapter, the author initially used SAS PROC MEANS to obtain descriptive statistics of all dependent and independent variables. Table 10 shows the statistics for the entire data set and for data aggregated into before/after, Go/NOGO, and Gap/Lag categories.

Table 10: Descriptive Statistics – MB-CLT

	ALL DATA		BEFORE		AFTER		GO		NO_GO		GAPS		LAGS	
Variable	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**
Sample Size	551	.	307	.	244	.	125	.	426	.	366	.	185	.
Response Variables														
GO	0.23	0.419	0.18	0.381	0.29	0.455	1.00	0.000	0.00	0.000	0.22	0.414	0.24	0.430
NO_GO	0.77	0.419	0.82	0.381	0.71	0.455	0.00	0.000	1.00	0.000	0.78	0.414	0.76	0.430
LAG	0.32	0.468	0.32	0.467	0.36	0.480	0.36	0.482	0.33	0.470	0.00	0.000	1.00	0.000
Binary Factors														
ADY	0.04	0.196	0.03	0.160	0.06	0.233	0.11	0.317	0.02	0.136	0.05	0.211	0.03	0.163
AST	0.20	0.397	0.19	0.389	0.21	0.407	0.63	0.484	0.07	0.252	0.16	0.366	0.27	0.445
COM	0.00	0.060	0.00	0.057	0.00	0.064	0.02	0.126	0.00	0.000	0.00	0.052	0.01	0.074
FLASH	0.14	0.347	0.00	0.000	0.32	0.466	0.29	0.455	0.10	0.295	0.17	0.378	0.08	0.265
FOLL	0.48	0.500	0.47	0.500	0.50	0.501	0.38	0.488	0.51	0.500	0.50	0.501	0.45	0.499
HEV	0.02	0.127	0.01	0.114	0.02	0.142	0.03	0.177	0.01	0.108	0.01	0.090	0.03	0.178
MUP	0.28	0.447	0.28	0.448	0.27	0.447	0.22	0.413	0.29	0.456	0.30	0.457	0.24	0.427
NEAR	0.58	0.494	0.58	0.494	0.58	0.494	0.57	0.497	0.58	0.493	0.59	0.492	0.56	0.498
PLT	0.63	0.484	0.64	0.482	0.61	0.488	0.32	0.468	0.72	0.451	0.70	0.459	0.48	0.501
PREV	0.65	0.479	0.68	0.467	0.60	0.490	0.56	0.498	0.67	0.470	0.95	0.228	0.05	0.227
PXW	0.07	0.247	0.09	0.288	0.03	0.178	0.14	0.353	0.04	0.201	0.05	0.211	0.10	0.304
QUE	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000
TRIG	0.03	0.173	0.01	0.081	0.06	0.241	0.10	0.296	0.01	0.108	0.03	0.163	0.04	0.191
TRTMT	0.44	0.497	0.00	0.000	1.00	0.000	0.57	0.497	0.41	0.492	0.43	0.496	0.47	0.500
G_NEAR	0.23	0.419	0.28	0.450	0.16	0.367	0.25	0.434	0.22	0.415	0.21	0.408	0.26	0.440
G_FAR	0.17	0.380	0.21	0.407	0.13	0.338	0.16	0.368	0.18	0.383	0.16	0.371	0.19	0.397
G_COMBO	0.54	0.499	0.47	0.500	0.64	0.482	0.41	0.493	0.58	0.494	0.57	0.496	0.49	0.501
Continous Factors														
DECEL	5.02	6.909	4.06	4.627	5.67	7.453	1.67	0.780	5.69	6.646	3.25	4.903	8.71	8.792
DIST1	364.70	278.574	406.47	283.038	328.22	267.173	592.32	283.537	307.12	241.867	437.74	284.136	212.33	192.202
D_WAIT	4.88	5.724	5.68	6.301	3.88	4.727	5.11	6.144	4.81	5.601	7.34	5.587	0.00	0.000
O_GAP*	3.79	3.562	3.51	3.024	4.16	4.157	8.74	4.267	2.42	1.596	3.79	3.562	.	.
T_GAP*	3.80	3.499	3.45	2.860	4.25	4.168	8.73	4.067	2.42	1.537	3.80	3.499	.	.
O_LAG*	5.04	4.231	5.24	4.038	4.81	4.450	11.49	2.642	2.96	1.917	.	.	5.04	4.231
T_LAG*	4.99	4.183	5.29	4.025	4.65	4.352	11.23	3.003	2.99	1.917	.	.	4.99	4.183
SPEED_FT	41.15	9.776	42.43	8.785	40.39	9.299	41.35	10.316	41.58	8.677	40.81	9.742	41.88	9.834
TTC_V	8.99	6.438	9.70	6.687	8.09	6.005	14.39	6.072	7.40	5.638	11.01	6.438	4.99	4.182

*** Sample Sizes for these variables are lower because they only include the gap/lag events observed in each category**

During the observation period, 23% of all interaction events resulted in a GO decision and 32% were lag events. In 20% of the cases, pedestrians exhibited assertive behavior. In the data, 28% of observations were associated with multiple pedestrians, meaning that 72% of events were for individual travelers. Vehicle platoons were observed in 63% of events, which is consistent with the discussion in the previous chapter. Of all decisions, 23% had a vehicle present in the near lane only, 17% in the far lane only, and the remaining 54% of events had vehicles approaching in both lanes. The mean waiting time of all pedestrians was 4.9 seconds.

In the before and after comparison of the data, a larger overall percentage of events resulted in a GO decision after treatment installation resulting in a drop in the average waiting time from 5.7 to 3.9 seconds. The majority of independent variables is consistent across both conditions. Consistent with the analysis of the yielding data, pedestrians activated the treatment in 32% of the events. The treatment did not seem to result in a significant increase in the proportion of assertive behavior.

Comparing events that resulted in a GO to the NOGO decisions, the GO decisions appear to be correlated with greater pedestrian assertiveness, a higher activation rate of the treatment, and less platooning. GO events are also associated with a lower necessary deceleration rate on the side of the driver, expectedly indicating that vehicles are probably further away from the crosswalk. This notion is supported by a difference in DIST1 while the average approach speed is comparable.

A comparison of gap and lag events shows similar proportions of GO and NOGO events. Lags are associated with greater pedestrian assertiveness, a lower likelihood of the treatment being active, and a lower occurrence of platoons. Lags are furthermore associated with higher average deceleration rates, which are explained because any subsequent (gap) vehicles will always be able to decelerate at a slower rate to come to a stop at the crosswalk than the first (lag) vehicle. By definition, the pedestrian waiting time for lags is zero, because it is the first event after pedestrian arrival. Table 11 presents the descriptive statistics for the gap categories near/far/combo.

Table 11: Descriptive Statistics – MB-CLT – Near/Far/Combo

	ALL DATA		NEAR		FAR		COMBO	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Sample Size	551	.	125	.	96	.	298	.
Response Variables								
GO	0.23	0.419	0.25	0.434	0.21	0.408	0.17	0.377
NO_GO	0.77	0.419	0.75	0.434	0.79	0.408	0.83	0.377
LAG	0.32	0.468	0.38	0.488	0.38	0.487	0.31	0.461
Binary Factors								
ADY	0.04	0.196	0.00	0.000	0.00	0.000	0.00	0.000
AST	0.20	0.397	0.15	0.360	0.30	0.462	0.15	0.355
COM	0.00	0.060	0.00	0.000	0.00	0.000	0.00	0.000
FLASH	0.14	0.347	0.09	0.284	0.07	0.261	0.15	0.359
FOLL	0.48	0.500	0.41	0.493	0.51	0.503	0.50	0.501
HEV	0.02	0.127	0.03	0.177	0.02	0.144	0.01	0.100
MUP	0.28	0.447	0.18	0.382	0.27	0.447	0.31	0.464
NEAR	0.58	0.494	1.00	0.000	0.00	0.000	0.59	0.493
PLT	0.63	0.484	0.63	0.484	0.68	0.470	0.62	0.487
PREV	0.65	0.479	0.62	0.488	0.63	0.487	0.68	0.465
PXW	0.07	0.247	0.07	0.260	0.14	0.344	0.02	0.152
QUE	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000
TRIG	0.03	0.173	0.01	0.089	0.04	0.201	0.02	0.129
TRTMT	0.44	0.497	0.31	0.465	0.33	0.474	0.52	0.500
G_NEAR	0.23	0.419	1.00	0.000	0.00	0.000	0.00	0.000
G_FAR	0.17	0.380	0.00	0.000	1.00	0.000	0.00	0.000
G_COMBO	0.54	0.499	0.00	0.000	0.00	0.000	1.00	0.000
Continous Factors								
DECEL	5.02	6.909	4.50	5.316	5.01	6.497	5.09	6.494
DIST1	364.70	278.574	410.69	314.747	399.34	284.166	336.59	262.468
D_WAIT	4.88	5.724	5.34	7.129	4.31	5.359	4.67	5.125
O_GAP*	3.79	3.562	4.01	3.128	4.88	4.371	3.27	3.200
T_GAP*	3.80	3.499	3.91	3.073214	4.89	4.449383	3.17	3.070936
O_LAG*	5.04	4.231	5.55	4.697	5.06	4.199	4.43	3.960
T_LAG*	4.99	4.183	5.45	4.608	5.11	4.228	4.46	3.978
SPEED_FT	41.15	9.776	42.14	9.110	43.55	8.914	40.83	8.962
TTC_V	8.99	6.438	9.83	7.748	9.28	6.371	8.25	5.885

*** Sample Sizes for these variables are lower because they only include the gap/lag events observed in each category**

The analysis of different gap types in Table 11 shows a comparable rate of GO decision across all three categories. Far side gaps are correlated with greater pedestrian assertiveness, while combo gaps result in a more frequent activation of the flashing crosswalk. Pedestrian waiting time seems to be slightly higher for near gaps and lags, but that difference is not significant due to very high standard deviations.

5.3.2 Variable Interactions

In the next analysis step the author used SAS PROC CORR to investigate interactions between the dependent and independent variables, as well as test for any multicollinearity among independent variables. Tables B-35 and B-36 show the correlation matrices for gap and lag events, respectively. The tables are formatted to highlight any correlation parameters greater than 0.3 (or less than -0.3) and p-values less than 0.05. Again, the following discussion will merely highlight some of the more interesting trends.

Table B-35 indicates that GO decisions in gaps are correlated with the presence of an adjacent yield, pedestrian assertiveness, the activation of the flashing beacon, and trigger behavior. They are inversely correlated with the presence of platoons or a previous vehicle that failed to yield. Looking at the continuous variables, a GO decision is correlated with lower deceleration rates, greater distance from the crosswalk, and higher gap times.

In the analysis of GO decisions for lag events, table B-36 suggests that GO decision are correlated with greater assertiveness, the activation of the flasher, and the presence of a previous pedestrian in the crosswalk. For the continuous variables, a GO decision is associated again with lower deceleration rates, greater distance, and larger gap times.

The correlation analysis supports what is expected based on gap acceptance theory. The occurrence of a GO event is strongly correlated with the size of the gap or lag in the conflicting traffic stream. Given that yield events are not included in this analysis, the size of the conflicting gap or lag is a good indicator of whether or not a pedestrian will cross. However, the matrices further showed strong correlation with other variables that go beyond the traditional approaches for pedestrian gap acceptance. The use of logistic regression techniques allows the inclusion of these variables in the development of predictive models for the likelihood of a GO decision. But before moving into the estimation, the following section takes a closer look at the association between lag size and decision outcome.

5.3.3 Exploratory Analysis for Pedestrian GO Lags

The discussion above highlights the importance of the gap or lag size in the traffic stream to the pedestrian decision on whether or not to cross (in the absence of a yield). This finding is both intuitive and in line with previous research on the subject. However, the event-based nature of the data collection approach allows for an even closer analysis of this particular variable for lag events.

Most traditional gap acceptance approaches rely on observations taken at the conflict point. In particular, the size of a gap between vehicles is measured as the temporal difference between successive vehicle arrivals. For most vehicular applications (say two-way stop-controlled intersection), this is a valid approach, because a vehicle in the major street flow is very unlikely to alter its desired time-space trajectory in the approach of the intersection. Given the interactive nature of pedestrian crosswalks this is not necessarily true. While in some events the vehicle maintains its trajectory through the crosswalk at a constant speed, more often than not drivers will slow down in anticipation of pedestrian activity. Therefore, the actual observed arrival time at the crosswalk may or may not be the same as the expected arrival time calculated from the time of pedestrian arrival. This expected lag time, however, is what the pedestrian uses to make the decision on whether or not to cross. The lag time in turn is influenced by the decisions of both driver and pedestrian in response to this initial state.

The speed and distance to the crosswalk at the time of pedestrian arrival at the crosswalk were recorded and it was therefore possible to analyze pedestrian decisions based on the expected arrival times. Figure 32 shows a plot of speed versus distance at the time of pedestrian arrivals for all lag events. The event outcomes are symbolized by squares for GO events and stars for NOGO decisions. The figure further shows radial lines of constant lag times to provide a visual reference. Note that gap events cannot be analyzed in this fashion, because their expected arrival at the crosswalk is preceded by other vehicles.

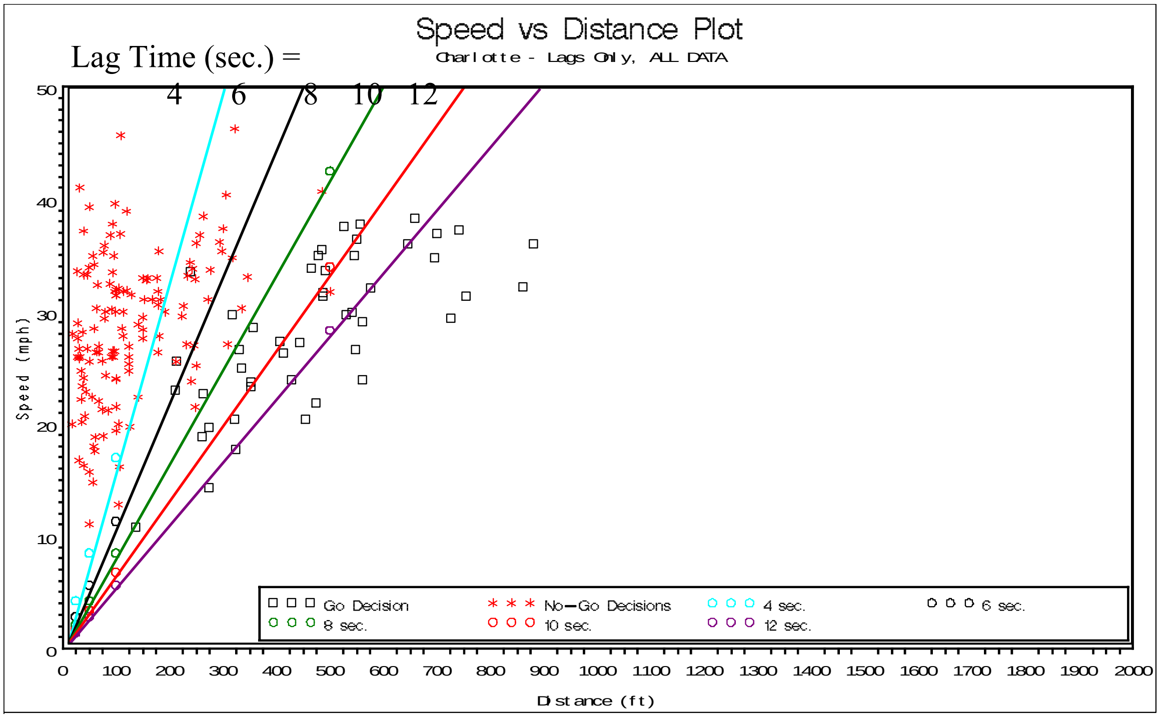


Figure 32: Plot of GO and NOGO events for Lag Analysis – MB-CLT

From the plot, it is clearly evident that zero GO events were observed at lag times less than 4 seconds and that only few were observed at lags between 4 and 8 seconds. Most GO decisions occur at lags greater than 8 seconds with NOGO decisions expectedly showing the opposite trend. In the previous section, the graphical and Ramsey-Routledge methods estimated critical lag times of 6.5 and 8.6 seconds, respectively. The radial lines offer a visual confirmation of these parameters.

The line that best separates these two event outcomes can be estimated using statistical procedures such as Fisher's Discriminate Function. This method was not applied here, because the more modern logit regression approach conceptually achieves the same goal;

dividing the clusters of observations into two categories using a mathematical discriminate.

Comparing the event plot back to the graphical representation of yield events in Chapter 4, it can be anticipated that the logit regression models for lag (and presumably gap) events may achieve a better overall statistical fit.

5.4 Crossing Model Development for MB-CLT

The methodology chapter discussed the application of logistic regression methods in the context of these data. Due to the categorical nature of the dependent variable, the logistic procedure is the appropriate method of analysis. However, as was done for the driver yielding models it is good practice to first apply multilinear regression (MLR) to get a general sense of what to expect from the logit models. Following the MLR analysis, the author will explore a range of binary logistic models. Similar to the analysis of the driver yielding models, the modeling approach explores full, unrestricted, and restricted models. Models for gap and lag events are evaluated separately.

5.4.1 Multilinear Regression Models

Table B-37 shows the multilinear regression models for the MB-CLT site. The full model suggests that AST, TRIG, G_NEAR, G_COMBO, DECEL, and O_LAG are good potential variables in the regression model. Further analysis in the unrestricted approach results in a four-variable model predicting the likelihood of GO as a function of pedestrian assertiveness, vehicle status in the near lane, treatment presence, and observed lag size. The treatment effect indicates that pedestrians are more likely to cross after the in-pavement flashing crosswalk was installed. The restricted model is very similar, with the exception that it uses the expected lag time. The adjusted R-square statistics of the full, unrestricted, and restricted MLR models are 0.79, 0.78, and 0.76, respectively.

The corresponding models for gaps are shown in Table B-38. The likelihood of GO in a gap for the full model shows that AST, MUP, PREV, PXW, TRTMT, D_WAIT, G_FAR, G_COMBO, O_GAP and T_GAP are all good explanatory variables. The unrestricted model 2 includes variables AST, MUP, PREV, PXW, TRTMT, D_WAIT, and O_GAP. Restricted model 2 utilizes variables AST, FLASH, NEAR, PLT, D_WAIT, and T_GAP to predict the likelihood of GO. The adjusted R-square statistics of the full, unrestricted and restricted MLR models are .76, .73, and .70, respectively.

These initial results from the MLR analysis already suggest that pedestrian gap acceptance behavior is more readily predictable than driver yielding behavior. With highly significant parameters and good overall model fit statistics there is a lot of promise for the following logistic regression analysis. The preliminary models show good fit using size of gaps and lags and a treatment effect. They also suggest an impact of pedestrian waiting time (D_WAIT) in increasing the likelihood of GO.

5.4.2 Binary Logit Models for MB-CLT

Lag Events

Table B-39 contains all models for lag events for site MB-CLT. The two unrestricted models are results of the SAS modeling algorithm with B-39-b using the observed and B-39-c the expected lag values. The resulting models both contain the variables AST and G_FAR in addition to the lag time variable. The latter model further contains the variable describing whether the treatment was activated (FLASH). Unrestricted model 1 has the better statistical fit with AIC 24.602, -2 log L 16.602 and max-rescaled R-square 0.9538. Unrestricted model 2 has an AIC of 28.458 and -2 log L of 18.458, which is a statistically poorer fit (p=0.0016). The resulting equation 20 for unrestricted model 1 is given below followed by a graphical representation of the model in Figure 33.

Equation 20: PCM - Mid-Block Lag, Unrestricted Model 1, MB-CLT

$$\text{logit}[P(GO=1)] = -15.496 + 3.4780\ AST - 4.753\ G\_FAR + 1.855\ O\_LAG$$

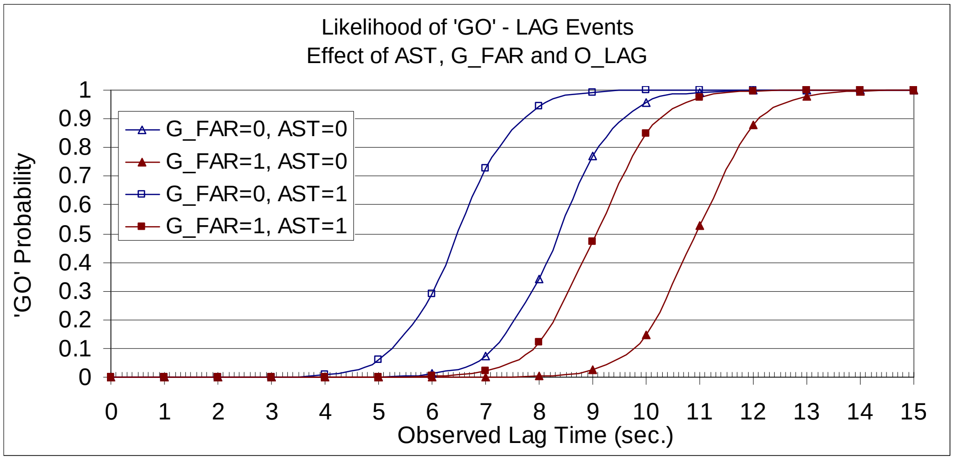


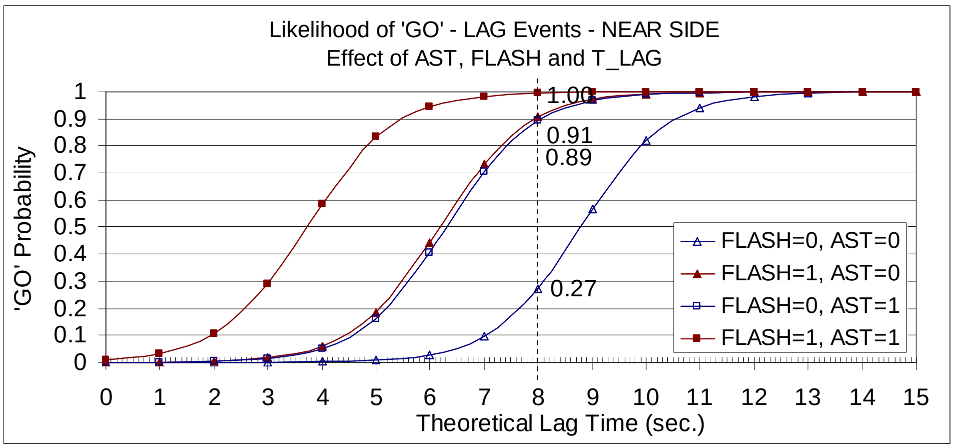
Figure 33: Model Probability Plot for Lags – Unrestricted Model 1 - MB-CLT

The figure expectedly shows an increasing probability of GO as a function of the observed lag time. The left-most curve corresponds to the likelihood of crossing for an assertive pedestrian who is faced with a "non-far" lag (i.e. either a near only, or combo lag). With an odds ratio of 32.45, pedestrian assertiveness has a very large effect on an increased likelihood of GO. This curve represents the group of events that would use the lowest lag times. For example, the 50^{th} percentile lag for this group is approximately 6.5 seconds. For a non-assertive pedestrian, the probability distribution shifts to the right indicating higher lags. The 50^{th} percentile lag for a "G_FAR=0" event is approximately 8.4 seconds. The remaining two curves follow this trend, with non-assertive pedestrians and G_FAR=1 lags generally requiring longer lag times.

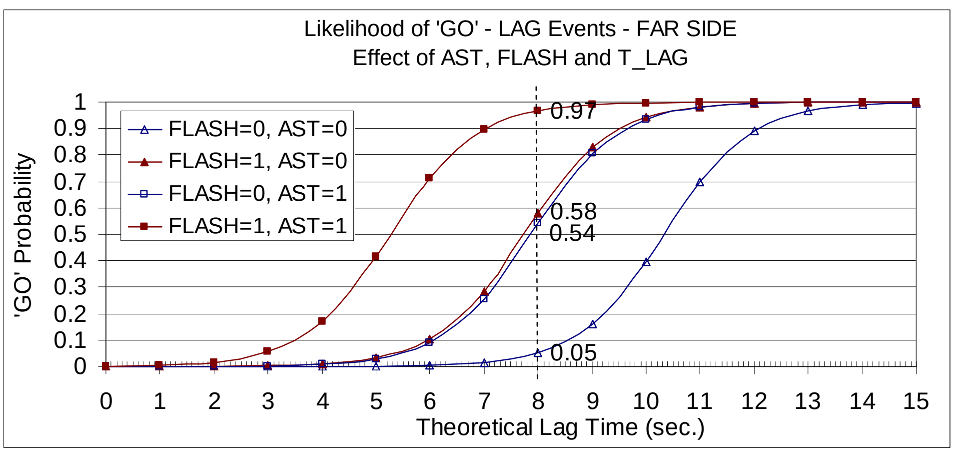
Table B-39 further shows five different restricted models featuring different combinations of variables. The model fit statistics for these models are all very comparable and hence the model with the most practical application is selected as the best fit. Restricted Model 5 predicts the likelihood of GO as a function of pedestrian assertiveness (AST), activation of the treatment (FLASH), whether the vehicle is in the near lane (NEAR), and the expected lag time to the first vehicle arrival. The resulting equation and probability plots are shown below (in Equation 21 and Figure 34).

Equation 21: PCM - Mid-Block Lag, Restricted Model 5, MB-CLT

logit[P(GO=1) = -12.930 + 3.092 AST+ 3.239 FLASH + 1.941 NEAR + 1.252 T_LAG



a) Near-side crossing



b) Far-side crossing

Figure 34: Model Probability Plot for Lags – Restricted Model 5 - MB-CLT

The probability plots show the predicted likelihood of GO for vehicle encounters on the near side (34 -a) and far side (34 -b) relative to the position of the waiting pedestrian.

Both plots show an increasing probability of GO with increasing expected lag time. The four curves from left to right (lower likelihood of GO given the same lag time) represent assertive pedestrians who activate the flasher, non-assertive pedestrians who activate the flasher, and assertive and non-assertive pedestrians who don't activate the treatment. Looking at a constant lag time of, for example, 8 seconds (vertical line in the figures), these four categories have a likelihood of crossing of 0.27, 0.89, 0.91, and 1.00 for a crossing in a near-side lag. For a crossing in a far-side lag, all four curves shift to the right towards higher expected lag times. For a constant lag time of 8 seconds the likelihood of crossing for the four categories then are 0.05, 0.54, 0.58, and 0.97.

Restricted Model 5 has an AIC statistic of 34.874, which indicates that some statistical fit is sacrificed compared to unrestricted model 1 (AIC=24.602). The max-rescaled R-square statistic for the restricted model is still very high with 0.9292.

Gap Events

Table B-40 shows the corresponding logit models for the likelihood of a GO decision in a gap event. Unrestricted Model 2 has the best statistical fit and predicts the GO response as a function of AST, PREV, TRTMT, G_FAR and O_GAP in equation 22. Figure 35 shows the corresponding probability plot. Due to the number of variables, parameters for PREV and G_FAR are fixed in the plot.

Equation 22: PCM - Mid-Block Gap, Unrestricted Model 2 – MB-CLT

$$\text{logit}[P(GO=1)] = -3.944 + 5.362\ AST - 5.102\ PREV + 1.436\ TRTMT - 3.251\ G\_FAR + 1.165\ O\_GAP$$

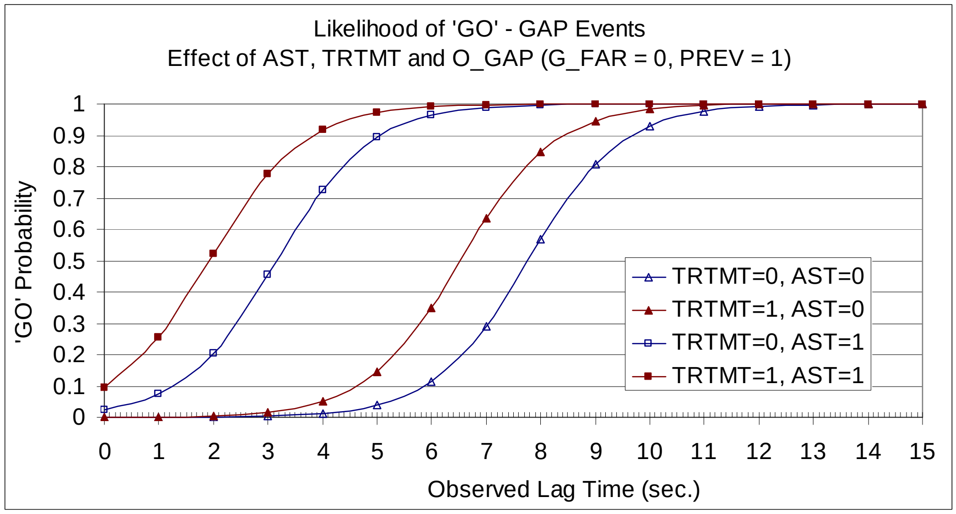


Figure 35: Model Probability Plot for Gaps – Unrestricted Model 2 - MB-CLT

The plot suggests an increasing likelihood of GO with pedestrian assertiveness and with installation of the treatment (curve shift to the left). The likelihood of GO increases with greater lag times.

The selection of the restricted models for this category proves challenging, with several models demonstrating good statistical fit and practical applicability. From a total of 7 restricted models shown in Table B-43, models e through j all use AST, T_GAP and a variation of the treatment effect (either TRTMT or FLASH). They differ in the use of variables NEAR and D_WAIT. Of these two, the latter one is of greater practical significance as it gives evidence for a reduction of the gap selection threshold over time. The concept of a decaying critical gap was hypothesized in chapter 2 and represents impatient behavior on behalf of the waiting pedestrians.

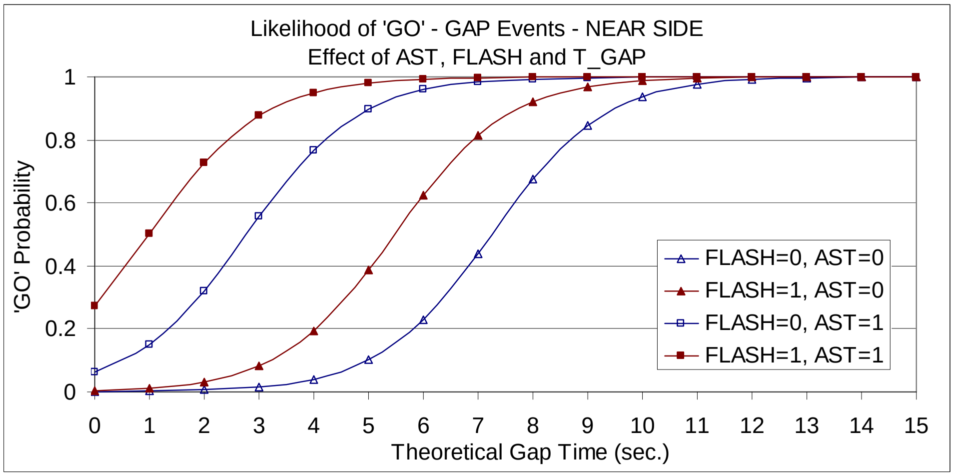
From a statistical standpoint, restricted model 2 has the lowest AIC (97.709), but its parameter estimate for D_WAIT is not significant for the given sample. For restricted model 6 the parameter estimate for D_WAIT is significant at the 90% confidence level and an overall AIC of 102.276. The -2 log likelihood difference between the two models is significant at p=0.0104.

Taking a closer look at the D_WAIT variable, its effect seems to be significant in combination with TRTMT, but not with either FLASH or NEAR. In the correlation analysis in Table B-36 the TRTMT and D_WAIT variables show a slight, but significant correlation (coefficient=-0.20, p-value=0.0001) suggesting lower pedestrian waiting time after treatment installation. In fact, table 10 also shows this significant reduction in waiting time after treatment installation from 5.7 to 3.9 seconds. The parameter estimates of TRTMT and AST in restricted model 6 are therefore confounded by a correlation between the two variables.

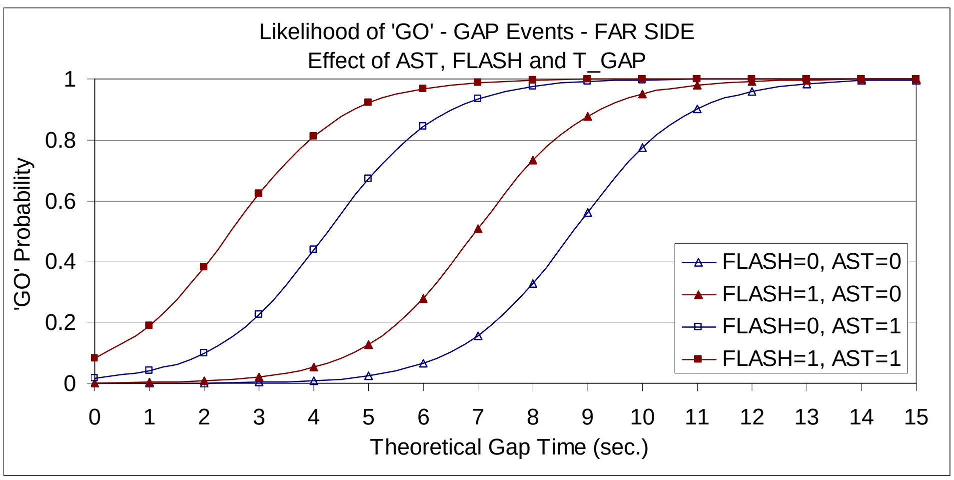
Because it is uncertain whether the effect of pedestrian waiting time is true or a product of multicollinearity, it will not be considered in the selected restricted model. Of the remaining restricted models that do not use D_WAIT, restricted model 3 has the lowest AIC statistic (101.337) and all model parameters are significant at the 95% confidence level. The model is expressed numerically in Equation 23 and graphically in Figure 36.

Equation 23: PCM - Mid-Block Gap, Restricted Model 3, MB-CLT

logit[P(GO=1) = -8.511 + 4.360 AST + 1.726 FLASH + 1.454 NEAR + 0.974 T_GAP



a) Near-side crossing



b) Far-side crossing

Figure 36: Model Probability Plot for Gaps – Restricted Model 3 - MB-CLT

The activation of the treatment and pedestrian assertiveness both increase the likelihood of GO with odds ratios of 5.618 and 78.267, respectively. Gaps on the near side increase the likelihood of GO by a factor 4.279. With a one-second increase in theoretical gap time the likelihood of GO increases with an odds ratio of 2.648.

With the large effect of AST, this model predicts that some assertive pedestrians will make GO decisions at very short gap times. In a model implementation these would result in some risky decisions with pedestrians stepping into the roadway in clearly unsafe conditions. The mean GO gap for the site from table 10 was 8.74 seconds with a standard deviation of 4.27 seconds. In light of this high standard deviation it is expected that the logit would predict some very short accepted gaps. The advantage of this analysis approach is that these short accepted gaps can be associated with assertive pedestrians who activate the flashing treatment with a vehicle in the near lane.

5.4.3 Site Summary

The predictive models for the MB-CLT site were found to be highly sensitive to the size of the gaps or lags in the traffic stream. This finding is expected from gap acceptance theory and supports the validity of the selected analysis approach. The logistic regression models go beyond the traditional methods in that the models account for difference between different types of pedestrians in a heterogeneous population. The assertiveness variable shows up consistently in the models with a larger probability of GO for the assertive class of pedestrians.

Most models further include some effect of the treatment (before & after) and/or whether the treatment was activated. While the clear intention of the in-pavement flashing beacon is to increase pedestrian awareness and promote driver yielding, it appears that it also encourages pedestrians to accept shorter gaps and lags in their GO decisions. While this clearly reduces the delay experienced by pedestrians it is also associated with an increased risk. Pedestrians who accept a shorter, presumably unsafe gap/lag run the risk of creating a pedestrian-vehicle conflict if the approaching driver fails to react. In a microsimulation implementation of these different algorithms, it would be possible to quantify the increased likelihood of such conflict when coding both the pedestrian crossing model and the driver yield model simultaneously.

The gap analysis suggested an impact of pedestrian waiting time on increasing the likelihood of GO. The effect was found to be correlated with the treatment installation, because pedestrians experienced significantly lower delay in the after condition. The waiting time variable was therefore not included in the selected model. Future research at pedestrian crosswalks with a significant amount of pedestrian waiting time may provide further insight in this variable.

In comparison to the traditional gap acceptance approaches, inferences can be made about the overall fit of the logit models. While this comparison falls short of a true model validation, it assures that the logit model predictions are within the observed data ranges. The average critical lag estimates from graphical and RR methods were 6.5 and 8.6 seconds. For example, in restricted model 5 the $50^{\%}$ likelihood of GO for a non-assertive pedestrian accepting a near-side lag without activating the treatment is approximately 8.8 seconds. For an assertive pedestrian this lag time is reduced to 6.2 seconds and to about 3.6 seconds if the same pedestrian were to activate the treatment. The three 50^{th} percentile lag likelihoods for a far-side crossing are approximately 10.4, 7.8 and 5.2 seconds, respectively. This sort of comparison gives confidence that the logit predictions are generally within the range of lag times that were estimated from the traditional methods.

The mean critical gap estimates from the graphical, MLE, and RR methods were 4.1, 5.7 and 5.7 seconds, respectively. In comparison, restricted model 3 predicts a $50^{\%}$ likelihood of GO in a near-side gap of approximately 7.3 seconds for a non-assertive pedestrian who doesn't activate the treatment. With activation of the treatment, that gap time is reduced to 5.4 seconds and for an assertive pedestrian to 2.7 seconds. While this last gap estimate seems low, it is reasonable considering the large standard deviation of critical gaps predicted from the traditional methods. For far-side gaps, the 50% GO likelihood gap times are expectedly higher (by a factor of 15.762 equal to the odds ratio of the effect).

5.5 Event-Based Analysis for MB-RAL

5.5.1 Descriptive Statistics

The descriptive statistics for the MB-RAL site (Table 12) show an overall rate of 'GO' decisions of 60%. This is significantly higher than the observations at the MB-CLT site, which is indicative of relatively lower frequency of NOGO decisions. In other words, pedestrians at the MB-RAL site did not encounter as many gaps and lags that resulted in NOGO decisions. In fact, the average observed gap at this site is 7.2 seconds, compared to 3.8 seconds at MB-CLT. Correspondingly, the average waiting time of pedestrians is only 1.6 seconds (it was 4.9 seconds at the MB=CLT site). The dataset further shows 40% assertive behavior and only 28% of vehicles traveling in platoons.

Table 12: Descriptive Statistics – MB-RAL

	ALL DATA		BEFORE		AFTER		GO		NO_GO		GAPS		LAGS	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Sample Size	768	.	465	.	303	.	459	.	309	.	219	.	549	.
Response Variables														
GO	0.60	0.491	0.59	0.493	0.61	0.488	1.00	0.000	0.00	0.000	0.57	0.496	0.61	0.489
NO_GO	0.40	0.491	0.41	0.493	0.39	0.488	0.00	0.000	1.00	0.000	0.43	0.496	0.39	0.489
LAG	0.71	0.452	0.72	0.449	0.71	0.456	0.73	0.446	0.70	0.461	0.00	0.000	1.00	0.000
Binary Factors														
ADY	0.02	0.151	0.02	0.122	0.04	0.187	0.02	0.153	0.02	0.149	0.06	0.245	0.01	0.085
AST	0.40	0.491	0.42	0.494	0.38	0.486	0.64	0.479	0.05	0.208	0.26	0.440	0.46	0.499
COM	0.00	0.036	0.00	0.000	0.00	0.057	0.00	0.047	0.00	0.000	0.00	0.000	0.00	0.043
FLASH	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000
FOLL	0.21	0.410	0.18	0.385	0.26	0.442	0.20	0.399	0.24	0.425	0.22	0.415	0.21	0.409
HEV	0.03	0.171	0.02	0.152	0.04	0.195	0.03	0.178	0.03	0.159	0.04	0.188	0.03	0.163
MUP	0.26	0.438	0.27	0.444	0.24	0.430	0.22	0.418	0.31	0.464	0.33	0.471	0.23	0.422
NEAR	0.63	0.482	0.64	0.480	0.62	0.486	0.64	0.480	0.62	0.486	0.61	0.489	0.64	0.479
PLT	0.28	0.450	0.25	0.431	0.34	0.473	0.20	0.399	0.40	0.492	0.38	0.487	0.24	0.428
PREV	0.25	0.436	0.26	0.438	0.25	0.432	0.22	0.412	0.31	0.464	0.80	0.398	0.03	0.183
PXW	0.20	0.398	0.20	0.399	0.19	0.397	0.22	0.418	0.16	0.363	0.04	0.199	0.26	0.438
QUE	0.02	0.124	0.02	0.138	0.01	0.099	0.00	0.047	0.04	0.186	0.02	0.134	0.01	0.120
TRIG	0.07	0.260	0.05	0.213	0.11	0.316	0.12	0.323	0.01	0.080	0.04	0.199	0.09	0.280
TRTMT	0.39	0.489	0.00	0.000	1.00	0.000	0.40	0.491	0.38	0.487	0.41	0.492	0.39	0.488
G_NEAR	0.43	0.496	0.44	0.497	0.43	0.495	0.49	0.500	0.36	0.481	0.35	0.477	0.47	0.500
G_FAR	0.21	0.405	0.19	0.396	0.23	0.420	0.22	0.418	0.18	0.386	0.17	0.376	0.22	0.416
G_COMBO	0.33	0.469	0.34	0.474	0.30	0.461	0.25	0.435	0.43	0.496	0.41	0.493	0.29	0.455
Continous Factors														
DECEL	3.45	4.880	3.62	5.715	3.20	3.195	1.88	0.868	5.80	6.998	2.45	6.410	3.85	4.053
DIST1	355.61	226.828	360.91	236.772	347.47	210.781	468.46	203.746	187.96	138.634	450.14	234.644	317.90	212.400
D_WAIT	1.56	3.228	1.50	3.229	1.66	3.231	1.52	3.228	1.63	3.233	5.48	3.882	0.00	0.000
O_GAP*	7.17	5.285	6.17	4.221	8.64	6.279	10.45	4.480	2.82	2.271	7.17	5.285	.	.
T_GAP*	6.96	4.444	6.20	4.302	8.05	4.442	10.00	3.109	2.93	2.131	6.96	4.444	.	.
O_LAG*	9.11	6.010	9.03	6.215	9.24	5.686	12.37	5.361	4.05	2.340	.	.	9.11	6.010
T_LAG*	8.26	5.187	8.55	5.575	7.79	4.487	11.04	4.599	3.93	2.260	.	.	8.26	5.187
SPEED_FT	37.90	7.585	38.40	7.247	37.12	8.028	39.10	6.800	36.11	8.316	37.27	7.503	38.14	7.610
TTC_V	9.30	5.554	9.33	5.732	9.26	5.278	12.07	4.893	5.20	3.593	11.93	5.586	8.26	5.188

*** Sample Sizes for these variables are lower because they only include the gap/lag events observed in each category**

In a before and after comparison, the treatment did not have a significant effect on the rate of GO decisions or pedestrian assertiveness. The apparent higher occurrence of vehicle platoons is not significant. The average pedestrian waiting time also appears unchanged and the treatment also did not have a significant effect on the average vehicle speeds. Overall, the before and after data sets look very similar suggesting that the treatment implementation did not have the same effect on pedestrian crossing behavior that it had on the likelihood of driver yielding. At this level of analysis, the treatment appears ineffective.

A comparison of GO and NOGO decisions shows clearly that GO events are associated with a very high rate of pedestrian assertiveness and a lower occurrence of platoons. Expectedly, the necessary deceleration rate of vehicles is lower for GO events, related to the average distance at pedestrian arrival being much longer. The average speed observation is actually lower for NOGO decisions.

Gap and lag events resulted in similar overall rates of GO and NOGO decisions. Lags are associated with more pedestrian assertiveness and by definition always have a pedestrian waiting time of zero. Gap events further rarely show a previous pedestrian already in the crosswalk, which is probably explained by the fact that the prior gap or lag was not crossable.

Separating the events into the near, far, and combo types (Table 13), does not reveal any additional trends in the data.

Table 13: Descriptive Statistics – MB-RAL – Near/Far/Combo

Variable	ALL DATA Mean	ALL DATA StdDev	NEAR Mean	NEAR StdDev	FAR Mean	FAR StdDev	COMBO Mean	COMBO StdDev
Sample Size	768	.	334	.	159	.	250	.
Response Variables								
GO	0.598	0.491	0.668	0.472	0.648	0.479	0.464	0.500
NO_GO	0.402	0.491	0.332	0.472	0.352	0.479	0.536	0.500
LAG	0.715	0.452	0.772	0.420	0.767	0.424	0.640	0.481
Binary Factors								
ADY	0.023	0.151	0.000	0.000	0.000	0.000	0.000	0.000
AST	0.404	0.491	0.434	0.496	0.440	0.498	0.344	0.476
COM	0.001	0.036	0.000	0.000	0.000	0.000	0.000	0.000
FLASH	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FOLL	0.214	0.410	0.237	0.426	0.157	0.365	0.204	0.404
HEV	0.030	0.171	0.027	0.162	0.025	0.157	0.036	0.187
MUP	0.259	0.438	0.249	0.433	0.189	0.392	0.324	0.469
NEAR	0.634	0.482	1.000	0.000	0.000	0.000	0.564	0.497
PLT	0.281	0.450	0.296	0.457	0.214	0.411	0.284	0.452
PREV	0.254	0.436	0.219	0.414	0.233	0.424	0.332	0.472
PXW	0.197	0.398	0.198	0.399	0.245	0.432	0.176	0.382
QUE	0.016	0.124	0.015	0.122	0.006	0.079	0.024	0.153
TRIG	0.073	0.260	0.072	0.259	0.101	0.302	0.052	0.222
TRTMT	0.395	0.489	0.386	0.488	0.434	0.497	0.368	0.483
G_NEAR	0.435	0.496	1.000	0.000	0.000	0.000	0.000	0.000
G_FAR	0.207	0.405	0.000	0.000	1.000	0.000	0.000	0.000
G_COMBO	0.326	0.469	0.000	0.000	0.000	0.000	1.000	0.000
Continous Factors								
DECEL	3.455	4.880	3.292	3.944	3.174	3.201	3.951	6.740
DIST1	355.606	226.828	373.696	248.349	367.121	202.291	322.214	210.173
D_WAIT	1.564	3.228	1.079	2.623	1.295	2.845	1.898	3.391
O_GAP*	7.173	5.285	8.724	5.292	8.639	6.077	6.077	4.420
T_GAP*	6.955	4.444	7.835899	4.599921	7.967373	4.227987	5.763578	4.222203
O_LAG*	9.113	6.010	9.545	6.560	9.734	5.638	7.968	5.272
T_LAG*	8.256	5.187	8.707	5.651	8.673	4.840	7.291	4.596
SPEED_FT	37.895	7.585	38.738	7.566	37.594	7.122	37.063	7.763
TTC_V	9.304	5.554	9.578	5.912	9.731	5.190	8.581	5.256

*** Sample Sizes for these variables are lower because they only include the gap/lag events observed in each category**

5.5.2 Variable Interactions

The correlation matrices for the MB-RAL site are provided in tables B-41 and B-42 for gaps and lags, respectively. The GO response variable for gaps is correlated with assertiveness, trigger behavior, the treatment, and variables describing the duration of the gaps. It is also inversely correlated with the occurrence of platoons, a prior non-yield, and combo gaps.

For lag events, the GO dependent variable is correlated with assertiveness, the presence of a pedestrian in the crosswalk, trigger behavior and the lag size. An inverse correlation is evident for vehicle platoons, and a previous vehicle that failed to yield. The treatment variable is not significant for lags.

Again, the GO response consistently shows strong correlation with the size of the gap or lag in the vehicle stream. Intuitively, assertive pedestrian behavior is associated with a greater likelihood to cross the road. Pedestrian crossings further appear to be more difficult when there is platooning in the vehicle stream and for more complicated combo gaps and lags.

5.5.3 Explanatory Analysis for Pedestrian Gap Acceptance

The analysis of the previous gap acceptance data set introduced the concept of discriminate analysis to determine the threshold between GO and NOGO decisions for lag events. Figure 37 shows the corresponding event plot for all lag events at the MB-RAL site.

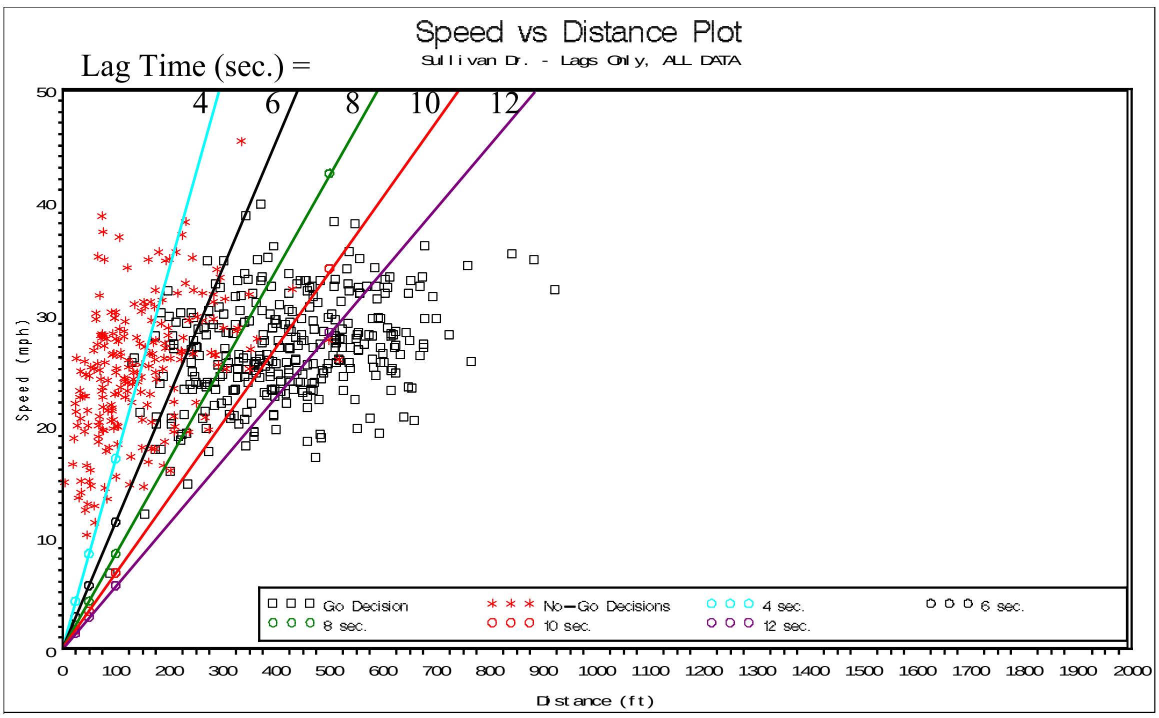
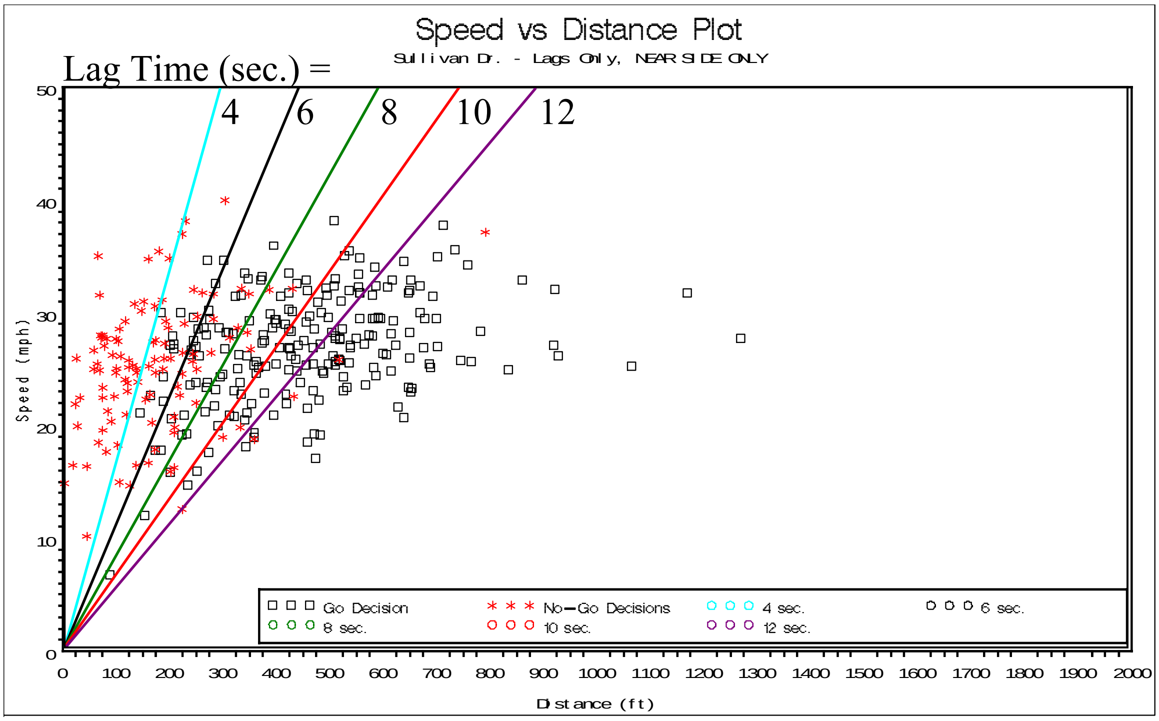
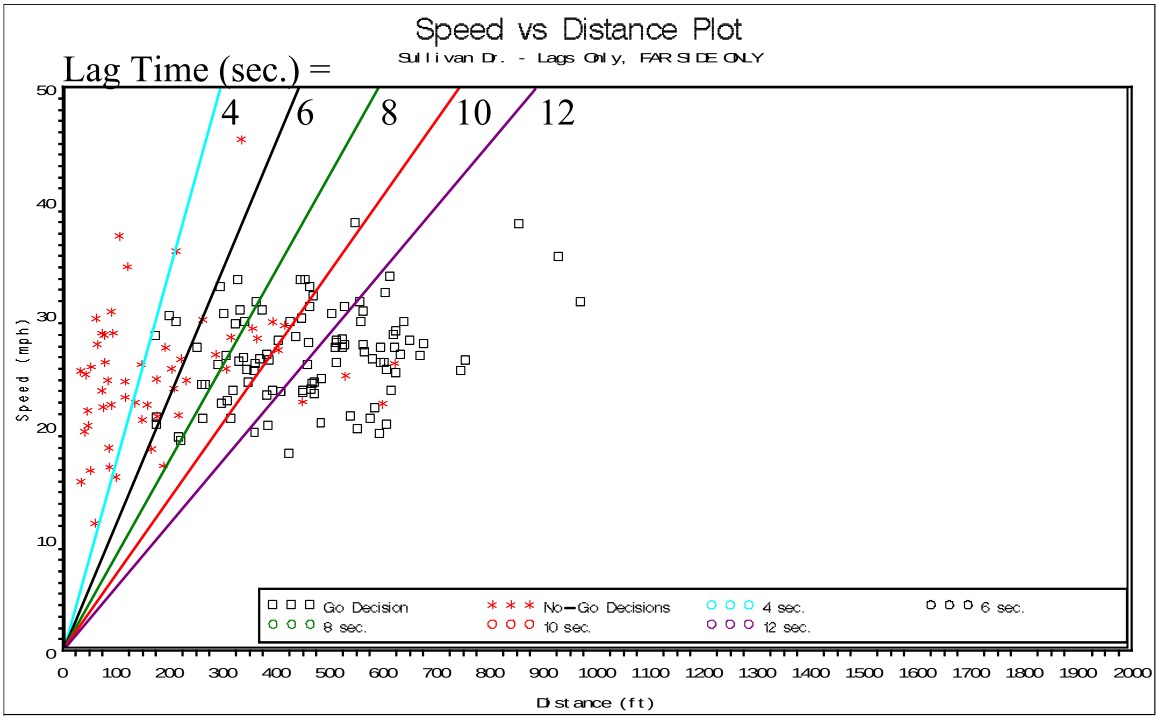


Figure 37: Plot of GO and NOGO Events – MB-RAL – All Data

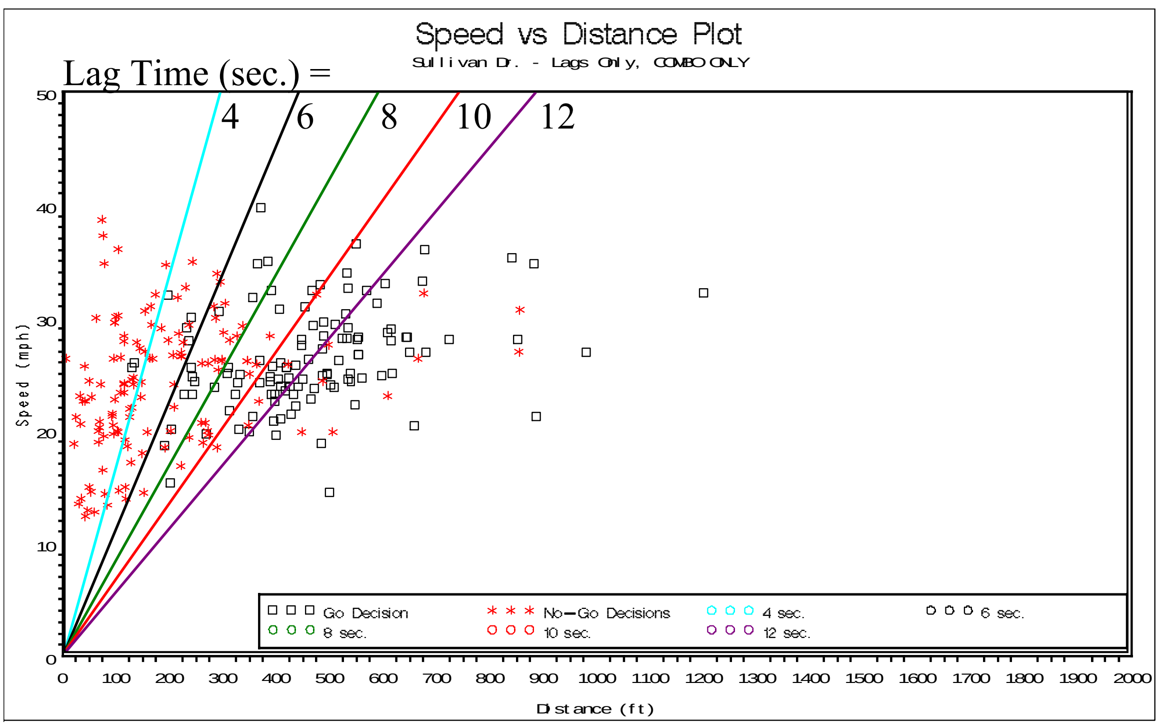
The plot indicates that virtually no GO events were associated with lags less than 4 seconds and that virtually no lags over 10 seconds resulted in a NOGO decision. In the traditional gap acceptance methods, the graphical and RR methods estimated critical lags of 6.4 and 7.4 seconds, which are consistent with Figure 37. Given the large number of lag events observed at this site, it is further possible to generate similar plots for near, far, and combo lags (Figure 38).



a) Near Side Lags Only



b) Far Side Lags Only



c) Combo Lags Only

Figure 38: Plot of GO and NOGO Events – MB-RAL – by Lag Type

The plots by event type in Figure 38 indicate that the GO/NOGO threshold for near side gaps seems to be somewhat lower than for far side gaps, with the cluster of GO events shifted further towards the 4-second lag line. Also, fewer near-side lags over 10 seconds resulted in a NOGO decision. For combo gaps, the threshold function appears to be less clearly defined, made evident by a significant overlap of GO and NOGO events.

5.6 Crossing Model Development for MB-RAL

The following section lays the groundwork for the development of predictive logistic models for the likelihood of a pedestrian GO decision at the MB-RAL site. After an initial analysis using multilinear regression methods, binary logistic regression techniques are applied. Consistent with the analysis of the MB-CLT site, the modeling approach distinguished between unrestricted and restricted models, which are further differentiated by gap and lag events.

5.6.1 Multilinear Regression Models

Table B-43 shows the resulting MLR models for lags at the MB-RAL site. The full model is sensitive to AST, PREV, PXW, TRIG, G_COMBO, DECEL, and SPEED_FT. Interestingly, this does not include the actual size of the lag, although it is implicitly accounted for through other continuous variables. In unrestricted model 2, the GO response is predicted as a function of AST, PXW, G_COMBO, DECEL, and SPEED_FT. The model has an adjusted R-Square of 0.60.

The restricted models were forced to include the expected lag variable as was done for the other site. When eliminating the other continuous variables, the effect of T_LAG is highly significant. Restricted model 2 predicts an increasing likelihood of GO with pedestrian assertiveness, the treatment installation and the lag size (adjusted R-Square is 0.68).

The analysis of gap events (Table B-44) shows significant effects for AST, NEAR, PLT, PXW, TRIG, and T_GAP in the full model. The resulting unrestricted model uses those same parameters in a model with good overall model fit (adjusted R-Square equals 0.78). When restricting the variables to those with application to microsimulation, the resulting model utilizes AST, NEAR, PLT, and T_GAP. With adjusted R-Square equal 0.76, the overall model fit of this model is only slightly worse than the best unrestricted model. Contrary to the MB-CLT site, the effect of pedestrian waiting does not appear to be significant here.

5.6.2 Binary Logit Models for MB-RAL

Lag Events

Table B-45 shows the binary logit models for the likelihood of GO in a lag for the MB-RAL site. Unrestricted model 1 minimizes the AIC statistic (107.523) and predicts an increasing likelihood of GO with pedestrian assertiveness and a longer observed lag time. The likelihood of GO is further decreased by a factor of 0.26 with the presence of multiple pedestrians. This variable has not shown up in other models thus far and suggests that pedestrians may exhibit more conservative crossing behavior when walking with another person. A group of pedestrians may be more likely to be involved in a conversation and may thus be less pressed for time in their decision to cross. This finding is also consistent with gap acceptance theory laid out in the Highway Capacity Manual (HCM 2000), which hypothesis an increase in critical gap size with an increase in the number of pedestrians waiting (although this increase occurs at group sizes much larger than what was observed here). The following equation and figure plot the probability functions for unrestricted model 1 as a function of observed lag time.

Equation 24: PCM - Mid-Block Lags, Unrestricted Model 1, MB-RAL

$$\text{logit}[P(GO=1) = -9.766 + 5.369\ AST - 1.348\ MUP + 1.089\ O\_LAG$$

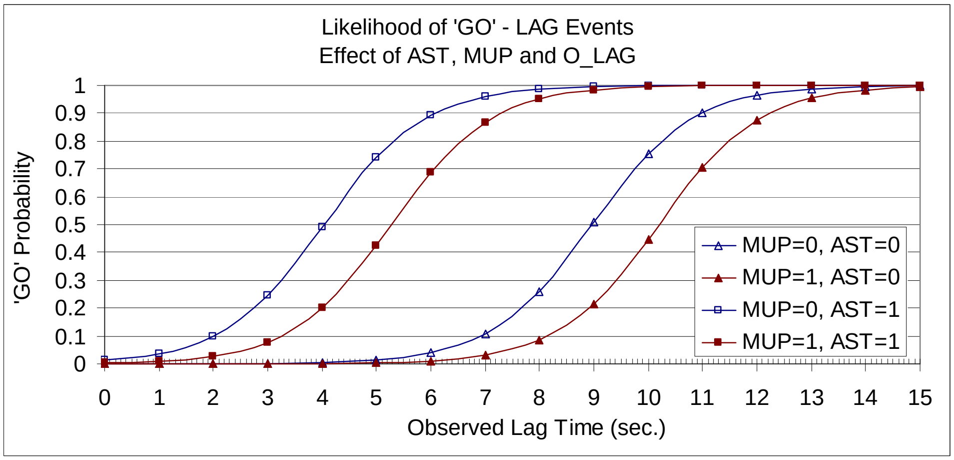


Figure 39: Model Probability Plot for Lags – Unrestricted Model 1 - MB-RAL

As expected, the figure shows an increase in the likelihood of GO with increasing lag time. Furthermore, pedestrian assertiveness significantly increases the likelihood of GO at a given lag size indicated by an overall shift of the probability distribution to the left. The presence of multiple pedestrians has the opposite effect, resulting in a shift to the right on the observed lag scale. Given similar lag and assertiveness characteristics, a group of pedestrians tends to wait for longer lags to cross.

Moving to the restricted models, all five alternatives shown in Table B-45 again have very similar overall model fit statistics. The selected model is therefore the one with the greatest practical application. Restricted model 2 predicts the likelihood of GO in a lag as a function of assertiveness, the location of the vehicle relative to the pedestrian (in the near or far lane), the presence of the treatment and the size of the conflicting lag. Compared to unrestricted model 1, the AIC is higher at 121.727. The probability plots in Figure 40 show a visual representation of the selected model for lags in the near and far lane.

Equation 25: PCM - Mid-Block Lags, Restricted Model 2, MB-RAL

logit[P(GO=1) = -10.215 + 6.019 AST + 0.642 NEAR + 0.786 TRTMT + 1.053 T_LAG

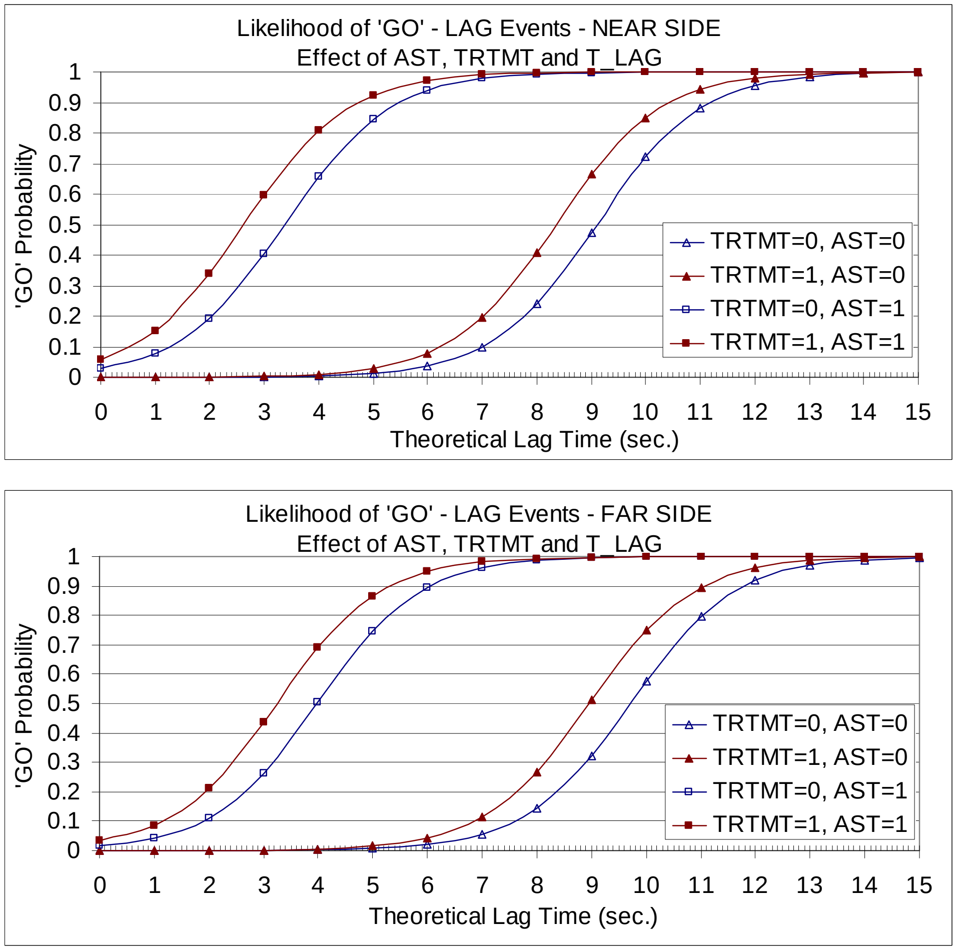


Figure 40: Model Probability Plot for Lags – Restricted Model 2 - MB-RAL

Figure 40 shows an increasing probability of GO with pedestrian assertiveness and with installation of the treatment. Similar to the observations at the MB-CLT site, the curves for near side crossings are shifted to the left relative to far side crossings, indicating lower GO thresholds for near-side lags. Even with a slightly higher AIC statistic compared to unrestricted model 1, the max-rescaled R-Square for restricted model 2 is still high at 0.9198, indicating very good overall model fit.

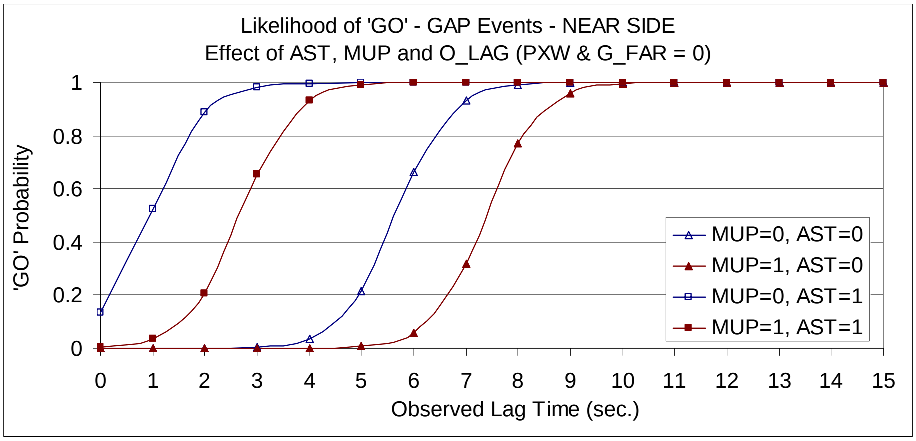
While the multilinear models did not reveal the effect of the treatment, the logistic regression results clearly show a shift of the probability curve to the left. This supports the notion that arose at the MB-CLT site showing that pedestrians were more willing to accept shorter lags after the treatment was installed. Therefore, while the treatment was effective in promoting driver yielding, as shown in the previous chapter, it also led to more assertive pedestrian behavior. This might be attributable to a sense of entitlement that leads pedestrians to alter their decision after they get visual confirmation that they in fact have the right-of-way. A similar effect was observed in previous research, where the introduction of zebra striping at a mid-block crosswalk actually led to an increase in collisions over the base unmarked case (Zeeger et al. 2001).

Gap Events

The logistic models for the likelihood of GO in a gap for the MB-RAL site are shown in Table B-46. The equation and probability plots for unrestricted model 1 are given below:

Equation 26: PCM - Mid-Block Gaps, Unrestricted Model 1, MB-RAL

$$\text{logit}[P(Y=1) = -16.426 + 9.308AST - 3.415\,MUP + 5.246NEAR - 9.271\,PXW + 3.997\,G\_FAR + 1.975\,T\_GAP$$



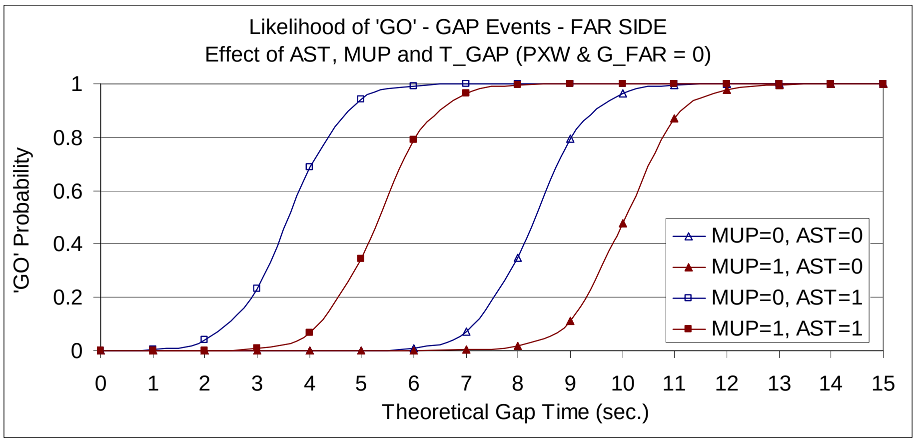


Figure 41: Model Probability Plot for Gaps – Unrestricted Model 1 - MB-RAL

Again, the plots above keep two of the parameters (PXW and G_FAR) fixed. Consistent with earlier models, the likelihood of a GO gap is increased by pedestrian assertiveness and a near-side gap, and is decreased for multiple pedestrians waiting at the crosswalks. With an extremely high model parameter, the effect of pedestrian assertiveness has a drastic effect on the likelihood of GO evident by the large shift in the figures.

The selected restricted model (Table B-46-f) uses variables AST, NEAR, and T_GAP in the following equation:

Equation 27: PCM - Mid-Block Gaps, Restricted Model 3, MB-RAL

$$\text{logit}[P(Y=1) = -10.938 + 5.268\ \text{AST} + 2.758\ \text{NEAR} + 1.335\ \text{T\_GAP}$$

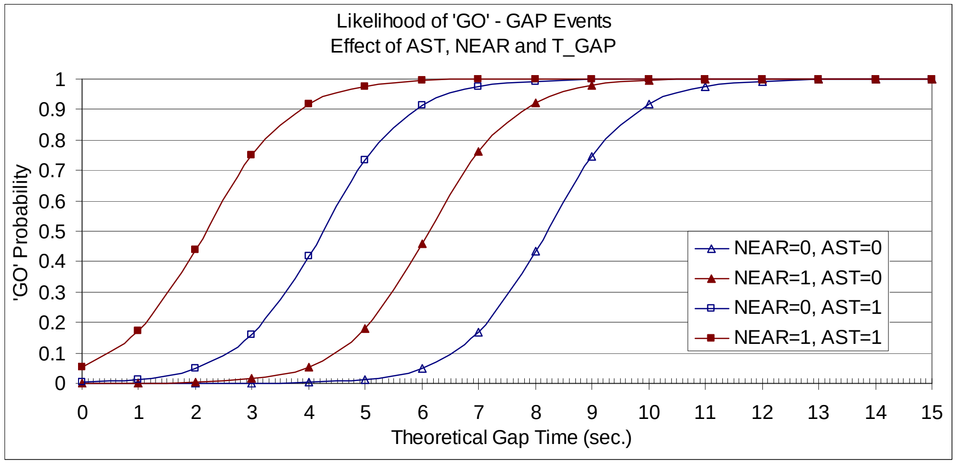


Figure 42: Model Probability Plot for Gaps – Restricted Model 3 - MB-RAL

The likelihood of a GO decision in a gap increases with pedestrian assertiveness, a near-side crossing, and longer expected gap times. This model also allows for a portion of assertive pedestrians to accept very short near-side gaps. With a 50th percentile GO gap of just over 2 seconds, there is some potential for pedestrian-vehicle conflicts. This model does not take into account the speed of the approaching vehicle. Presumably, this apparent 'risky' behavior would be less evident with a fast approaching vehicle.

Restricted model 3 has an AIC statistic of 55.096 and -2 log L of 47.096, which is significantly higher than the -2 log L for unrestricted model 1 (28.037, AIC=42.037). The max-rescaled R-Square statistics are high for both the unrestricted and restricted models at 0.9531 and 0.9175, respectively. While the restricted set of variables sacrifices some statistical power over the best-fit model, the restricted approach still results in a model that fits the data well.

5.6.3 Site Summary

The analysis of the MB-RAL crosswalk showed consistent sensitivity to the size of gaps and lags as would be expected from theory. Consistent with the MB-CLT site the pedestrian assertiveness variable is highly significant in explaining an increased likelihood of a GO decision. Many models also include the binary indicator of whether the approaching vehicle is in the near or far lane, with near-side gaps and lags generally being accepted at shorter lengths.

The effect of the treatment installation is inconsistent for this site and only shows up in a subset of the models. However, where it is included, it results in an increased likelihood of GO given the same gap/lag size, which is consistent with findings from the MB-CLT site. Again, the treatment intended to increase driver yielding results in pedestrians accepting shorter and presumable risky gaps and lags in traffic. Compared to the MB-CLT site, the variable D_WAIT did not show up as significant in any of the models. The likely reason for this is that the average waiting time at the MB-RAL site was very short, with most pedestrians being able to cross the road within just a few seconds. The high rate of GO lag events is also an indication that the majority of pedestrians were able to cross this facility without delay. This is not to say that these pedestrians would not have grown impatient (and lowered their crossing threshold) had they experienced greater delay. But, for the observed sample of gap crossings, the effect of waiting time is not significant.

Short of full validation of the logit models, the regression results can be compared to critical gap and lag estimates from the traditional analysis approaches. The graphical and RR methods estimated critical lags of 6.4 and 7.4 seconds, respectively. Through the logistic regression analysis of event-based interaction data, the likelihood of GO in a lag can be analyzed in light of additional variables. Restricted Model 2 predicts a 50% likelihood of GO in a near-side lag at a theoretical lag time of 9.1 seconds for a non-assertive pedestrian in the before case. After treatment installation, that 50% lag time is reduced to approximately 8.3 seconds, suggesting a significant impact of the treatment. For an assertive pedestrian the before and after 50% likelihood lag times are approximately 3.3 and 2.6 seconds, respectively. For a far-side lag all theoretical lag times are increased.

For the gaps analysis, the graphical, MLE, and RR methods estimated critical gaps of 4.8, 6.6, and 6.2 seconds, respectively. Restricted model 3 for the likelihood of GO in a gap at the MB-RAL site shows a 50% likelihood of GO of 8.2 seconds for a non-assertive pedestrian and a far-side gap (6.1 seconds for a near-side gap). The 50 percent GO likelihoods for an assertive pedestrian in a near and far gap are 2.2 and 4.2 seconds, respectively. The estimated averages of the traditional gap acceptance methods are within the range of predictions resulting from the logit models, giving confidence to that estimation approach.

5.7 Chapter Summary

The analysis of pedestrian crossing behavior at the two studied mid-block crosswalks showed the expected sensitivity of the pedestrian GO decision to the size of the encountered lags or gaps. This is consistent with conventional gap acceptance theory. The form of the logistic regression models expresses the pedestrian decision by a probability function that accounts for more variables than traditional gap acceptance approaches. The probabilistic nature of the model algorithm takes into account the heterogeneity of the pedestrian population.

The analysis further revealed that some observable characteristics of pedestrians and drivers can explain some of the apparent variability in the decision-making process. The pedestrian crossing models were generally very sensitive to pedestrian assertiveness. This particular variable was characterized by the walking pace of pedestrians *while approaching the crosswalk* and had a significant impact on gap and lag selection behavior. The models further indicated that pedestrians are willing to accept shorter lags and gaps relative to vehicles in the near lane, presumably because they clear the conflict zone more quickly.

Two pedestrian crossing treatments, a pedestrian-actuated in-pavement flashing beacon and an in-road pedestrian warning sign, were shown to impact pedestrian behavior. At both sites the respective treatment (or its activation) consistently resulted in a significant increase in the log odds of GO for both gap and lag events. Thus, a pedestrian was more likely to accept a shorter gap or lag in the after condition. Both treatments are intended to increase pedestrian visibility and make drivers aware of the crosswalk, but they also seem to affect pedestrian behavior. While the analysis in Chapter 4 demonstrated the effectiveness of the treatments in increasing the odds of drivers yielding, this chapter showed that they also increase the odds of a pedestrian GO decision.

The analysis of pedestrian waiting time appeared to have some impact on increasing the likelihood of GO at the MB-CLT site. However, the variable was confounded with the treatment variable and the effect therefore could not be isolated. At the MB-RAL site, no such impact was evident, which is explained by overall low waiting times. To further explore this relationship, future research should look at additional data at sites with some pedestrian delay present.

A comparison to the traditional gap acceptance estimation approaches showed that the logit models are generally in the range of gap and lag times. Evidently, the difference in these simpler approaches is that the logit analysis can account for more explanatory factors. While some of the traditional gap acceptance approaches can estimate a distribution of critical gaps and lags, they cannot discern what factors contribute to this variability. In fact, an attempt to quantify an effect of the pedestrian crossing treatments on gap acceptance behavior did not yield statistically significant results. By controlling for other factors such as pedestrian assertiveness and the difference between near and far-side gaps, the logit approach was able to show a statistically significant impact of the treatments on increasing the likelihood of a pedestrian GO decision.

6 YIELDING AND CROSSING AT ROUNDABOUTS

The previous two chapters dealt exclusively with driver and pedestrian behavior at unsignalized mid-block crosswalks. A similar interaction between the two road users can be observed at roundabout crossings. Modern roundabouts are becoming an increasingly common intersection control strategy in the United States with over 1,000 existing roundabouts registered at the time of this dissertation (Kittelson Associates, 2008). This chapter applies the same data collection and analysis methodology to these types of facilities.

6.1 Roundabout Crosswalks

Modern roundabouts have demonstrated safety benefits over stop-controlled intersections. Before and after collision statistics at intersections controlled by stop-signs later converted to roundabouts in North Carolina found a drastic reduction in crashes of 54% and 48% for low-speed and high speed sites after accounting for traffic flows (NCDOT, 2007). National research confirms those safety benefits for both single and multilane roundabouts (Rodegerdts et al, 2007).

Roundabouts are furthermore designed to enable safe pedestrian crossings. The Roundabout Informational Guide published by the Federal Highway Administration (FHWA, 2000) highlights the importance of safe pedestrian facilities. The deliberate reduction of vehicle speeds, the strategic placement of pedestrian crosswalks away from the circulating lane, and the use of splitter islands between the entry and exit leg of the roundabout, are intended to make these facilities safe to cross for pedestrians. Figure 43 adopted from the FHWA guide shows the proper design of a pedestrian crosswalk with the aforementioned pedestrian safety features highlighted by the author.

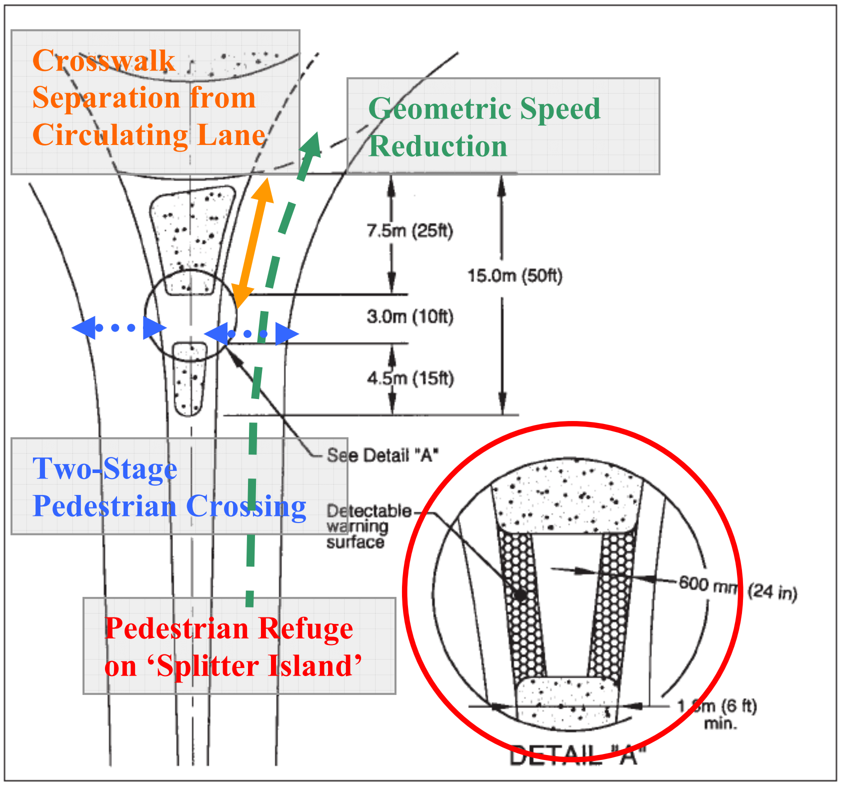


Figure 43: Roundabout Crosswalk Geometry (adopted from FHWA, 2000)*

While the FHWA Guide does not provide any methods for estimating pedestrian capacity or delay at roundabouts, it does account for the impact pedestrians have on the entering capacity. In a methodology borrowed from Brilon et al. (1993) higher pedestrian flows reduce the entering capacity by up to 20%. As with similar approaches in the Highway Capacity Manual, this method assumes that pedestrians have priority at marked crosswalks and that <u>all</u> drivers comply with this right-of-way rule.

A more recent analysis of operations at US roundabouts (NCHRP 3-65) found a range of yielding behavior by facility type. Driver yielding was observed most frequently at the entry lane of single-lane roundabouts (85%) and the lowest yielding rate was observed at the exit lane of two-lane roundabouts (38%). These findings support the general hypothesis in this research that yielding rates at unsignalized facilities is a behavioral parameter with large variability warranting a more detailed analysis. In terms of pedestrian behavior, NCHRP 3-65 found frequent running by pedestrians, especially on the last phase of the crossing (i.e. from the splitter island to the far curb). The same research further found that 17% of pedestrians crossed outside of the crosswalk at single-lane roundabouts (12% at two-lane facilities) and observed 4 conflicts in 760 pedestrian observations, corresponding to a rate of 0.5%. There is currently no ongoing research with sufficient data to enable the derivation of a pedestrian capacity procedure at roundabouts.

This chapter investigates pedestrian-driver interactions at a single-lane roundabout site in Raleigh, NC (RBT-RAL). While the data presented in this chapter is not statistically adequate to draw general conclusions on pedestrian facility performance at roundabouts, it provides a good baseline for further analysis by identifying the factors that are pertinent to the interaction at these types of facilities and suggests a methodology for accounting for those factors. .

6.2 Yielding Models for Roundabout Crossing

Previous studies consistently found higher yielding behavior at the entry leg of a modern roundabout. It can be surmised that entering drivers anticipate delay upon approaching the circle because of the yield control and therefore are more willing to accept additional delay by yielding to pedestrians. Exiting drivers on the other hand have effectively cleared the delay zone and may be less willing to stop once more for pedestrians. Yielding behavior was furthermore found to be influenced by pedestrian behavior, with assertive pedestrians prompting more yields.

In the analysis of yielding behavior, the difference between entry and exit yields will be accounted for, as will be the behavior of the pedestrian. Furthermore, the analysis includes an evaluation of the effect of a downstream conflict, which is expected to be more relevant at the entry leg to the roundabout. Subsequent vehicle arrivals are expected to yield at a higher rate, given that they expect delay. Other variable definitions for the roundabout models are consistent with the mid-block chapter models and can be referenced in the glossary.

6.2.1 Event Based Analysis

Descriptive Statistics

Using the same analysis methodology as was applied to the mid-block data, the RBT-RAL yielding data are first analyzed using SAS PROC MEANS. The resulting statistics are shown in Table 14.

Table 14: Descriptive Statistics for RBT-RAL Yield Data

	ALL DATA		ENTRY		EXIT		YIELDS		NON-YIELDS	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Sample Size	100	.	47	.	53	.	40	.	60	.
Response Variables										
YIELD	0.400	0.492	0.404	0.496	0.396	0.494	1.000	0.000	0.000	0.000
Y_ORDERED	1.570	0.769	1.574	0.773	1.566	0.772	2.425	0.501	1.000	0.000
Y_TYPE*	0.425	0.501	0.421	0.507	0.429	0.507	0.425	0.501	.	.
Binary Factors										
ADY	0.060	0.239	0.000	0.000	0.113	0.320	0.075	0.267	0.050	0.220
AST	0.190	0.394	0.128	0.337	0.245	0.434	0.200	0.405	0.183	0.390
COM	0.020	0.141	0.021	0.146	0.019	0.137	0.050	0.221	0.000	0.000
Decel_Tau	0.140	0.349	0.213	0.414	0.075	0.267	0.025	0.158	0.217	0.415
DSC	0.040	0.197	0.064	0.247	0.019	0.137	0.100	0.304	0.000	0.000
ENTRY	0.470	0.502	1.000	0.000	0.000	0.000	0.475	0.506	0.467	0.503
FOLL	0.520	0.502	0.532	0.504	0.509	0.505	0.625	0.490	0.450	0.502
HEV	0.060	0.239	0.000	0.000	0.113	0.320	0.100	0.304	0.033	0.181
MUP	0.180	0.386	0.128	0.337	0.226	0.423	0.200	0.405	0.167	0.376
NEAR	0.450	0.500	0.638	0.486	0.283	0.455	0.425	0.501	0.467	0.503
PLT	0.710	0.456	0.723	0.452	0.698	0.463	0.750	0.439	0.683	0.469
PREV	0.410	0.494	0.426	0.500	0.396	0.494	0.325	0.474	0.467	0.503
PXW	0.260	0.441	0.170	0.380	0.340	0.478	0.400	0.496	0.167	0.376
QUE	0.070	0.256	0.085	0.282	0.057	0.233	0.125	0.335	0.033	0.181
TRIG	0.020	0.141	0.043	0.204	0.000	0.000	0.000	0.000	0.033	0.181
TTC_TAU	0.350	0.479	0.447	0.503	0.264	0.445	0.200	0.405	0.450	0.502
Continous Factors										
DECEL	5.25	6.56	7.04	7.25	3.67	5.47	2.96	2.69	6.78	7.84
DIST1	105.36	72.56	117.54	85.80	94.56	57.08	115.29	69.02	98.73	74.65
SPEED_FT	24.20	8.78	30.25	7.83	18.85	5.51	21.45	9.22	26.04	8.04
TTC	4.69	3.31	3.76	2.54	5.51	3.69	5.72	3.64	4.00	2.89

* The Sample Size for Y_TYPE is only 40 observations, because it only considers HY and SY events

The data in the table indicate an overall yielding rate of 40% at the roundabout, with 42.5% considered to be hard yields. Of the 100 yield events observed, only 6% had an adjacent yield and only 4% had a downstream conflict. So while these variables have much practical significance, it appears they will not be useful in the model development phase due to the limited sample size at this particular roundabout. The average vehicle speed is 24.2 feet/sec (16.5 mph), with 71% of vehicles traveling in platoons and 7% of the events representing observations in slow moving queues. On the pedestrian side, 19% exhibited assertive behavior, 18% of the pedestrian events had multiple pedestrians present, 26% had a pedestrian still present in the crosswalk, and 2% actively triggered a yield.

Contrasting the entry and exit portions of the crosswalk, the overall yielding rates are not statistically different. Approximately the same rate of hard yields was observed for both sides of the crossing. The exit portion of the crossing shows higher pedestrian assertiveness and a lower likelihood of downstream conflicts. The average speed at the exit leg is significantly lower than at the entry leg, a direct result of roundabout geometry. Accordingly, the necessary deceleration rate at the exit leg is much lower than at the entry leg.

In comparing yield and non-yield events, pedestrian assertiveness did not vary between the two types. The same is true for the presence of an adjacent yield. Also unexpected was an inverse correlation between yielding and a yield trigger event, likely a result of low sample size as only two triggering events were recorded. The presence of a downstream conflict shows perfect correlation with the yield outcome. Yield events are expectedly associated with the presence of a prior pedestrian in the crosswalk, the presence of a vehicle queue, and statistically lower necessary deceleration rates and speeds.

Variable Interactions

A correlation analysis was performed using SAS PROC CORR (Table C-47). The dependent variable YIELD was found to be correlated with the presence of a downstream conflict, the presence of a prior pedestrian in the crosswalk, and the expected time to collision. An inverse correlation is evident for the two threshold parameters, the necessary deceleration rate and the speed of the vehicle.

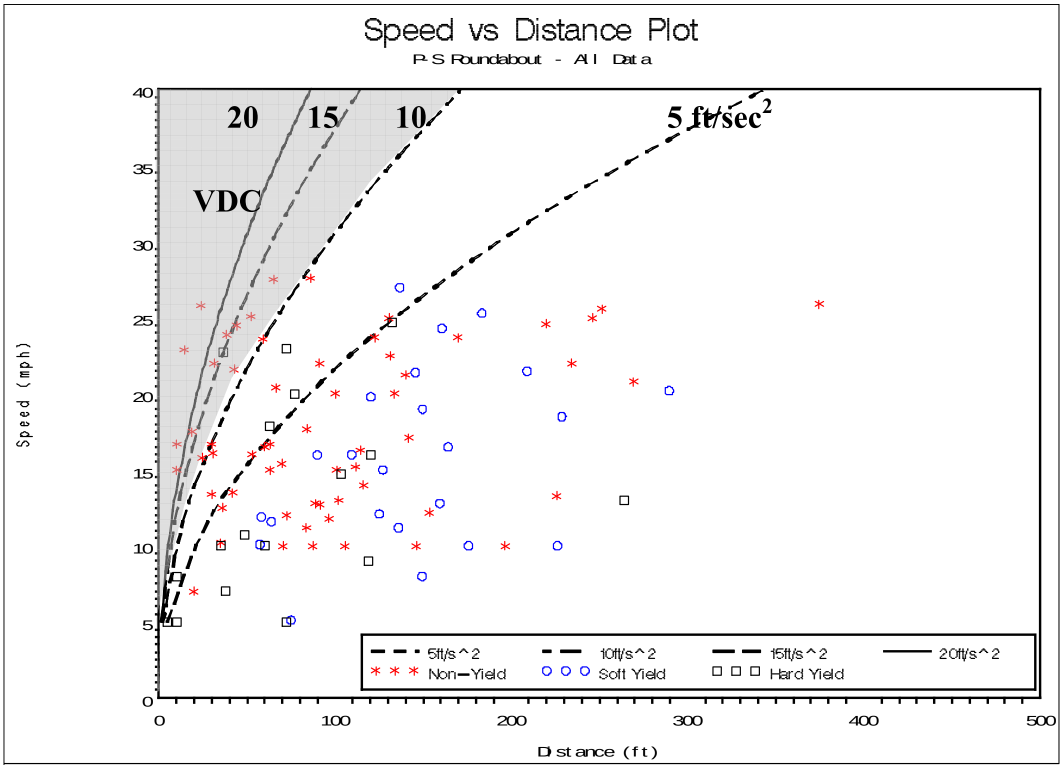
The ordered response variable shows the same relationships, with additional positive correlations for the presence of heavy vehicles and queue indicators. The Y_TYPE variable shows positive correlation with a downstream conflict, with higher necessary deceleration rate and with lower expected time to collision.

A separate analysis was performed for yield events at the entry versus exit (Tables C-48 and C-49). For yield events at the exit, only the presence of a pedestrian in the crosswalk and the time to collision variables show significant correlation. The entry leg yield data show stronger effects of deceleration rates, downstream conflicts, and vehicle speed.

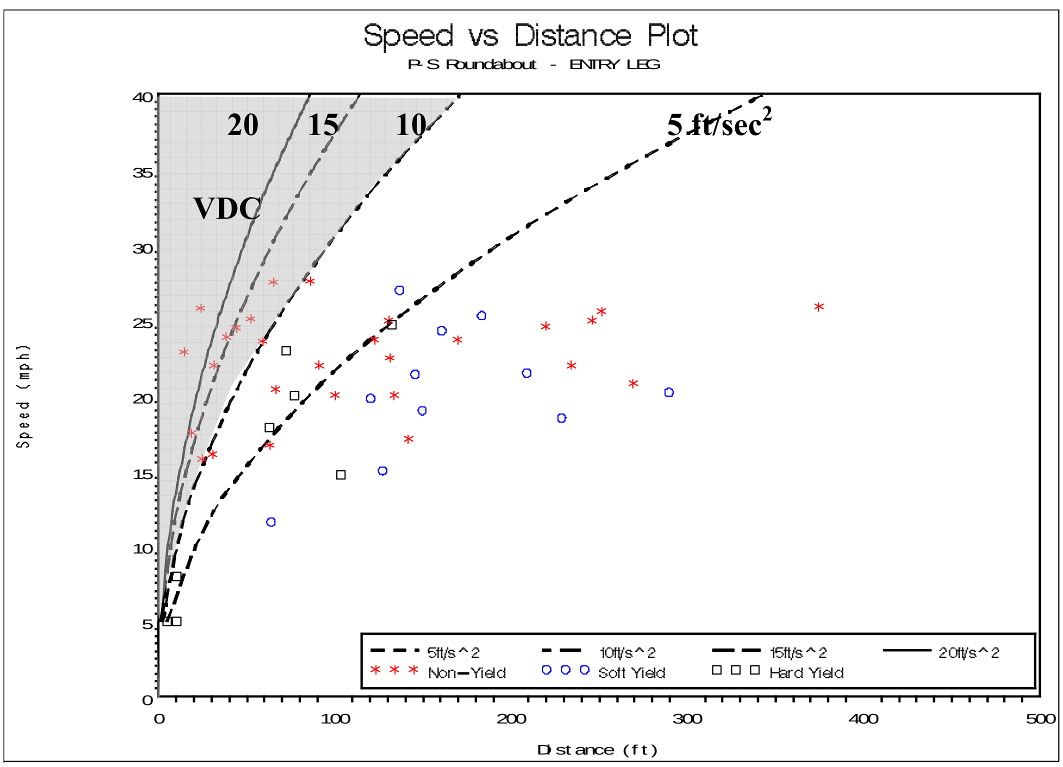
Vehicle Dynamics Constraints

The discussion of yielding behavior in Chapter 4 highlighted the impact of vehicle dynamics constraints (VDC) on the ability of drivers to yield. It was demonstrated that there is a threshold regarding yield occurrence that is sensitive to the deceleration rate necessary to come to a full stop in advance of the crosswalk. The discussion further hypothesized that this threshold approximately corresponds to a deceleration rate of 10 ft/sec^2, which is similar to the assumption used in timing the duration of the clearance interval at signalized intersections. The subsequent logistic regression assumed that no yielding is possible for those vehicle events that exceed this threshold. Subsequently, these observations were removed from the analysis data set.

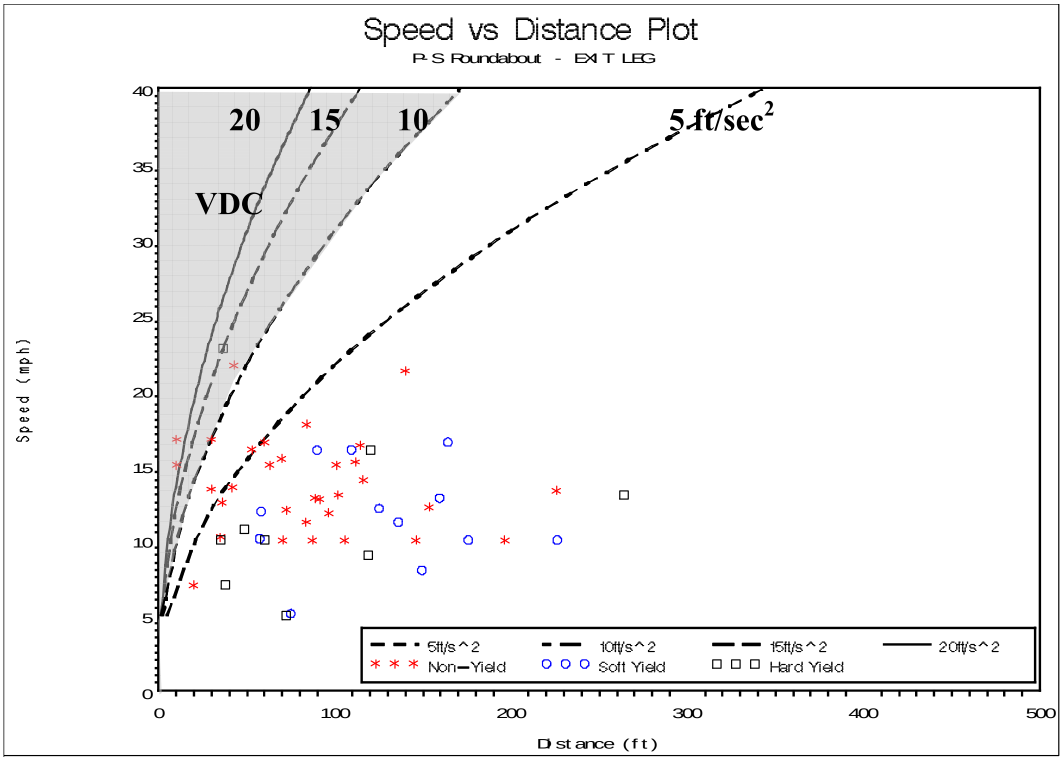
The corresponding VDC plot for RBT-RAL is given in Figure 44 for all observations (a) and for entry (b) and exit (c) events separately.


Speed vs Distance Plot
P-S Roundabout - All Data
20
15
10
5 ft/sec²
VDC
Speed (mph)
Distance (ft)
5ft/s^2
10ft/s^2
15ft/s^2
20ft/s^2
Non-Yield
Soft Yield
Hard Yield

a) All Data


Speed vs Distance Plot
P-S Roundabout - ENTRY LEG
20
15
10
5 ft/sec²
VDC
Speed (mph)
Distance (ft)
5ft/s^2
10ft/s^2
15ft/s^2
20ft/s^2
Non-Yield
Soft Yield
Hard Yield

b) Entry Leg



c) Exit Leg

Figure 44: Speed-Distance Plot with Decel. Thresholds, RBT-RAL

The data plots for RBT-RAL agree with the prior hypothesis with the exception of one event, where a vehicle yielded at a required rate of 15 ft/sec^2. This particular vehicle approached the exit leg of the crosswalk at a speed of 22.7 ft/s (15.5 mph) and was at a distance of 37 feet from the crosswalk when an assertive pedestrian arrived on the splitter island after crossing the entry leg. Additional data are needed to ascertain whether there is an empirical basis for a higher VDC threshold at roundabouts. In order to stay consistent with the analysis at the mid-block crossings, the same assumption for VDC was applied to the RBT-RAL data, effectively treating this one event as an outlier. The variable HEV did not show any associations with the predictor variables, and these vehicle types were therefore included in the general analysis. Queue presence events showed some correlation with yields at the exit lane, but the low sample size makes it hard to justify the inclusion of this effect. Accordingly, the seven observations which included vehicle queues were removed from the analysis.

6.2.2 Yield Model Development for RBT-RAL

The analysis of descriptive statistics and an evaluation of 2x2 interaction tables indicated sample size limitations for several of the independent variables. In particular, only two events were observed with COM=1, both of which resulted in a yield. Similarly, all 4 DSC=1 observations resulted in a yield, and both TRIG=1 events were associated with non-yields. In all three cases, the effect is a sparse 2x2 contingency table, which necessitates the exclusion of these variables as potential predictors from the logistic regression analysis. Furthermore, the sample size for variables describing a heavy vehicle (HEV) and the presence of a queue (QUE) only have 6 and 7 observations, respectively. After removing events with VDC = 1 and QUE = 1, the resulting data set contains 80 observations.

The RBT-RAL yield models were developed for all 80 events with the difference in entry (n=34) and exit yields (n=46) being accounted for through a binary indicator. Due to limited sample size, no separate models were tested for the two categories. The following analysis uses the full, unrestricted, and restricted models consistent with those developed in previous chapters.

Multilinear Regression Models

The analysis initially evaluates the effect of different independent variables in a multilinear regression approach (MLR). The resulting models are shown in Table C-50. In the full model, only the ENTRY variable has an overall significant effect on the response suggesting higher yielding at the entry leg (positive coefficient). In the development of the unrestricted model, the model contained significant effects for ENTRY, PXW, and SPEED_FT with an overall adjusted R-square of 0.14. In the second restricted model, a model with adjusted R-square of only 0.09 predicts the likelihood of yielding with variables ENTRY, DECEL, and SPEED_FT. The poor statistical fit of these models confirms the variability in yielding behavior observed at the roundabout site and further points to sample size limitations.

Binary Logit Models

In the binary logit approach (table C-51), the effect of ENTRY again appears in the full model, suggesting a higher likelihood of yielding at the roundabout entry leg. This effect drops out in the unrestricted model, which includes PXW as the only significant parameter. With an odds ratio of 3.2, the log odds of a yielding occurring increase 3.2 times with the presence of a prior pedestrian in the crosswalk. The max-rescaled R-Square statistic is only 0.0925. This model is clearly not useful as a predictor for yielding behavior and will therefore not be explored further.

The second restricted model predicts the likelihood of yielding as a function of ENTRY and DECEL with only the latter parameter estimate being significant at the given sample size. The model has a poor max-rescaled R-square fit of 0.0832. Restricted model 3 attempts to separate the two components of the DECEL variable and gives a three-variable model with ENTRY, DIST1, and SPEED_FT. This model generally fits the data better with a lower AIC criterion (107.338) and larger R-square (0.1543). However, the effect of DIST1 is not significant. Restricted model 4 only uses the effects of ENTRY and SPEED_FT. The model minimizes the AIC statistic at 106.002, but the slight difference in -2 log likelihood is not statistically better than restricted model 3 or the unrestricted model. The max-rescaled R-Square statistic is slightly lower than for restricted model 3 at 0.1444. Ultimately, restricted model 4 is selected as the best fit model because it minimizes the AIC statistic and has statistically significant parameter estimates.

With an odds ratio of 0.877, restricted model 4 predicts that an increase of 1ft/sec in vehicle speed reduces the odds of yielding by a factor of 0.877. An ENTRY event increases the odds of a yield 7.4 times. The effect of this seemingly large odds ratio for the ENTRY=1 is expected to be balanced out in the application of the model by the fact that the exit speeds at a roundabout are typically much lower than the entry speeds. Figure 45 shows the resulting probability plot of this model with corresponding equation 28.

Equation 28: DYM – Binary Logit, Restricted Model 4, RBT-RAL

$$\text{logit}[P(Y=1) = 1.9461 + 2.0222\ \text{ENTRY} - 0.1317\ \text{SPEED\_FT}$$

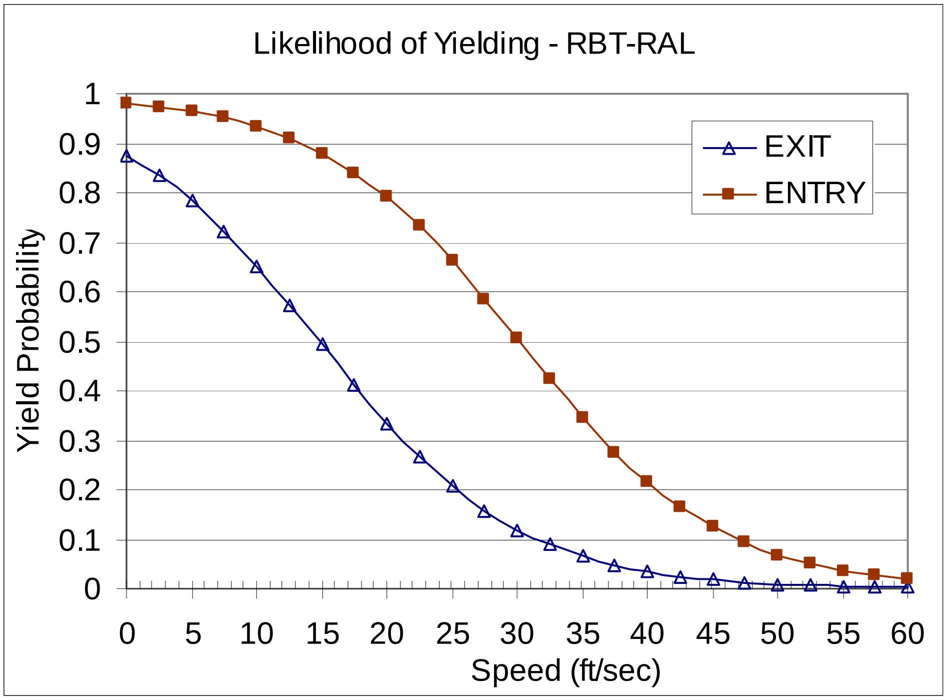


Figure 45: Yield Probability Plot, RBT-RAL - Restricted Model 4

The figure shows a base yielding rate of 87.5% and 98.1% at the exit and entry legs for zero speed. With increasing vehicle speed, the likelihood of yielding decreases. Virtually no vehicle is predicted to yield above 60ft/s, which would be an unrealistically high speed for this roundabout site. Vehicles at the entry are more likely to yield than those at the exit leg, but this difference is balanced by the difference in speeds between the two. Table 14 cited average speeds at entry and exit legs of 30.3 and 18.9 ft/sec, respectively. The corresponding yield probabilities for these speeds from the graph are approximately

50% and 37% for the entry and exit leg, respectively. These estimates are in the general range of the average observed yielding rates at the site, which were approximately 40% for both entry and exit leg. The effect of the ENTRY variable is consistent with previous research on roundabouts that generally found higher yielding rates at roundabout entry legs (NCHRP 3-65).

The parameters of the above model are intuitive, with the model predicting higher yielding at the entry leg and a lower likelihood of yielding with increasing vehicle speed. However, it surprisingly does not account for the effect of the vehicle distance from the crosswalk in an explicit (DIST1) or implicit form (DECEL). A possible explanation for this is that the geometric design of the roundabout generates a very specific speed distribution with drivers decelerating as they approach the circle. In a microsimulation implementation of this model that re-calculates the likelihood of yielding every time step, the same driver may in fact be more likely to yield as the vehicle moves closer to the crosswalk (and decelerates). This may explain the generally higher yielding rates at this compact urban roundabout compared to the mid-block crossings.

Other variables that were significant in the mid-block models, mainly pedestrian assertiveness and vehicle platooning, are not significant at the given sample size for the roundabout yield model.

Cumulative Logit Models

The cumulative logit model for ordered responses builds on the assumption that the three discrete event outcomes - non-yield, soft yield, and hard yield - can be ordered sequentially. The interpretation of the resulting model is more cumbersome than the binary model, but is worth exploring given the rather poor performance of the simpler models (see Table C-52).

The unrestricted model uses the forward selection algorithm with p=0.05 and results in a single-variable model with PXW. The parameter coefficient is negative, indicating that the presence of a prior pedestrian in the crosswalk increases the odds in the direction of the hard yield response. The proportional odds assumption was rejected at the 90% confidence level. Also, while statistically significant, the single-variable model has no practical significance for reasons consistent with the discussion of the binary models. The max-rescaled R-square for the model is poor at 0.0785 and the AIC statistic is 153.71.

In the development of a restricted cumulative logit model, restricted model 3 results in a reasonable two-variable model using ENTRY and SPEED_FT. The proportional odds assumption for this cumulative logit model yields a p-value of 0.9214 indicating that the model is valid. This suggests that the slope parameters for ENTRY and SPEED_FT were indeed shown to have the consistent effects on both levels of the yield response. The negative coefficient of ENTRY indicates increasing odds towards the hard yield response for the entry leg. Correspondingly, an increase in approaching speed decreases those odds, effectively making a non-yield more likely.

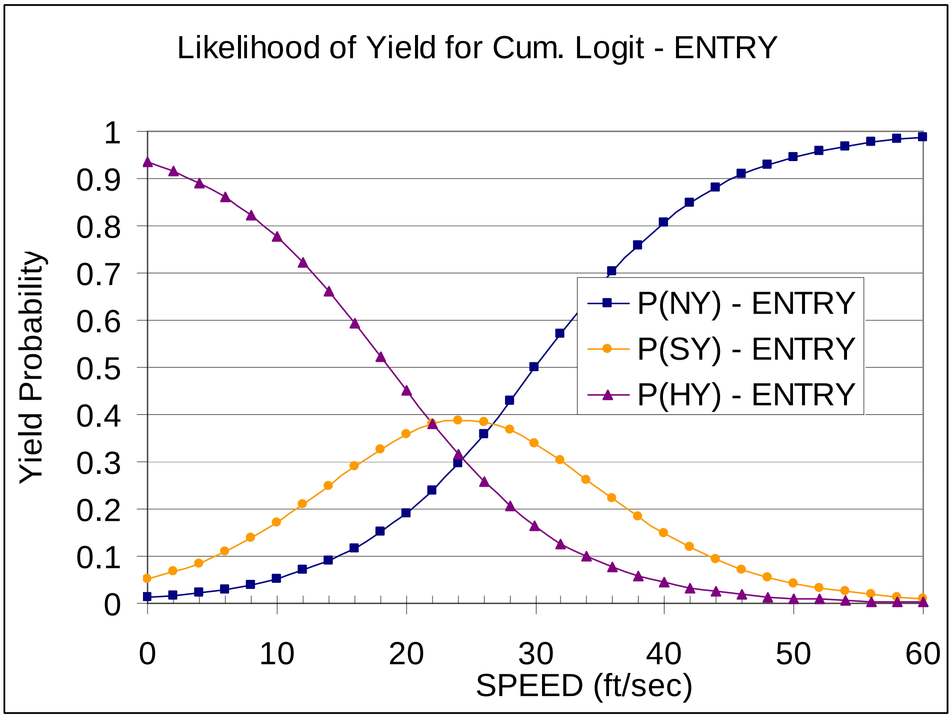
All parameters in the model except for INTERCEPT 2 are significant. The model has a max-rescaled R-Square of 0.1744 and minimizes the AIC statistics at 148.36. Unfortunately, the AIC statistic does not allow comparison among model forms, so it cannot be discerned if this model fits the data better than the binary logit model without some form of validation effort. Equation 29 describes the model.

Equation 29: DYM Cumulative Logit, Restricted Model 3, RBT-RAL

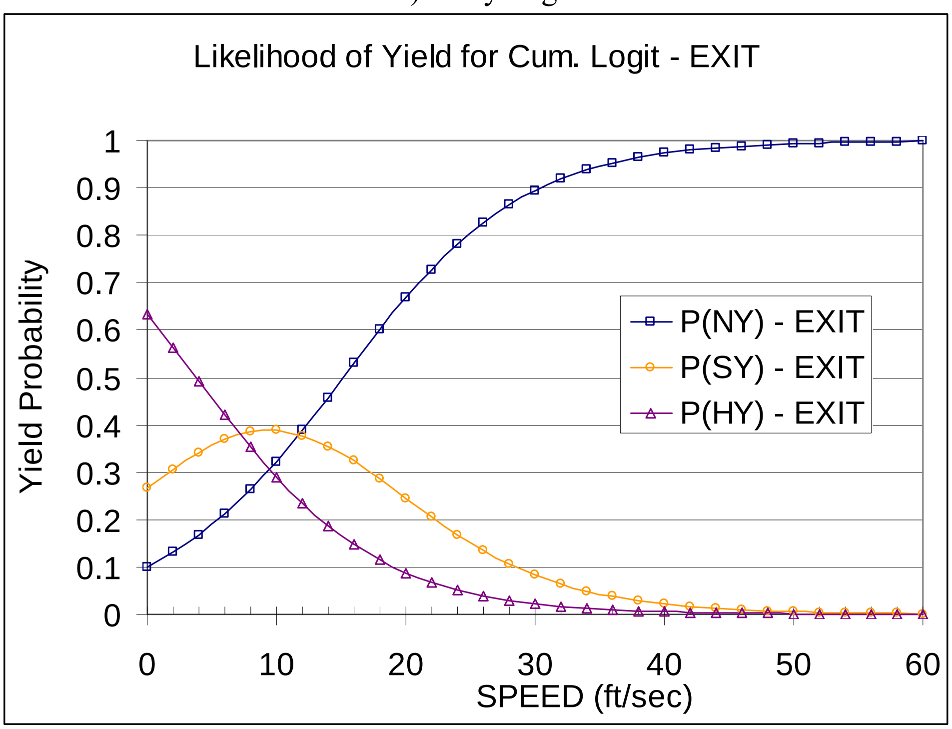
$$\text{Logit}[P(Y \leq 1)] = -2.1843 - 2.139\text{ENTRY} + 0.144\text{SPEED\_FT}$$

$$\text{Logit}[P(Y \leq 2)] = -0.5445 - 2.139\text{ENTRY} + 0.144\text{SPEED\_FT}$$

The predictions of the cumulative logit model can be converted to distinct probability estimates using equation 10 in the methodology chapter. Figure 46 shows the resulting probability plots for the likelihoods of NY, SY, and HY as a function of vehicle speed and entry versus exit crossing.



a) Entry Leg



b) Exit Leg

Figure 46: DYM Probability Plots for Cumulative Logit Restricted Model 3 - RBT-RAL

Figure 46-a contains three probability curves describing the likelihood of non-yield, soft yield and hard yield. The sum of the three probabilities always equals 1 at a constant speed. The figures show that hard yields are most likely to occur at low speeds. Soft yields are predicted to occur at intermediate speeds. Once the approaching vehicle speed is traveling above 30ft/sec, a non-yield becomes the most likely event outcome.

For the exit leg, all probability curves shift to the left towards lower speeds. Given the same approaching vehicle speed, the likelihood of HY and SY are thus higher at the entry than the exit leg. In interpreting the figures, it is important to point out that the sum of P(SY) and P(HY) is very close to the overall yield probability predicted in the binary logit model.

Multinomial Logit Models

Because the proportional odds assumption was not rejected in the cumulative logit model, there is no statistical reason to explore the more complex multinomial logit approach. However, for completeness Table C-53 presents the results for this model form. This approach does not assume an ordered nature of the response, thereby estimating the likelihood of the soft yield and hard yield outcomes separately and relative to the selected baseline, the non-yield event. The unrestricted model utilizes variables PXW and DIST1 and has significant parameters for both levels of Y_ORDERED. The odds ratio for the PXW effect is higher for Y_ORDERED =3, meaning that a previous pedestrian in the crosswalk has a stronger effect on the odds of a hard yield than of a soft yield. An increase in DIST 1 has a weak effect on an increase in the odds of a soft yield outcome, evident by a positive coefficient and an odds ratio close to 1.0. The negative coefficient for DIST1 at response level Y_ORDERED=3 suggests that the log odds of a hard yield decrease with greater vehicle distance from the crosswalk at the time of pedestrian arrival.

The final restricted model has higher AIC and SC information criteria than the unrestricted model but lower R-square estimates. It uses variables ENTRY and SPEED_FT, consistent with the selected restricted binary model. Interpreting the model, events taking place at the entry leg result in increased log odds of both soft yield and hard yield events, indicated by odds ratios greater than 1. With increasing vehicle speed, the odds of both yield types decrease.

Nested Logit Models

Given the reasonable fit of the cumulative and multinomial logit models, it is worth exploring the difference in soft yield and hard yield events further. The nested logit approach predicts the likelihood of yielding at two levels. In the first level, the overall likelihood of yield is predicted, which naturally coincides with the binary logit approach presented above. This section explores the second level of the nested approach. Assuming that a vehicle yields, the following model uses the response variable Y_TYPE and predict the likelihood of a hard yield occurring.

In the unrestricted model in Table C-54, the forward selection algorithm arrives at a single-variable model using DIST1. Consistent with the unrestricted multinomial model above, the likelihood of a hard yield (Y_TYPE=1) decreases with increasing distance of the vehicle from the crosswalk at the time of pedestrian arrival. With each additional foot, the log odds of a hard yield decrease by a factor of 0.964. This model makes intuitive sense in that a driver at a longer distance has more time before arriving at the crosswalk and therefore is more likely to slow down to a rolling yield. Although this model is in the unrestricted category, it actually has practical application and could readily be implemented in microsimulation using a decision function based on space headway.

The restricted models in the nested approach use only the continuous variables DECEL and SPEED_FT. The best model fit statistics are evident for restricted model 3, which uses both variables in a three-parameter model. The model fit is comparable (AIC =

30.028) and is slightly better than the unrestricted model (AIC = 31.186), but the difference in -2 log likelihood is not significant. The max-rescaled R-Square statistic is 0.6143, which is much larger than for the first-level nested model.

The log odds of a hard yield decrease with increasing vehicle speed and increase with greater DECEL rate. These trends are as hypothesized and consistent with earlier models. Even though the unrestricted model can theoretically be implemented in simulation, restricted model 3 (equation 30) is the better choice from a practical perspective, because it accounts for both distance and vehicle speed at the decision point. Figure 47 shows the likelihood of a hard yield as a function of DECEL and vehicle speed.

Equation 30: DYM – Nested Logit Level 2, Restricted Model 3, RBT-RAL

$$\text{logit}[P(HY=1) = 1.6143 + 1.9268\ DECEL - 0.3377\ SPEED\_FT$$

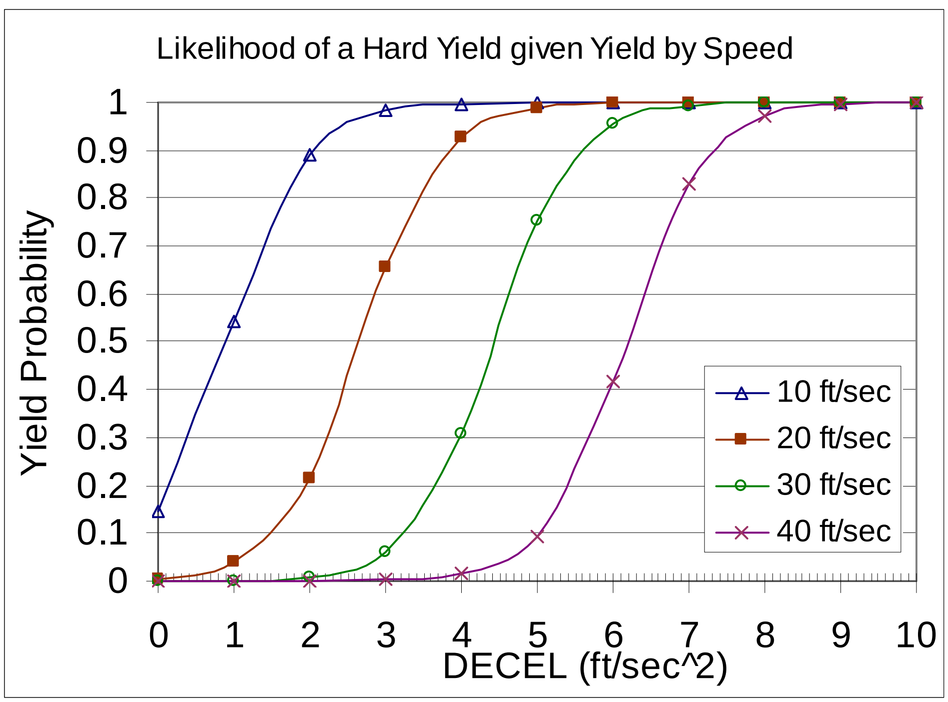


Figure 47: Yield Probability Plot, Nested Logit Level 2, Restricted Model 3 - RBT-RAL

In interpreting the plot, the likelihood of a hard yield is virtually zero for vehicles with DECEL rates approaching zero. These vehicles are far from the crosswalk and have ample time to simply slow down to a soft yield. In combination with the pedestrian crossing model, most pedestrians would likely accept the gaps or lags for these vehicles. With increasing DECEL rate, the odds of HY increase. An increase in vehicle speed shifts the probability curve to the right towards higher DECEL rates. At the same DECEL rate, faster vehicles are less likely to need to do a hard yield because they are effectively farther away from the crosswalk. For example, requiring a DECEL rate of 3 ft/sec^2 a vehicle traveling at 4 0ft/sec is effectively 267 feet from the crosswalk and its likelihood P(HY|Y) is basically zero. At the same DECEL rate, a vehicle traveling at 20 ft/sec is only 67 feet from the crosswalk and its P(HY|Y) is 65%. Another way to interpret this relationship is that a driver is more likely to yield hard at a lower time to collision. The two example vehicles described above imply that the vehicles would have arrived at the crosswalk in 5.6 and 3.3 seconds, respectively, if they maintained the initial speeds. The vehicle with the shorter time to collision is more likely to perform a hard yield when deciding to yield.

6.2.3 Yielding Model Summary

Despite sample size limitations, the models predicting driver yielding behavior at the RBT-RAL roundabout show a lot of promise for extension of this research approach in the future. While the model fit statistics are sub-optimal for the some of the resulting models, the parameter estimates are intuitive and result in the hypothesized effects.

Consistent with the yielding models for the mid-block crosswalk, the nested logit approach is the preferred approach for both statistical and practical reasons. While the more complex cumulative and multinomial logit approaches both result in valid models, the cumbersome application and interpretation of these models tilts the preference to the binary models. The nested logit is also preferred for reasons of consistency with the mid-block crossing models.

The two-level approach to initially predict the likelihood of yielding and then the likelihood of a hard yield given yield is intuitive and supported by the data. The overall yielding behavior is consistently predicted to be higher at the entry leg and associated with lower deceleration rates. Once a yield decision is made, the likelihood of a hard yield increases with the DECEL rate and decreases with speed for reasons discussed in the previous section.

6.3 Pedestrian Crossing Models at Roundabouts

6.3.1 Event Definitions

This section analyzes the event data collected at the Pullen-Stinson roundabout (RBT-RAL) for parameters describing pedestrian crossing behavior. Just as for the mid-block crosswalks, a pedestrian arriving at a roundabout crossing will judge when to cross based on the events associated with his/her arrival. Presumably, the most important predictor for these crossing events is the time amount of time until the next vehicle arrival, measured in the form of lags or gaps. However, other factors, including pedestrian assertiveness, the leg being crossed, and the presence of an approaching platoon of vehicles to name just a few, are believed to affect the decision-making process.

A roundabout crossing is inherently different from the mid-block crossing, because the design of the crosswalk physically separates the entry and the exit portion of the crossing as shown in Figure 43. The resulting two-stage crossing allows the pedestrian to cross one lane at a time, virtually independent from traffic conditions in the other lane.

For the purpose of this analysis, pedestrian crossing events are categorized into gaps and lags, by entry versus exit crossings, and by event outcome (GO vs. NOGO). The analysis further accounts for the difference in observed and expected gap and lag times. Given the proximity of the roundabout crossing to the circulating lane, a larger difference between these observed and expected gap/lag times is expected. At the roundabout, all vehicles are forced to slow down upon entering the circle and continue low speeds throughout the roundabout. Because of the geometrically prescribed slow speed profile in the roundabout, pedestrians may have come to anticipate a certain amount of deceleration by the approaching driver. In fact, pedestrians may base their crossing decision on this *anticipated* gap/lag accounting for some deceleration. The effect of these geometric speed constraints would most likely manifest itself in low expected critical gaps (relative to higher observed critical gaps).

The following section presents the results from the three traditional gap acceptance approaches.

6.3.2 Conventional Gap Acceptance Approaches

Graphical Method

The graphical method aims to quantify the critical gap and lag times for pedestrians from the intersection of the cumulative distributions of GO and NOGO decisions. Figure 48 shows the resulting plots for expected and observed gaps and lags for RBT-RAL. The critical gap and lag estimates are given in Table 15.

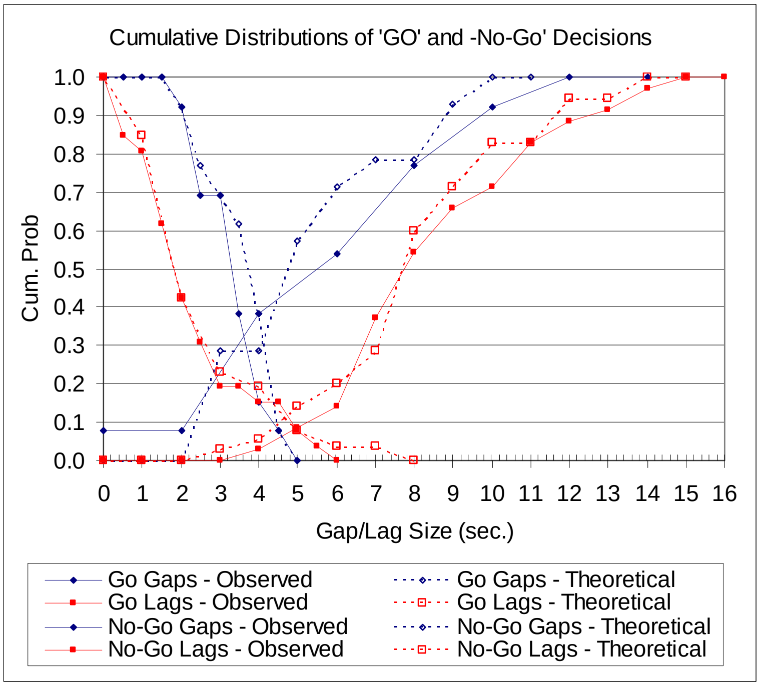


Figure 48: Graphical Method for RBT-RAL Pedestrian Data

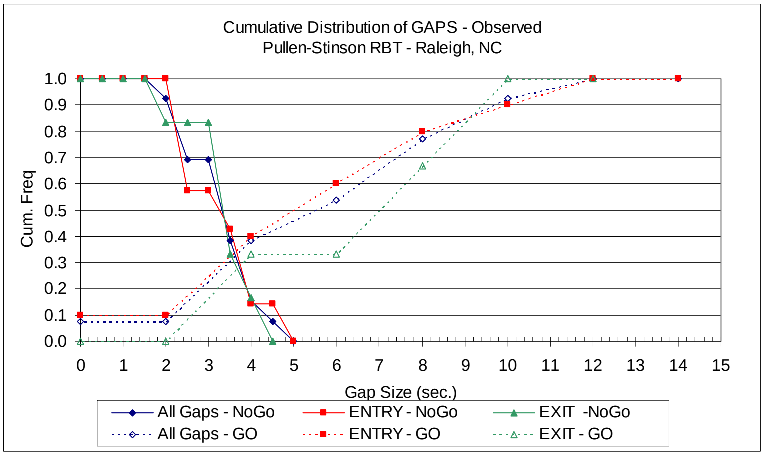
Table 15: Critical Gap/Lag Results - All Data

Event Type	Observed	Expected
Critical Gap (sec.)	3.6	4.2
Critical Lag (sec.)	5.0	4.7

The plots in Figure 48 make evident the impact of low sample size on the distributions. The cumulative distribution curves resemble a step function for bins with a low number of observations. Accordingly, the results in Table 15 are to be treated with caution and could shift significantly with more data. The crossing distance at the roundabout is approximately 16 feet, which corresponds to a crossing time of 4.6 seconds at a 3.5 ft/sec walking speed. This time is on the same scale as the expected critical gap and lag times estimated by the graphical method.

Consistent with observations at the mid-block sites, critical lags are higher than gaps because they include decision time in addition to actual crossing time. As hypothesized above, the expected critical lag is lower than the observed critical lag. Whether this difference is truly attributable to the pedestrians' anticipating a decelerating vehicle is hard to determine at this time. The observed and expected gaps show the opposite trend, underlining the importance of the sample size.

Figure 49 and Table 16 show a more detailed assessment of the data by entry and exit leg, but are also impacted by similar concerns for sample size.



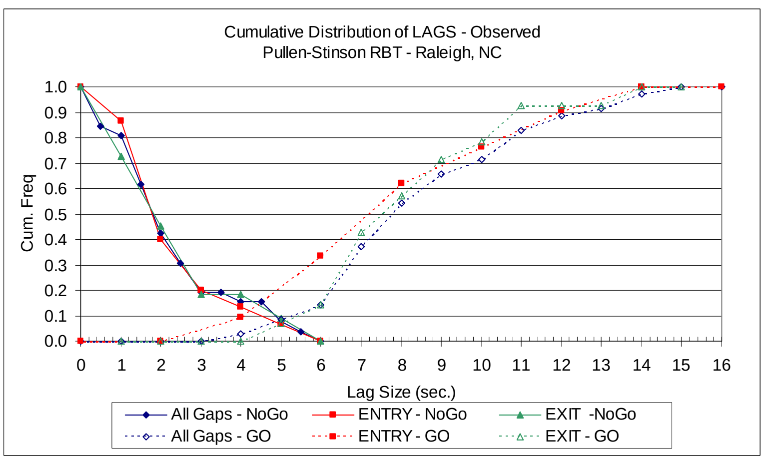


Figure 49: Graphical Method for RBT-RAL Pedestrian Data – by Entry/Exit Leg

Table 16: Critical Gap/Lag Results, Observed – by Entry/Exit

Event Type	All	Entry	Exit
Critical Gap (sec.)	3.6	3.6	3.7
Critical Lag (sec.)	5.0	4.2	5.1

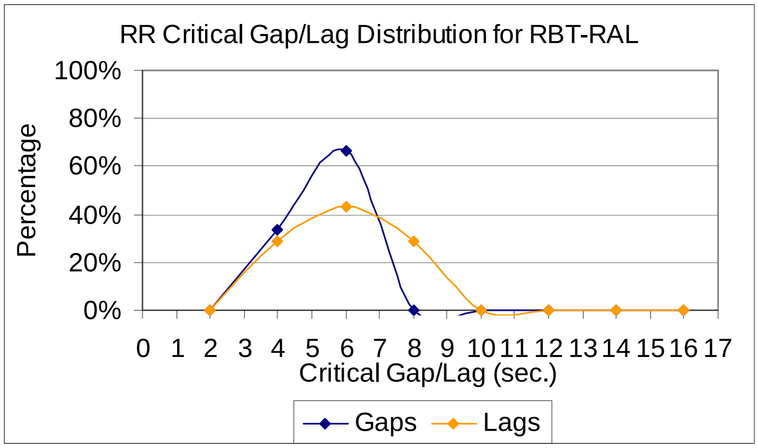
Maximum Likelihood Estimation

The critical gap estimation procedure by Troutbeck (2001) uses maximum likelihood estimation to estimate the population parameters of a normal distribution (mean and standard deviation) that maximize the likelihood of obtaining the given sample of observations. Just as for the graphical method, sample size concerns place a limitation on the results obtained in this section. Troutbeck's methodology uses pairs of largest rejected and accepted gap for the same subject. The methodology by definition is not applicable to the analysis of lag events, because the same subject cannot accept and reject a lag in a strictly observational study.

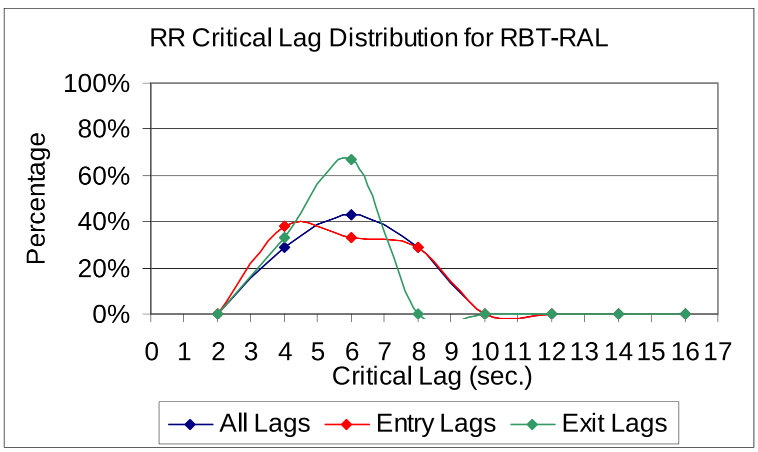
The RBT-RAL data set only contained four true pairs of gap observations (3 Entry and 1 Exit), which is too low a sample to apply the procedure.

Ramsey-Routledge Method

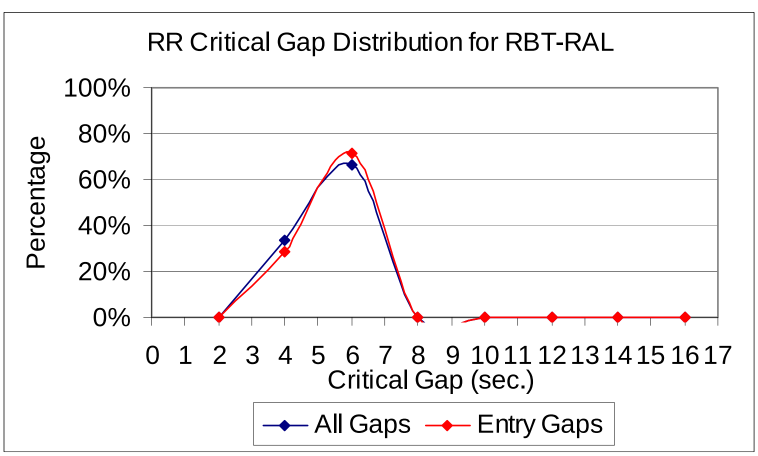
In the Ramsey-Routledge procedure, the distribution of critical gaps or lags is calculated independent of any assumptions regarding the shape of the distribution. The procedure is able to work with a larger sample size than MLE, because it uses the frequency distributions of GO and NOGO decisions and is not limited to paired data. The results shown in Figure 50 and summarized in Table 17 show distributions and mean estimates for all categories except for the critical gap at the exit leg because of low sample size.



a) Gap and Lag Comparison – All Data



b) Lag Comparison



c) Gap Comparison

Figure 50: Gap/Lag Distribution from RR Methodology for RBT-RAL

Table 17: Summary of RR Results for RBT-RAL

	Critical Gap (sec.)			Critical Lag (sec.)		
	Mean	**SD**	**n**	**Mean**	**SD**	**n**
All Data	5.33	2.35	12	6.00	2.53	35
Entry	5.42	2.36	9	5.81	2.50	21
Exit	.	.	.	6.57	2.59	14

The results above consistently show a lower critical gap than the critical lag. Also evident is a lower critical lag time for the entry than for the exit crossing. However, these numbers need to be interpreted with caution because of the very low sample sizes. While the RR method was able to arrive at an estimate, the recommended sample size for 2-second gap/lag bins is 100 according to ITE (2000). Accordingly, the gap and lag distributions may shift significantly with greater sample size.

Summary of Traditional Methods

Table 18 summarizes the findings from all three methods for the roundabout site.

Table 18: Summary Comparison of Gap Acceptance Approaches for RBT-RAL

	Critical Gap (sec.)	Critical Lag (sec.)
Graphical Method	3.6	5.0
MLE Method	.	.
RR Method	5.3	6.0

(.) No estimate possible due to low sample size

The table shows lower critical values for gaps than lags for the graphical and RR methods, which is explained by additional pedestrian decision time that is included in lags. The underlying assumptions of the maximum likelihood estimation method resulted in too low a sample size to arrive at an estimate. In comparison to the mid-block sites, the critical gap and lag times are intuitively lower for this two-stage crossing. While the graphical and RR methods were able to arrive at estimates for critical gap and lag times, the results need to be interpreted with caution due to the generally low sample size of observations.

6.3.3 Event-Based Analysis

The application of the traditional gap acceptance models to the RBT-RAL data estimated critical gap and critical lag values for overall pedestrian behavior as well as separated by entry and exit leg crossings. All methods yielded differences between gaps and lags, and between entry and exit legs that were not statistically significant for the given sample size.

In the following event-based analysis approach, observations at the entry and exit leg can be combined into one model by introducing a binary indicator variable. While additional data collection would be desirable, the given sample appears to be sufficient for applying the proposed logistic regression concept to the pedestrian crossing behavior at the roundabout crossing.

Descriptive Statistics

The observations of pedestrian crossing behavior were analyzed in SAS PROC MEANS to identify general trends in the data (Table 19).

Table 19: Descriptive Statistics for Pedestrian Crossing Model - RBT-RAL

	ALL DATA		GO		NO_GO		GAPS		LAGS		EXIT		ENTRY	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Sample Size	88	.	49	.	39	.	27	.	61	.	35	.	53	.
Response Variables														
GO	0.557	0.500	1.000	0.000	0.000	0.000	0.519	0.509	0.574	0.499	0.514	0.507	0.585	0.497
NO_GO	0.443	0.500	0.000	0.000	1.000	0.000	0.481	0.509	0.426	0.499	0.486	0.507	0.415	0.497
LAG	0.693	0.464	0.714	0.456	0.667	0.478	0.000	0.000	1.000	0.000	0.714	0.458	0.679	0.471
Binary Factors														
ADY	0.057	0.233	0.102	0.306	0.000	0.000	0.037	0.192	0.066	0.250	0.143	0.355	0.000	0.000
AST	0.307	0.464	0.510	0.505	0.051	0.223	0.222	0.424	0.344	0.479	0.257	0.443	0.340	0.478
FOLL	0.455	0.501	0.408	0.497	0.513	0.506	0.481	0.509	0.443	0.501	0.486	0.507	0.434	0.500
HEV	0.045	0.209	0.061	0.242	0.026	0.160	0.000	0.000	0.066	0.250	0.114	0.323	0.000	0.000
MUP	0.159	0.368	0.143	0.354	0.179	0.389	0.259	0.447	0.115	0.321	0.200	0.406	0.132	0.342
NEAR	0.648	0.480	0.592	0.497	0.718	0.456	0.741	0.447	0.607	0.493	0.514	0.507	0.736	0.445
PLT	0.568	0.498	0.408	0.497	0.769	0.427	0.667	0.480	0.525	0.504	0.600	0.497	0.547	0.503
PREV	0.432	0.498	0.327	0.474	0.564	0.502	0.889	0.320	0.230	0.424	0.457	0.505	0.415	0.497
PXW	0.057	0.233	0.082	0.277	0.026	0.160	0.037	0.192	0.066	0.250	0.057	0.236	0.057	0.233
QUE	0.023	0.150	0.000	0.000	0.051	0.223	0.000	0.000	0.033	0.180	0.029	0.169	0.019	0.137
TRIG	0.068	0.254	0.102	0.306	0.026	0.160	0.037	0.192	0.082	0.277	0.057	0.236	0.075	0.267
Continous Factors														
DECEL	4.404	6.390	1.748	0.817	7.741	8.492	2.006	1.151	5.465	7.409	3.476	6.245	5.017	6.469
DIST1	200.610	153.610	280.684	148.214	100.004	87.284	255.889	147.622	176.142	150.954	127.404	82.242	248.953	170.489
D_WAIT	1.387	2.909	1.348	3.129	1.437	2.646	4.521	3.688	0.000	0.000	1.441	3.212	1.352	2.722
O_GAP*	4.870	3.311	6.524	3.885	3.090	0.883	4.870	3.311	.	.	4.160	3.571	5.288	3.184
T_GAP*	4.688	2.478	6.262	2.424	2.992	0.965	4.688	2.478	.	.	4.565	2.598	4.760	2.483
O_LAG*	6.261	4.227	9.328	2.649	2.132	1.564	.	.	6.261	4.227	5.929	4.001	6.491	4.419
T_LAG*	6.097	4.026	8.931	2.644	2.281	1.735	.	.	6.097	4.026	5.749	3.387	6.338	4.448
SPEED_FT	28.106	8.784	29.556	8.934	26.285	8.350	28.844	8.572	27.780	8.927	19.248	5.118	33.956	4.926

*** Sample Sizes for these variables are lower because they only include the gap/lag events observed in each category**

The results show that of 88 observations, 56% resulted in a GO decision and 69% were categorized as lags (first events). For GO decisions, 51% of pedestrians were characterized as 'assertive' compared with only 5% for the NOGO decisions. The NOGO event outcome also seems associated with more vehicle platoons and significantly higher necessary deceleration rate. As expected, the gap and lag time measurements are significantly different for GO and NOGO outcomes.

Comparing gap and lag events, approximately the same percentage of events resulted in GO and NOGO decisions, but overall, much fewer gap events were observed. Gap events show a higher deceleration rate. The average speeds of the two event types are not significantly different.

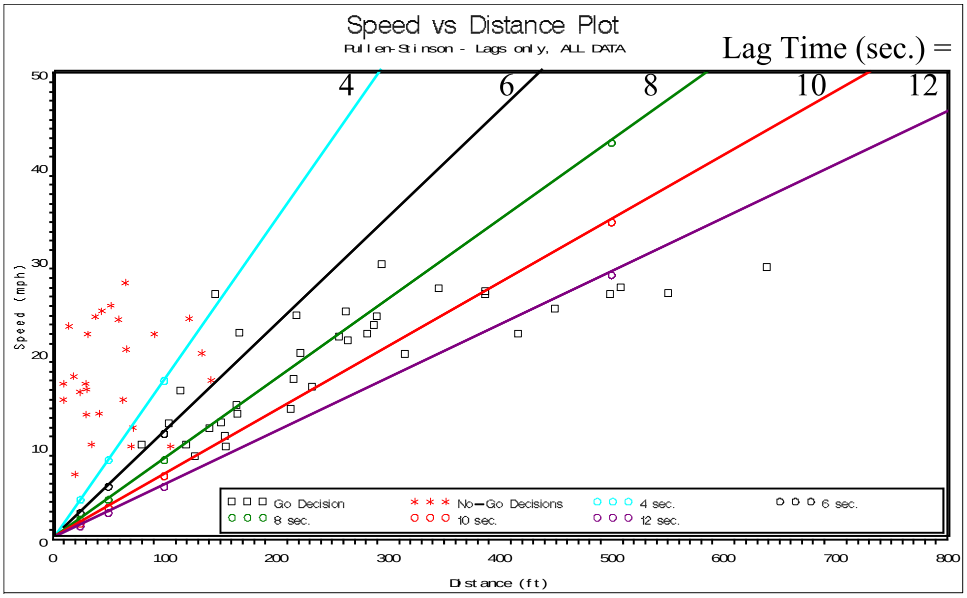
Events at the entry and exit leg show similar distributions of GO and NOGO outcomes and the percentage of lag observations. No adjacent yields and no heavy vehicles were observed at the entry leg. The average approach speeds are expectedly higher at the entry leg, resulting in higher average necessary deceleration rates.

Variable Interactions

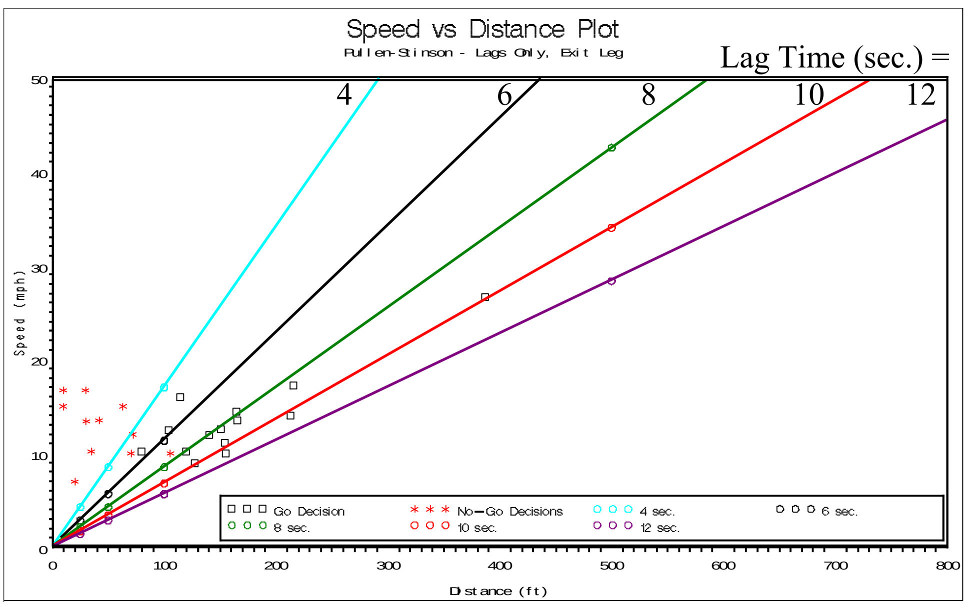
Correlation coefficients for the RBT-RAL data for lags and gaps are given in Tables C-55 and C-56. The GO response for lags is associated with pedestrian assertiveness, deceleration rate and the duration of the lag. The GO response for gap events is associated with similar variables, as well as vehicle platoons, and a previous non-yield.

Exploratory Analysis for Pedestrian Lags

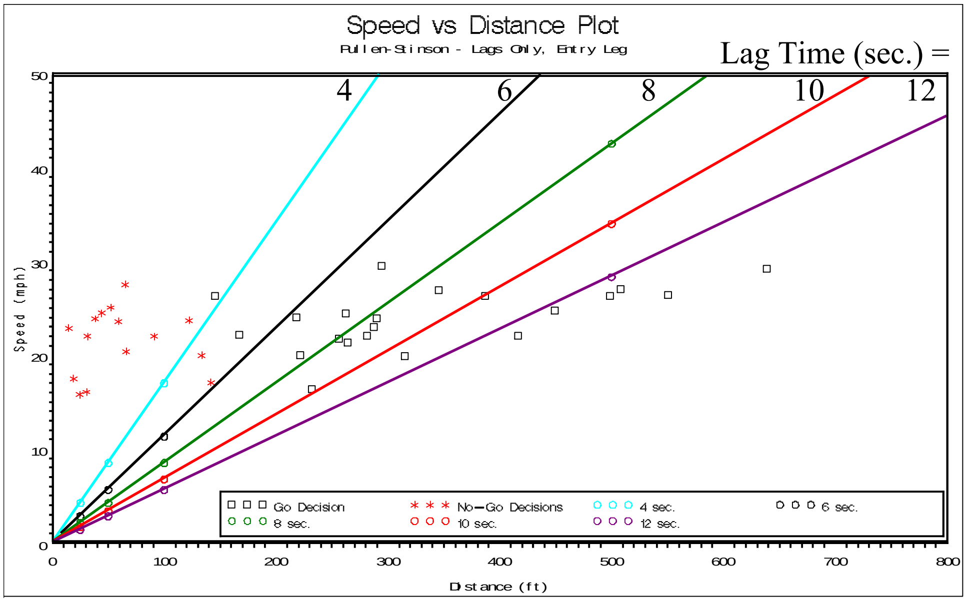
The analysis is intended to visually assess the critical lag threshold, as was introduced in Chapter 5. Figure 51 shows the corresponding plots for all pedestrian crossing lag events collected at the roundabouts, as well as, divided by observations at the entry and exit leg.



a) All Data



b) Exit Leg Only



c) Entry Leg Only

Figure 51: Exploratory Analysis of Lags for RBT-RAL

Figure 51-a shows that one GO decision was observed above an expected lag of 4 seconds, with four additional GO decisions between 4 and 6 seconds. Similarly one NOGO decision was observed at a expected lag more than 6 seconds, and four NOGO events between 4 and 6 seconds. The majority of GO and NOGO events are above 6 seconds and below 4 seconds, respectively. As expected, the expected lag threshold line is lower than what was observed at the mid-block crossings, presumably because of a lower crossing time necessary for each leg in the two-stage crossing. Dividing the data into events at the exit and entry leg shows similar patterns, although exit observations are generally at lower speeds.

6.3.4 Crossing Model Development for RBT-RAL

Multilinear Regression Models

The multilinear regression is an extension of the correlation analysis, which gives the analyst a sense of the general responsiveness of a regression model to the data, prior to applying the actual logit models. Table C-57 gives the model results for lags and C-58 gives results for the gap data collected at the roundabout.

The full model for predicting the likelihood of GO for lag events shows significant effects of AST and O_LAG. Narrowing down the field of variables based on regression fit, the unrestricted model uses the four variables AST, NEAR, PREV and O_LAG with an adjusted R-square of 0.79. By limiting the variables to those with practical application, restricted model 2 still has an adjusted R-square of 0.74 with variables AST, NEAR, and T_LAG. Despite sample size limitations in the traditional gap acceptance approaches, these early regression models show a lot of promise for the subsequent logit analysis.

The full linear model for GO decisions in gaps shows significant effects of AST, NEAR and PLT. Unrestricted model 2 uses variables AST, NEAR, PLT and O_GAP at an adjusted R-square value of 0.74. In restricted model 2, the likelihood of GO in a gap is increased by pedestrian assertiveness, an event at the entry leg and increasing expected gap size. The arrival of a platoon of vehicles decreases the likelihood of GO.

Binary Logit Models

The multilinear regression approach ignores the categorical nature of the dependent variable. The logistic regression approach presented in this section is adequate for predicting the binary response. Other categorical models, including cumulative, multinomial or nested logit models do not apply to this variable.

Lag Events

Table C-59 shows the logistic regression results of the likelihood of GO for lag events at the roundabout. The unrestricted model utilizing the observed lag time predicts a large increase in the likelihood of GO with pedestrian assertiveness and lag size. The model has a very high max-rescaled R-Square of 0.9803 and an AIC of 9.403. The model shows a large negative intercept and correspondingly large odds ratios that make interpretation difficult. A more practical model is given in restricted model 2, which uses the expected lag time along with pedestrian assertiveness. The model has a worse AIC statistic of 21.240 indicating that the overall model fit is statistically worse than the unrestricted model. However, with a max-rescaled R-Square value of 0.9026 the model still provides a reasonable overall fit for the data. The log odds of GO increase by a factor of 3.6 for each one-second increase in lag time. Furthermore, an assertive pedestrian increases the odds of GO by a factor of 22.1. The resulting probability plot in Figure 52 uses equation 31.

Equation 31: PCM - Restricted Model 2 - RBT-RAL - Lags

$$\text{logit}[P(GO=1) = -7.6989 + 3.0943\ AST + 1.2723\ T\_LAG$$

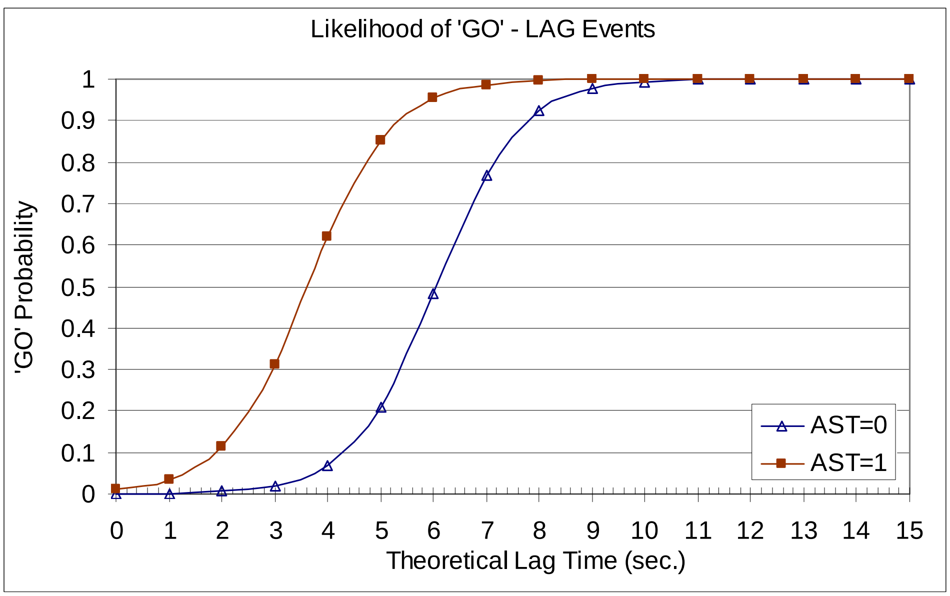


Figure 52: Probability Plot for P(GO) in a Lag – Restricted Model 2 - RBT-RAL

The figure shows an increasing likelihood of GO as a function of the expected lag time. The 50th percentile GO lag is at just over 6.0 seconds for a non-assertive pedestrian. For an assertive pedestrian the entire curve shifts to the left towards lower lag sizes. Accordingly, the 50th percentile GO lag for an assertive pedestrian is 3.6 seconds. For comparison, the critical lag values predicted by the three traditional methods ranged between 5 and 6 seconds.

Gap Events

The binary logit models for gap events are shown in Table C-60. Unrestricted model 2 predicts the likelihood of GO in a gap as a function of FOLL, D_WAIT, and O_GAP. The presence of a close follower is conceptually similar to the presence of vehicle platoons. With a close follower, it was hypothesized initially that a vehicle would be less likely to yield in fear of a potential rear-end collision. The model here suggests that this variable also has an effect on pedestrian behavior, reducing the likelihood of GO with an odds ratio of 0.009. This model further includes pedestrian waiting time as a significant variable. With increasing waiting time, the log odds of a pedestrian GO decision increase by a factor of 2.14 for each one second in pedestrian delay. The odds of GO also increase by a factor of 4.58 for each one second increase in the size of the observed gap. The model has an AIC statistic of 22.631 and a max-rescaled R-Square of 0.7598. The model equation 32 is represented graphically in Figure 53.

Equation 32: PCM - Unrestricted Model 2 - RBT-RAL - Gaps

$$\text{logit}[P(GO=1) = -8.0971 - 4.6675\ FOLL + 0.7599\ D\_WAIT + 1.5208\ O\_GAP$$

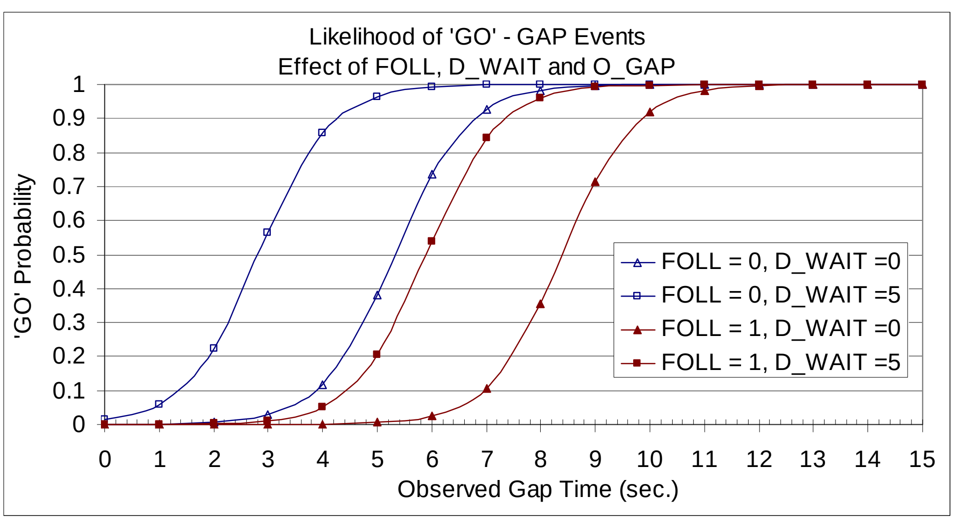


Figure 53: Probability Plots Gaps, Unrestricted Model 2, RBT-RAL - Gaps

The probability plots in Figure 53 show that in the presence of a vehicle with a close follower, the likelihood of GO shifts to the right towards higher lag times. With increasing wait time at the crosswalk the likelihood of GO increases. In other words, a pedestrian's gap threshold for deciding to go decays the longer the wait time at the crosswalk. The effect is consistent with prior research relating gap acceptance to waiting time (Mahmassani and Sheffi, 1981). However, the integrity of this model is questionable, because of the large odds ratio associated with the wait time effect. For each second of wait time, the log odds of GO increase by a factor of 2.14, indicating that virtually any pedestrian would simply cross the road after very little delay. More data collection is necessary to verify this effect.

Restricted model 3 provides a more reasonable estimate of the effect. With the introduction of the expected gap time variable, the waiting time parameter is no longer significant although the overall model fit is comparable to the unrestricted model above. Waiting time was included here, because it had shown practical and statistical significance in the unrestricted model. The resulting model has an odds ratio of 1.14 associated with a one-second increase in waiting time. The model is also responsive to the expected gap size. Figure 54 shows the resulting probability plots.

Equation 33: PCM - Restricted Model 3 - RBT-RAL - Gaps

$$\text{logit}[P(GO=1) = -8.6936 + 0.1275\ D\_WAIT + 2.0271\ T\_GAP$$

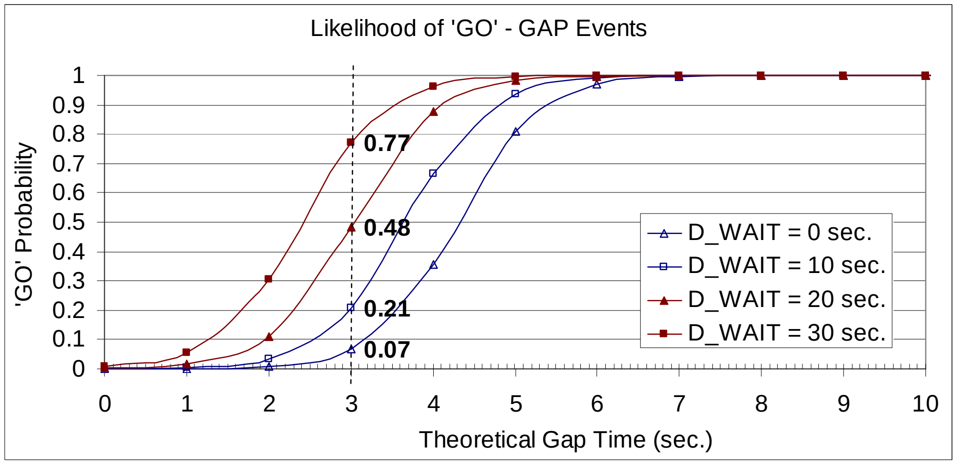


Figure 54: Probability Plots, Restricted Model 3, RBT-RAL - Gaps

The probability curve for GO in a gap shifts to the left with increasing waiting time. The vertical line indicates that without any wait time, 7% of pedestrians would decide to GO in a 3 second gap. After a wait time of 10 seconds, 21% of pedestrians would decide to GO. At wait times of 20 and 30 seconds, the same size gap would be accepted by 48% and 77% of pedestrians, respectively. The model has an AIC statistic of 22.934, which not statistically different from the AIC for unrestricted model 2. The max-rescaled R-Square for the model is 0.7087.

6.3.5 Crossing Model Summary

The analysis of pedestrian crossing behavior at the studied roundabout resulted in logistic regression models that were sensitive to the size of the lag or gap encountered by the pedestrian. As expected from theory, an increase in the time to the next vehicle arrival (or difference between successive vehicles) increases the likelihood that the pedestrian decision is GO.

Consistent with the mid-block chapter, separate logit models were developed for lag and gap events given their differences. The selected restricted model for crossing in a lag is sensitive to the expected lag time and pedestrian assertiveness. The latter parameter predicts lower lag thresholds for pedestrians that exhibit assertive behavior in their walking styles. Other factors were not significant at the given sample size of observations.

The model describing the likelihood of GO in a gap is a function of the expected gap time, but is not sensitive to assertiveness. Instead, the model predicts a lower gap time with an increase in pedestrian waiting time. This suggests that pedestrian lower their gap threshold the longer they have to wait for a crossing opportunity. This type of impact of waiting time on a reduced critical gap time has also been identified for drivers at roundabouts (Polus et al., 2003) and at other facility types (Mahmassani and Sheffi, 1981).

In comparing model fit statistics, the selected restricted lag model has a higher max-rescaled R-square (0.9026) than the corresponding gap model (0.7087). Both models show better fit than the yielding models. This suggests that lag crossing behavior is more consistent than gap crossings in the given data set. The good statistical fit is further important in light of the poor performance of the traditional gap acceptance models. Given consistent pedestrian behavior, the logit regression approach thus provides a good description of the gap/lag selection process even with a low sample size.

6.4 Chapter Summary

The analysis of pedestrian-vehicle interaction substantiated the initial research hypothesis that pedestrian-vehicle interaction at unsignalized crossings is a complex process, sensitive to microscopic parameters. Going beyond the classification of yielding behavior by a simple percentage, the event-based evaluation of yield events showed that the decision of drivers to yield to a pedestrian is a function of dynamic variables describing the state of the vehicle. Vehicles that are closer to the crosswalk and traveling at a higher speed are less likely to yield, or may be subject to vehicle dynamics constraints resulting in a zero yield probability. Accounting for these factors in logistic regression models allows for a probabilistic estimate of yielding and of the likelihood of a hard yield given yield in a two-level nested binary logit model. While a cumulative logit model for ordered responses provided a comparable overall model fit, the nested binary logit approach was preferred because of ease of interpretation and consistency with the mid-block yielding models.

The crossing decision by the pedestrian is subject to similar vehicle dynamics factors, represented through the expected arrival time of the vehicle at the crosswalk. Through binary logistic regression models, this chapter developed equations to predict the likelihood of a pedestrian GO decision as a function of gap and lag times, while taking into consideration factors of pedestrian assertiveness and wait time.

The restricted models for driver yielding and pedestrian crossing behavior are limited to variables with practical application that can be implemented in microsimulation. As hypothesized in the analysis framework chapter, these probability functions are two of the algorithms needed to characterize the interaction of these two modes in a simulation environment.

The selected models for gap/lag acceptance provided resulted in much better statistical fit than the driver yielding models. Given a relatively low sample size, the predictive ability of the yielding models is questionable. However, the pedestrian crossing models fit the data extremely well, suggesting that the low sample size of observations was sufficient for describing the more consistent behavior of pedestrians.

7 SIMULATION IMPLEMENTATION

This chapter extends the behavioral concepts brought forth in this research to the microsimulation environment. It begins with a summary of the logistic model forms that were developed in the previous chapters. The discussion also reviews the state of the practice in microsimulation as it pertains to modeling the interaction of pedestrians and vehicles at unsignalized crossings. The chapter then illustrates the potential for implementing the logistic models in a simulation environment and outlines requirements for simulation algorithms.

7.1 Site and Model Comparison

The data collection and analysis methodology developed in this research was applied to two mid-block locations and a single-lane roundabout crossing. The three sites all differ in crossing geometry and traffic patterns. The MB-CLT location is a 40-foot crossing across two lanes with 35 mph speed limit and the MB-RAL site is a 24-foot crossing across two lanes with 25 mph speed limit. The RBT-RAL roundabout crossing is a two-stage crossing across two 16-foot lanes at an approach speed of 25 mph. The mid-block crossing data includes the evaluation of two pedestrian crossing treatments. Table 20 summarizes the selected restricted logit models describing the likelihood of driver yielding.

Table 20: Summary of Restricted Models for Driver Yielding

Site	Model	Equation
MB-CLT	Nested Logit Level 1	logit[P(Y=1)] = -0.378+1.721AST+1.189FLASH-0.955PLT-0.382*DECEL
	Nested Logit Level 2	logit[P(HY=1)] = 1.525-1.475AST-1.580TRTMT+0.287DECEL
MB-RAL	Nested Logit Level 1	logit[P(Y=1)] = -0.124+2.487AST+0.617NEAR-0.491PLT+0.648TRTMT-0.344DECEL
	Nested Logit Level 2	logit[P(HY=1)] = 0.097-1.822AST+0.111DECEL
RBT-RAL	Nested Logit Level 1	logit[P(Y=1)] = 1.946+2.022ENTRY-0.132SPEED_FT
	Nested Logit Level 2	logit[P(HY=1)] = 1.614+1.927DECEL-0.338SPEED_FT

For all three sites, the driver yielding models have the form of a two-level nested binary logit model, first predicting the probability of yielding and then the probability of a hard yield. The first-level logit models for the mid-block sites consistently describe yielding as a function of assertiveness, the treatment presence or activation, the occurrence of vehicle platoons and the required deceleration rate. The narrower MB-RAL crosswalk furthermore shows a significant effect of pedestrians crossing from the near-side relative to the approaching vehicle. The effect of pedestrian assertiveness is stronger at MB-RAL, but the effect of vehicle platoons is weaker, as indicated by the value of the model parameters. For the vehicle dynamics variable DECEL, both sites show a similar decrease in the likelihood of yielding at higher necessary deceleration rates. The treatment effects are difficult to compare, because one site uses a variable describing the actual activation of the treatment, while the treatment at the other site is static.

The results from the level 1 logit at the roundabout show a different combination of variables and are hard to compare to the mid-block sites. For the two-stage roundabout crossing, the effects of pedestrian assertiveness and vehicle platoons are not significant and the NEAR, TRTMT and FLASH variables are not applicable. The model suggests a higher yielding rate at the roundabout entry.

The level 2 logit models for the mid-block sites once again include comparable effects of AST and DECEL on the odds of a hard yield. The MB-CLT site further found a reduced likelihood of a hard yield after treatment installation. The roundabout site similarly indicates an increased likelihood of HY with greater deceleration rate, but further predicts a reduction of those odds with vehicle speed. Because of the combination of these two dynamic variables a direct comparison between the two facility types is not possible.

A summary of the restricted models for pedestrian crossing behavior is given in Table 21.

Table 21: Summary of Restricted Models for Pedestrian Crossing

Site	Model	Equation
MB-CLT	Binary Logit - Lag	logit[P(GO=1)] = -12.930+3.092AST+3.239FLASH+1.941NEAR+1.252E_LAG
	Binary Logit – Gap	logit[P(GO=1)] = -8.511+4.360AST+1.726FLASH+1.454NEAR+0.974E_GAP
MB-RAL	Binary Logit – Lag	logit[P(GO=1)] = -10.215+6.019AST+0.642NEAR+0.786TRTMT+1.053E_LAG
	Binary Logit – Gap	logit[P(Y=1)] = -10.938+5.268AST+2.758NEAR+1.335E_GAP
RBT-RAL	Binary Logit – Lag	logit[P(GO=1)] = - 7.699+3.094AST+1.272E_LAG
	Binary Logit - Gap	logit[P(GO=1)] = -8.694+0.128D_WAIT+2.027E_GAP

The resulting pedestrian crossing models also show similarities between the two mid-block sites. The likelihood of crossing in a lag is described by AST, NEAR, E_LAG and the treatment effect in both cases. Again the treatment effect is stronger at the MB-CLT site and assertiveness has a larger impact at the MB-RAL site. The effect of a NEAR vehicle is expectedly greater at the MB-CLT site, which has a much wider cross-section of the roadway.

The lag model for the RBT-RAL uses the same variables as the mid-block sites, when considering that NEAR and TRTMT/FLASH are not applicable. The AST and T_LAG parameters are comparable to the mid-block sites. The larger intercept (smaller negative number) for the RBT-RAL site suggests that a pedestrian crossing is generally more likely there than at the mid-block sites for a fixed lag time. Given the shorter distance at each stage of roundabout crossing, this finding is quite intuitive.

The gap models for the mid-block sites differ only in the use of the treatment effect, which is only evident at the MB-CLT site. Activation of the treatment here results in an increased likelihood of crossing. For the roundabout model, an increasing expected gap size similarly increases the likelihood of a crossing decision. The model further predicts a greater likelihood of crossing with pedestrian waiting time.

For an implementation in microsimulation, the model algorithms need to be coded as a function of the independent variables in the logit models described above. Of the original list of variables, the following are represented in at least one of the models and thus need to be coded in the simulation: AST, D_WAIT, DECEL, E_GAP, E_LAG, ENTRY, FLASH, NEAR, PLT, SPEED_FT, and TRTMT. Before discussing the implementation in greater detail, the following section provides an overview of current pedestrian modeling practice in simulation.

7.2 Overview of Pedestrian Modeling in Microsimulation

In microsimulation software, vehicles and pedestrians are modeled as individual entities that move through the simulation obeying user-defined and model-specific algorithms. In most microscopic models, the clear focus of these algorithms is vehicle motion. Today's simulation models include algorithms describing car-following, lane-changing and gap acceptance behavior. New algorithms are continuously enhanced by software developers and agencies. Among those the 'Next Generation Microsimulation' effort (NGSIM) by the Federal Highway Administration is sponsoring the development of algorithms to improve the state of the practice of microsimulation. NGSIM recognizes the need to enhance pedestrian models and ranks this area 7th in a top 10 list of modeling stakeholder requirements (FHWA, 2004-1). The six higher ranked problem statements are lane selection on arterials, oversaturated freeway flow, freeway lane distribution, weaving sections, two-way left-turn lanes, and response to variable message signs. With limited resources, the initial NGISM effort naturally focuses on high-impact algorithms in the areas of freeways and signalized arterial systems. Given the resource requirements for algorithm development, it will be some time before NGSIM or A similar program will address the necessary pedestrian research for model development.

Despite the lack of detailed pedestrian-vehicle interaction algorithms, some of the commercially available simulation developers have enabled the analyst to represent pedestrians as separate entities in the models. Depending on the flexibility of the particular tool, the analyst may be able to define pedestrian walking speed and crossing behavior in some detail. In another NGSIM publication (FHWA, 2004-2), the authors found that several models explicitly model pedestrians as individual entities: SimTraffic, VISSIM, HUTSIM, PARAMICS, and AIMSUN. Other models may be able to model pedestrians implicitly through their impact on the vehicle mode. For a subset of the initial group of models, built-in gap acceptance algorithms for two-way stop-controlled operation may be adopted to approximate pedestrian behavior.

The willingness of drivers to yield to pedestrians may be represented through similar gap acceptance algorithms. As discussed in chapter 2, the yielding process can be interpreted as the driver screening the pedestrian stream for crossable gaps. A driver yields when no gaps are available. In a response to user needs, models are further beginning to implement improved algorithms of pedestrian-pedestrian interaction. These cellular automata models were discussed in Chapter 2, but are not the focus of this research (Blue and Adler, 2001, Holden and Cangelosi, 2003).

In the area of pedestrian-vehicle interaction, NCHRP 3-78a (TRB, 2008) selected the model VISSIM, because it proved to be the most flexible of the commercially available tools. In VISSIM, pedestrians are modeled explicitly as individual entities with user-definable speed distributions. The interaction between pedestrians and drivers can be simulated using *priority rules* that allocated user-defined critical gap thresholds to the entities. VISSIM further allows the analyst to code multiple *types* of pedestrians and allows the user to assign different gap acceptance characteristics to the different pedestrian types. The capabilities of VISSIM will be explored further in the next section.

As alternatives to VISSIM, several other microsimulation tools have varying levels of applicability to pedestrian modeling. *SimTraffic* is the microsimulation extension of the *Synchro* software package and automatically converts the hourly pedestrian demand user inputs from deterministic Synchro to generate pedestrian events in the simulation (Trafficware, 2004). SimTraffic assumes that pedestrians are channelized and uses built-in algorithms to describe the interaction with vehicular traffic.

In an analysis of the *CORSIM* software package, Rouphail and Eads (1997) found that the model implicitly accounts for the delay impact of pedestrians on turning movement traffic at signalized intersections. The model does not allow for an explicit analysis of pedestrian-vehicle interaction at unsignalized crossings, which is consistent with the NGSIM findings referenced above (FHWA, 2004-2).

The software tool *AIMSUN* (TSS, 2006) models pedestrians as individual entities similar to VISSIM. Pedestrian speed distributions and other characteristics can be user-defined. Priorities at unsignalized crossings can be defined manually for each intersection node. As other models, AIMSUN requires the analyst to specify which movement has priority, making it challenging to represent the interaction at unsignalized crossings. A review of the user guide for *Q-Paramics (*Quadstone, 2007) did not provide any reference to pedestrian modeling in the software, even though it was listed as a tool that explicitly models pedestrians by NGSIM.

In an effort to better represent pedestrian-vehicle interaction in a simulation environment, Schroeder and Rouphail (2007) first discussed an analysis framework similar to the one presented in this research. In the paper, the authors hypothesized that the interaction of pedestrians and drivers could be represented by four probability parameters: the probability of yielding, probability of yield detection, probability of gap occurrence, and the probability of gap detection. The "detection" terminology was changed to gap "utilization" in this dissertation, recognizing that only the decision outcome can be observed by the researcher. From analyzing the interaction at the crosswalk, an observer can reliably determine if a pedestrian utilizes a gap or not, but cannot make inferences about the detection abilities of the pedestrian. The predictive models in chapters 5 and 6 therefore describe gap utilization and not necessarily gap detection.

Using these four probability parameters, Schroeder and Rouphail (2007) conceptualized several treatment scenarios that were intended to test the responsiveness of the simulation model on changes in one or more of the probability parameters. The scenarios included treatments intended to increase yielding behavior, and treatments intended to enhance yield and gap detection of pedestrians with vision impairments. The analysis in VISSIM evaluated the measures of effectiveness of pedestrian delay, vehicle delay and the likelihood of pedestrian-vehicle conflicts at a one-lane, one-way pedestrian crossing.

While the probability parameters and the effect of the treatments were strictly hypothetical, the measures of effectiveness responded in the expected fashion. The analysis demonstrated the ability of microsimulation to analyze pedestrian-vehicle interaction accounting for both driver yielding and pedestrian crossing behavior. However, the authors recognized that a true evaluation of the interaction requires probability parameters based on actual field data.

7.3 The Research in the Simulation Context

To the author's best knowledge, the research presented herein offers for the first time the opportunity to describe pedestrian and vehicle interaction at sufficient level of detail for adaptation in microsimulation. While many studies have evaluated the rate of driver yielding (e.g. Fitzpatrick et al, 2006 and many others) few have considered the probabilistic nature of this behavior. Sun et al (2002) first developed logistic regression models using binary variables such as gender, age, and the presence of multiple pedestrians. These authors also investigated pedestrian gap acceptance and found differences by pedestrian age and as a function of waiting time. But without incorporating the speed and position of vehicles, the models lack the necessary traffic operational detail to be practically implemented in simulation.

Most microsimulation models operate on a sub-second update interval. Each unit that enters the system is assigned a range of global parameters describing characteristics such as the desired speed, vehicle type etc. These parameters are assigned based on user-defined (or default) distributions of these attributes that ideally have been calibrated with field data. As the unit moves through the network additional time-sensitive parameters are assigned. These may include speed reductions simulating the presence of a sharp curve or a speed limit sign and are assigned either temporally (within the restricted area) or permanently; the latter effectively overriding the global parameter. These time-sensitive parameters can be changed <u>explicitly</u> by user input, or may vary <u>implicitly</u> as a function of other model algorithms (such as car-following logic).

In the Schroeder and Rouphail (2007) paper, the authors assigned driver yielding and pedestrian crossing attributes globally. The propensity of drivers to yield was assigned randomly as the vehicle entered the network, from a user-defined vehicle distribution that included non-yielder and potential yielder driver types. When approaching the crosswalk, potential yielders screen the waiting area at the crosswalk and decelerate to a hard yield if a pedestrian was present. Non-yielders would proceed through the crosswalk ignoring the waiting pedestrian. All drivers were modeled to respond to pedestrians already in the crosswalk. In a similar fashion, three types of pedestrians were coded with conservative, typical, or risky crossing attributes. These attributes were drawn from a user-defined distribution as the units entered the network, thus representing a *quasi-heterogeneous* pedestrian population. The pedestrian GO decision at the crosswalk was calculated through the default gap acceptance algorithm using three different critical gap values for the three pedestrian types.

The simulation model VISSIM can be adopted to model the interaction of the two modes using priority rules (PTV, 2003). These priority rules (PR) are the developers' way of describing gap acceptance behavior. While VISSIM is just one of many models, the PR concept is useful to discuss the models developed in this research in the context of existing simulation practice.

The PR algorithm can model gap selection decisions based on both *temporal* and *spatial* attributes in the conflicting traffic stream. Using the *temporal* PR parameters, a pedestrian GO decision is dependent on the expected arrival time of the vehicle, which is a function of vehicle speed and distance from the crosswalk. If the given expected gap/lag time is below the pedestrian's risk threshold her decision will be NOGO. However, if in the next time step the vehicle decelerates because of another algorithm, the expected arrival time increases and the PR algorithm is re-evaluated with another set of initial conditions. In this implementation the pedestrian decision is *consistent*, always resulting in a GO decision if the expected gap time exceeds her risk threshold. Schroeder and Rouphail (2007) were able to model a *quasi-heterogeneous* pedestrian population by assigning different PR thresholds to different ‘types’ of pedestrians.

The *spatial* PR definition in VISSIM bases the gap selection decision on whether or not a user-defined distance on the conflicting roadway is occupied or not. Conceptually, both PR definitions can be used to describe the same risk threshold, but differ in their sensitivity to the speed distribution of the conflicting traffic stream. With the temporal definition, a faster traveling vehicle will be at a larger spatial distance than a slower vehicle for the same measured expected arrival time. Similarly, a vehicle just inside the spatial PR threshold will effectively arrive at the crosswalk more quickly with increasing speed. If the conflicting population has a small variance in speed the spatial and temporal PR definitions are similar.

In Schroeder and Rouphail (2007) the interaction was modeled by assigning pedestrians a temporal PR definition (with varying levels based on their risk threshold) and using a spatial definition for potential yielders in the vehicular traffic. This use was justified because the variance in the speed distribution of pedestrian traffic is small compared to vehicle speeds. The result is that a potential yielder will always yield if a pedestrian is in the waiting area (within the spatial PR boundary). As that vehicle slows down, its expected arrival time will increase and the pedestrian will initiate crossing once the expected arrival time exceeds her temporal PR threshold.

While this implementation is possible with existing gap acceptance algorithms in VISSIM there is no randomness in the decision-making process. Given time to decelerate, a potential yielder will always yield if a pedestrian is waiting at the crosswalk. The pedestrian will consistently accept a gap greater than her risk threshold.

This way of globally assigning gap acceptance (and thus yielding) behavior is common for all reviewed models, provided that they even allow this level of analysis detail. The discussed modeling approach ignores the true probabilistic nature of the interaction and does not account for behavioral *inconsistency*. For example, a driver encountering a waiting pedestrian may conclude one day that a 5 ft/sec^2 deceleration rate is acceptable, but not the next day. Drivers and pedestrians do not make consistent decisions and that approach presumes otherwise. Up to this point, research identifying the factors contributing to this inconsistency has been scarce.

With the findings from this research, a more realistic implementation can be achieved. The attributes for pedestrian-vehicle interaction represent both global and local parameters. For example, a driver is assigned a global desired speed parameter and vehicle characteristics that govern deceleration behavior. Similarly, a pedestrian who enters the network can be assigned an assertiveness attribute (or not). However, the actual decision models are not assigned globally, but become a function of the state of the system at the time of pedestrian arrival, t_1. Conceptually, the likelihood of yielding would be re-calculated every simulation time-step depending on vehicle dynamics characteristics (speed, distance...), incidental attributes (platoons, multiple pedestrians...), and the pedestrian behavior (assertiveness, pedestrian in crosswalk...). The resulting interaction model, then, is similar to the car-following principle in that the behavior of one entity is contingent on the behavior of another.

7.4 Algorithm Requirements

The logistic regression models developed in this research allow for stochastic variability in the decision-making process that goes beyond the implementation discussed above. The logit models are highly sensitive to dynamic variables describing the expected arrival time and the necessary deceleration rate of vehicles at the crosswalk. Because of the nature of the simulation software, these parameters are updated every simulation time step (typically 0.1 seconds) and correspondingly the probability functions are subject to change from one time step to the next. The vehicle dynamics element therefore requires the logit implementation to be in the form of *core model algorithms*. The assumption of *global* parameters in Schroeder and Rouphail (2007) does not allow for sufficient level of detail.

A true implementation of the results of this research in microsimulation therefore requires new software code and cannot be achieved with existing algorithms. In the case of VISSIM, it is possible to dynamically update vehicle (and pedestrian) attributes during the simulation by the use of VAP code (PTV 2003). The probability functions used to plot the behavior of the logit function in this research would be implemented in this external code and the probability estimates re-calculated as the simulation progresses.

Only a small portion of the logit variables would be implemented in the form of *global* parameters that are fixed throughout the simulation. Most of the variables found in the logistic regression models become *implicit* functions of other algorithms in the simulation. The dynamic variables such as vehicle speed and gap times are a function of car-following algorithms, speed distributions, and arrival patterns. These are *time-sensitive* variables that are dynamically updated as the simulation progresses. Table 22 lists the simulation variables and their suggested implementation.

Table 22: Variable Implementation

Variable	Implementation	Comments
AST	Global	As a pedestrian entity is generated, it is randomly assigned either assertive or non-assertive behavior from a user-defined distribution
ENTRY	Global	Pedestrian arrival distributions at the entry and exit leg of a roundabout are globally defined by the user
FLASH	Global	As a pedestrian entity is generated, it is randomly assigned whether he/she will activate the flashing beacon based on a user-defined distribution
TRTMT	Global	The presence and effect of a pedestrian crossing treatment is globally defined
D_WAIT	Implicit	Waiting time is a time-sensitive attribute that is among others a function of the actual yield and crossing algorithms
DECEL	Implict	The necessary deceleration rate is an implict function of the vehicle speed and distance at the time of pedestrian arrival
E_GAP	Implicit	The expected gap time between vehicle arrivals is an implicit function of other simulation algorithms
E_LAG	Implicit	The expected gap time between vehicle arrivals is an implicit function of other simulation algorithms
NEAR	Implicit	The relative position of pedestrian and vehicle is an implicit result of the simulation model
PLT	Implicit	The location of a vehicle within a platoon of other vehicles is an implicit function of car-following algorithms and vehicle arrival distributions.
SPEED_FT	Implicit	The speed of the vehicle is globally assigned from a user-defined distribution, but changes during the simulation as a function of other algorithms

Table 22 suggests that variables AST, ENTRY, FLASH, and TRTMT would become global attributes of the pedestrian (assertiveness and activation of the treatment) and of the system (roundabout entry vs. exit and treatment presence). The remaining variables (D_WAIT, DECEL, E_GAP, E_LAG, NEAR, PLT, and SPEED_FT) are implicit functions of the simulation algorithms. These algorithms include the driver yielding and pedestrian crossing algorithms themselves. For example, as a driver decides to yield the variables E_GAP/E_LAG, DECEL, and SPEED_FT are affected. Similarly, D_WAIT increases every time a pedestrian rejects a gap.

The actual logit functions are implemented in the form of core algorithms that read-in the state of the Table 22 variables every simulation time step and re-calculate the decision probability. The decision outcome then becomes a random variable. The yield and crossing responses then depend on the outcome of a random experiment following the logit probability function.

In the implementation, some assumptions need to be made about behavioral consistency. In a true randomized experiment it is feasible that an entity would change its decision outcome repeatedly, which is undesirable. It is therefore recommended that once a response is “true” the decision is fixed. Once a driver decides to yield and once a pedestrian decides to cross the action is followed through. More research would be necessary to predict variables that lead pedestrians and drivers to change their decisions.

7.5 Chapter Summary

This chapter discussed the extension of the probabilistic logit models to the area of microsimulation. The discussion demonstrated how current models represent pedestrian traffic and how the results from this research may help enhance existing algorithms.

The implementation of the driver yielding and pedestrian crossing models would occur through new core algorithms that supplement existing algorithms such as car-following. The new algorithms are necessary because the probability functions would be updated with every simulation time-step, based on the changing state of the explanatory variables.

The variables used in the logit models would be implemented in the form of global or time-sensitive model parameters. For example, pedestrian assertiveness would be assigned globally based on a user-defined population distribution of that variable. On the other hand, all dynamic variables, including vehicle speed and the expected gap/lag times, are time-sensitive parameters that are an implicit function of existing model algorithms.

8 CONCLUSIONS AND RECOMMENDATIONS

The research presented in this dissertation details the behaviors of pedestrians and drivers at unsignalized crosswalks. The work represents one key component of a larger framework for evaluating the interaction of these two modes. Special emphasis is given to quantifying the effects of different pedestrian crossing treatments on behavior.

8.1 Summary of Major Findings

This dissertation developed and applied a methodology to collect event-based interaction parameters of drivers and pedestrians at unsignalized crosswalks. The research identified various dynamic and binary explanatory variables that were hypothesized to affect the decision-making processes of drivers and pedestrians. With the use of logistic regression techniques the effects of the variables were related to the categorical responses: *driver yielding* and *pedestrian crossing behavior*. The research resulted in the following major findings:

- The research developed a methodology that is *transferable to other sites* and geographic locations. While the findings may be biased to region-specific behavioral attributes, the event-based data collection and analysis approach can readily be applied to other unsignalized and signalized pedestrian crossing locations. The methodology offers the opportunity to analyze the interaction at a greater level of detail than is possible in conventional site-aggregated studies, while keeping the amount of data collection time in the field at a manageable level.

- The analysis of driver yielding behavior supported the notion that drivers approaching the crosswalk are subject to *vehicle dynamics constraints* (VDC) similar to drivers forced to run a yellow light at a signalized intersection. By relating yield events to the necessary deceleration rate of drivers, the research identified that virtually no yields are observed at rates greater than 10 feet/sec^2. The vehicle dynamic characteristics were significant parameters in all yielding and crossing models even after VDC-constrained vehicles were excluded from the analysis.

- The research indicated that *pedestrian assertiveness* has a significant impact on an increased likelihood of drivers yielding and of pedestrian crossing. This effect was shown to be larger than that of any other explanatory variables, including the effect of yield-promoting treatments. A brisk pedestrian walking style thus was more effective in increasing driver yielding behavior than the costly installation of a treatment and was related to a greater likelihood of accepting a fixed-duration gap (or lag).

- The research was able to develop a *predictive model for yield types* that distinguishes between the hard and soft yield outcomes from all yield events. Previous research suggested that soft yields are more challenging to detect by blind pedestrians and by automated yield detection technologies.

- The evaluation of two *pedestrian crossing treatments* found that the treatments were effective in increasing yielding behavior, and furthermore resulted in more aggressive pedestrian crossing behavior. The variable describing the treatment installation resulted in an overall shift of the logit probability curves towards lower lag and gap times. The evaluation of a pedestrian-actuated treatment further showed that the *activation of the treatment* had a larger effect on yielding than the presence of the treatment itself.

- The statistical fit of the pedestrian crossing models was generally much stronger than for the corresponding driver yielding models. It is reasoned that the *pedestrian decision is strongly influenced by the temporal duration to the point of conflict*, because misjudgment has implications for personal safety. A driver does not feel a comparable urgency to yield even with sufficient time, resulting in a worse model fit.

- The research found supporting evidence for an *impact of waiting time* on an increased likelihood of pedestrian gap acceptance. The notion of a decaying critical gap has previously been demonstrated by others and was confirmed here for crossings that exhibited a perceptible amount of pedestrian delay.

- The comparison of yielding and crossing models for two mid-block sites showed many similarities in parameters, suggesting that the development of *universal models for mid-block crossings* may be feasible. The dynamic model variables can be normalized to account for differences in crosswalk geometry by defining the size of expected gaps or lags relative to the crossing width. More research is necessary to validate this notion, but these initial results are intriguing.

- The research results show promise for implementation in microsimulation. The probabilistic models can be used to *quantify system-level effects of the interaction* of pedestrians and vehicles in a way that is useful for a traffic engineering operational analysis. Using site-specific behavioral characteristics the simulation model can estimate the impact of a pedestrian crossing treatment on pedestrian and vehicular delay, or other measures of effectiveness. This allows the analyst to contrast different unsignalized treatments and compare them for example to signalized operations.

8.2 Revisiting Objectives

8.2.1 Objective 1

Devise a data collection methodology to evaluate the interaction of pedestrians and drivers at unsignalized pedestrian crossings at a microscopic or event-based level.

The data collection methodology described in Chapter 3 was successfully applied to three test sites in Raleigh and Charlotte, NC. Through the combination of time-synchronized video observations and laser speed measurements the author was able to collect a range of variables describing the interaction of the two modes at unsignalized crossings.

Laser speed measurements allowed the analyst to quantify variables describing the dynamic characteristics of the vehicle. From the vehicle speed and distance from the crosswalk at the time of a pedestrian arrival, the author was able to calculate necessary vehicle deceleration rates and expected arrival times at the crosswalk. These variables proved practically meaningful and statistically significant in model development.

Using the video observations it was further possible to define and extract a range of binary variables describing characteristics of driver and pedestrian, and the state of the system at the time of an interaction event. Among others, the video allowed the analyst to identify vehicle platoons, judge assertive pedestrian behavior and observe other concurrent events pertinent to the interaction.

The data collection methodology proved feasible and non-intrusive. More importantly, the author was able to obtain a very large sample size of observations from only a few hours of data. Depending on pedestrian and vehicle volumes, the analyst was able to record up to 100-200 events per hour from video. The data extraction and data reduction effort was cumbersome and required a 10:1 time investment. However, the actual time spent in the field was relatively short compared to a more traditional evaluation.

8.2.2 Objective 2

Demonstrate that pedestrian crossing and driver yielding behavior are sensitive to the dynamic characteristics of the approaching vehicle, behavioral characteristics of pedestrian and driver, concurrent events at the crosswalk, and the installation of crosswalk treatments.

With the successful application of the data collection methodology this research was able to explore a range of discrete and continuous variables and relate them to the decisions of pedestrians and drivers. The response variables were the driver decision on whether or not to yield to a pedestrian and the pedestrian decision on whether or not to begin crossing the road. These responses were related back to the state of different variables at the time a pedestrian arrived at the crosswalk while a driver was in the approach.

Gap acceptance theory traditionally uses the temporal dimension to explain GO decisions. The research presented here supports this theory, finding that pedestrian GO decisions were very sensitive to the expected arrival time of the vehicle at the crosswalk. The author found that driver yielding decisions are also very sensitive to these types of variables. In fact, this research proposes that driver yielding behavior is subject to vehicle dynamics constraints (VDC) and presents data showing that yielding is highly unlikely if the necessary deceleration rate to come to a stop exceeds a threshold of $10ft/sec^2$.

In addition to these dynamic variables, the research demonstrated that behavioral attributes impact the decision outcomes. An assertive pedestrian is generally prone to have lower gap thresholds and furthermore increases the likelihood that the approaching driver yields. There was further evidence that pedestrians make more conservative decisions when traveling in a group. Attempts to assess other behavioral variables such as the presence of non-verbal communication did not yield good observations, mainly because the video angle lacked sufficient detail.

The analysis also found that concurrent events tend to impact the decision outcomes. Drivers were less likely to yield when they were traveling in a platoon, presumably being apprehensive of the risk of a rear-end collision. The presence of an adjacent yield also showed correlation with increasing the likelihood of a yield in the other lane. An effect of downstream conflicts could not be determined at the given sample size.

Finally, two of the sites were evaluated in conditions before and after the implementation of a pedestrian crossing treatment. Both treatments were intended to *increase driver awareness* of the crosswalk and the presence of pedestrians. Consistent with previous research, the treatments resulted in an increase in the likelihood of drivers yielding. However, the analysis further showed that the treatments impacted pedestrian crossing decisions. By reinforcing the notion that pedestrians have the right-of-way at the crossing, pedestrians tended to lower their gap thresholds after treatment installation. The evaluation of a pedestrian-actuated treatment showed that the impact of the treatment on driver yielding is contingent upon pedestrian activation.

8.2.3 Objective 3

Describe driver yielding and pedestrian crossing behavior from collected event-based data accounting for attributes of vehicle dynamics, behavior, and the effect of treatments.

This dissertation successfully applied logistic regression techniques to event-based interaction data. While others have previously attempted to describe pedestrian and driver decisions through logit models, this research is the first time that a combination of continuous and discrete variables was used.

The driver yielding models successfully applied a nested binary logit approach. The first level logit described the likelihood of yielding as a function of deceleration rate, pedestrian assertiveness, vehicle platooning, and other variables. The second level logit then predicted the likelihood of a hard yield from all yield events. This is the first time a predictive model distinguished between the two types of yielding. The distinction of hard and soft yields is important for purposes of yield detection, both for pedestrians with vision impairments, and for testing automated yield detection methods.

The parameters in the driver yielding models are significant and consistent with the hypothesized effects of the variables. However, the overall model fit statistics suggest that not all of the variability in the data is explained by the models. Despite legislation, the requirement to yield is rarely enforced and driver compliance is therefore much lower as compared to the rate of stopping at a red signal indication. Accordingly, the decision outcome cannot be predicted perfectly because too many variables affect the outcome. Presumably, a driver who has sufficient time to stop and encounters other conditions that favor a yield may be easily swayed in the decision to yield. Unfortunately, these types of behavioral characteristics are unobservable in a field experiment.

The pedestrian crossing models show higher correlations between gap and lag duration and the decision to cross. The strong statistical fit of the pedestrian logit models is explained by the fact that a crossing decision in a short gap or lag time jeopardizes personal safety. A driver non-yield decision, despite a long lead time to the crosswalk has no comparable immediate consequences. Accordingly, the predictive crossing models generally fit the data better than the yield models. In addition to the strong effect of temporal variables, the pedestrian crossing models are sensitive to assertiveness and whether the vehicle is in the near or far lane. The models also consistently include the effect of the pedestrian crossing treatment. The variables for the treatment effect result in a shift of the crossing probability curve towards lower gap and lag sizes.

8.2.4 Objective 4

Demonstrate that driver yielding and pedestrian crossing models have application to microsimulation models where they can enhance existing interaction algorithms.

With the predictive logit models in place, Chapter 7 discussed the implementation of these models in a microsimulation environment. The chapter identified shortcomings in the way existing models treat the pedestrian mode and its interaction with vehicles; a notion supported by the ongoing FHWA NGSIM research effort. The discussion conceptually compared the logit models to the way car-following algorithms are implemented in current software. The author argued that a true implementation of the probability function would have to occur in the form of *core algorithms* that are dynamically updated and re-calculated every simulation step. This implementation goes beyond what was done in previous research and requires new code to enhance existing software. The actual variables that are used as input in the core algorithms include *global* driver and pedestrian attributes and *time-sensitive* variables, which are updated dynamically each simulation time step. All of the continuous variables and many of the discrete factors are implicit functions of existing simulation algorithms.

A successful implementation of the logit algorithms is important for a simulation-based evaluation of pedestrian crossing facilities. For example, this more realistic representation of pedestrian-vehicle interaction is required to adequately contrast signalized and unsignalized operation of pedestrian crosswalks at modern roundabouts. The signalization of roundabouts is controversial and the current methods for comparing these scenarios are insufficient.

8.3 Research Limitations

The findings from the data collection and resulting logit models presented in this research need to be interpreted in the context of the associated sample sizes. Observations at the two mid-block sites resulted in sufficiently large samples of several hundred data points each. The roundabout site provided a much smaller sample of interaction events and results should be supplemented with additional data collection.

For the mid-block sites the samples of observations were acceptable to illustrate the data collection and regression methodologies. The two sites showed significant differences in yielding and crossing behavior, illustrating that models are not readily transferable between sites without further research. Furthermore, other research has shown large site-to-site variations in yielding behavior and it is expected that models for behavior in rural North Carolina versus New York City would be much different.

The studied populations of drivers and pedestrians were relatively uniform. Most drivers at the sites represent daily commuter traffic and most pedestrians are students and staff at the two universities. More importantly, it is difficult to ascertain features of population heterogeneity from video observations. The resulting data and logit models therefore do not account for population parameters that are not observable.

In an effort to maximize the amount of data used for model development, no observational data were left out for later model validation. It is therefore not truly possible to compare alternate model forms beyond their statistical fit. The results were contrasted with more traditional analysis approaches and site-aggregated statistics. The analysis did not perform true model validation that would apply models to an independent data set not used in model specification and track the number of correct predictions.

The discussion in Chapter 7 falls short of a demonstrated proof of model implementation. The chapter merely demonstrates conceptually how the logit models would be represented in simulation. While implementation seems feasible, it is unclear whether the model will accurately represent the interaction of the two modes. It is argued above that many of the model variables are implicit results of other model algorithms (car-following, speed distribution, arrival patterns), which may need additional calibration before the observed interaction can be truly replicated.

The original analysis framework presented in Chapter 2 described the interaction through four probability parameters and this research only investigated two of them. The probability of gap occurrence and the probability of yield utilization have not been explored here.

Finally, the use of *expected arrival times* and *necessary deceleration rates* in the pedestrian crossing and driver yielding models assumes that vehicle dynamics are inferred accurately. However, it is not clear from this research if a pedestrian can truly judge the speed and distance of the closest vehicle. Presumably a driver can read the vehicle speed on the speedometer, but still needs to estimate the relative distance and/or arrival time to the crosswalk. The model parameters then may or may not represent what pedestrians and drivers actually perceive.

8.4 Areas of Future Research

The discussion distinguishes between *direct research expansion* and *indirect application of concepts* of the presented research. The first represents a continuation of the described effort to include more sites, additional treatments, and larger samples. Areas of indirect application of concepts may benefit from a similar analysis approach but are not directly related to this dissertation.

8.4.1 Direct Research Expansion

A direct expansion of this research should address the need for additional data on roundabouts and include an evaluation of roundabout treatments. Given the background of this research in a project dealing with the accessibility of roundabouts to pedestrians with vision impairments it makes intuitive sense to gather additional data at these facilities. For similar reasons, the analysis of special pedestrian populations, including those with vision impairments, is desirable. For blind pedestrians it is especially important to assess the probability of yield utilization.

It is also important to further explore the use of automated data collection methodologies. The methodology chapter pointed out that the video image processing approach is cumbersome for application to multiple sites due to the need to calibrate the software for each site and viewing angle. However, for longer data collection at the same site, the additional calibration effort may well be justified. Even with the use of image processing, it is expected that some variables need to be extracted manually from the video stream.

With the availability of additional data, a full validation effort of the logit models is also desirable. By relating model predictions back to observed data, it is possible to assess the quality of different model forms. More importantly, validation allows the analyst to better quantify the overall predictive ability of the model.

Another direct extension of this research is the actual implementation in microsimulation of the logit models. Using the principles laid out in chapter 7 an implementation in software would allow the analyst to investigate the effects of changing input variables on system performance. If supplemented with additional field data on speeds and arrival distribution the simulation could be calibrated to closely mirror field observations. By then comparing simulation outputs to field observed response variables the software implementation can be validated.

Additional extension of this research is possible in the area of conflict analysis. A number of research papers and reports have discussed the potential for using microsimulation for surrogate conflict analyses (e.g. FHWA, 2003). With calibrated decision-making algorithms, the simulation approach can be used to extract conflict data from the pedestrian-vehicle interaction models. Conceptually, the simulation model can then be used to not only contrast the operational impact of different treatments, but to further compare their impact on pedestrian safety. Schroeder and Rouphail (2007) demonstrated a method to extract pedestrian-vehicle conflicts from VISSIM.

In light of pedestrian safety concerns, there is also merit to a more detailed analysis of the impact of pedestrian waiting time on crossing behavior. For two of the studied sites, the logit analysis suggested that pedestrians lower their gap thresholds as waiting time increased. This class of decay function for gap acceptance behavior has previously been demonstrated for vehicular traffic and should be explored further in explaining pedestrian behavior.

Finally, given additional data from different sites it would be appropriate to combine them for the purpose of developing generic models for pedestrian crossing and driver yielding behavior. With the understanding that sites will differ in approach speeds and crossing widths, normalized explanatory variables would need to be defined to be universally applicable. For example, for pedestrian crossing behavior the gap and lag times could be expressed relative to the theoretical crossing time (which is a function of crossing distance and walking speed). Using this concept a *buffer time* can be defined, representing the difference between the critical gap/lag and the theoretical crossing time. These universal probability models are desirable because they allow the analyst to transfer the predicted behavior to new sites or to contrast different treatment alternatives.

8.4.2 Indirect Application of Concepts

In addition to the areas of research expansion listed above, the general methodology and analysis framework has application to other areas of microsimulation modeling and algorithm development. Conceptually, the method can be applied to derive other model algorithms that represent decision-making processes, provided that the response and explanatory variables can be observed and measured.

One example for this is the compliance at a red signal indication. The decision for a driver to violate a red signal indication can be expressed as a similar combination of speed and distance of the vehicle at the onset of amber, but may furthermore be correlated with other concurrent events. In a similar fashion, a logit model could be used to predict the likelihood of drivers stopping at the amber indication. Together with a simulation-based conflict analysis methodology, a combination of these two models may ultimately lead to enhancements in crash prediction models for rear-end crashes at signalized intersections.

While compliance of drivers at red signals is generally high, the compliance of pedestrians is typically much lower. Through a similar data collection approach, a pedestrian crossing model for signalized intersections could be developed that predicts the likelihood of GO at a red signal as a function of vehicle position and the behavior of other pedestrians. Similarly, a logit model could predict the likelihood of pedestrian GO during the flashing don't walk phase. The evaluation could be further expanded to describe pedestrian behavior at new hybrid signals.

Other examples of decision-making processes for vehicular traffic can be found in algorithms describing oversaturated conditions. In a saturated freeway merging section, for example, some drivers on the mainline will decelerate to allow on-ramp traffic to enter the freeway. This type of cooperative merging behavior is also observed at lower flows where drivers change lanes to create merging opportunities for ramp traffic. Cooperative behavior at oversaturated conditions is also evident at stop and yield controlled intersection, where mainline traffic commonly creates gaps for minor street traffic. In an implementation of these types of conditions in microsimulation, a logit-based algorithm may be used to describe this behavior.

9 REFERENCES

AASHTO (2001), *"Green Book". A Policy on Geometric Design of Highways and Streets – Fourth Edition*. Washington, DC. 2001

AIMSUN (2005) Webpage, *TSS Support FAQ*, Transportation Simulation Systems. http://www.aimsun.com. Last visited November 3, 2005.

Agresti, Alan. An Introduction to Categorical Data Analysis, Second Edition. John Wiley & Sons Inc., Hoboken, New Jersey. 2007

Akçelic, R. (2003), *A Roundabout Case Study Comparing Capacity Estimates from Alternative Analytical Models*, paper presented at the Seconds Urban Street Symposium, Anaheim, Ca. Referenced in Cambridge Systematics, *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

Ashmead, D., Guth, D., Wall, R., Long, R., & Ponchillia, P. (2005), *Street crossing by Sighted and blind pedestrians at a modern roundabout*. In ASCE Journal of Transportation Engineering, Vol. 131, No. 11, November 1, 2005, 812-821

Ben-Akiva, M. and S. Lerman (1985), *Discrete Choice Analysis*, MIT Press, Cambridge, MA. Referenced in Cambridge Systematics, *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

Bennet, S., A. Felton, and R. Akçelic (2001), *Pedestrian Movement Characteristics at Signalized Intersections,* 23rd Conference of Australian Institutes of Transport Research (CAITR 2001), Melbourne, Australia

Blue, V.J. and J.L. Adler (2000), *Cellular Automata Model of Emergent Collective Bi-Directional Pedestrian Dynamics.* In Artificial Life VII Bedau, M.A., McCaskill, J.S. Packard, N.H. and Rasmussen, S. MIT Press, 2000. Available at http://www.ulster.net/~vjblue/research.htm. Last visited October 31, 2005.

Brilon, W., B. Stuwe, and O. Drews. Sicherheit und Leistungsfähigkeit von Kreisverkehrsplätzen (Safety and Capacity of Roundabouts). Research Report. Ruhr-University Bochum, 1993.

Cambridge Systematics (2004), *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

Cassidy, M. et Al. (1995), *Unsignalized Intersection Capacity and Levels of Service: Revisiting Critical Gap,* Transportation Research Record 1484, pp. 16-23. Referenced in Cambridge Systematics, *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

Davis, Gregory and Vaughn Inman (2007), *Pedestrian Access to Roundabouts: Closed Course Test of Yielding Vehicle Detection System*. http://www.accessmanagement.gov/AM2004/AM0411p_Roundabouts.pdf. Last Accessed February 8, 2007.

Devore, Jay L (2000),. *Probability and Statistics for Engineering and the Sciences*. Fifth Edition. Brooks/Cole. Pacific Grove, California. 2000

Dunn, R., and R. Petty (1984). *Mid-Block Pedestrian Crossings – An Examination of Delay.* 12th Annual Australian Road Research Board Conference Proceedings, Hobart, Tasmania, Australia. August 1984.

FHWA (1999), *Injuries to Pedestrians and Bicyclists: An Analysis Based on Hospital Emergency Department Data.* Federal Highway Administration (FHWA). FHWA-RD-99-078, McLean, VA. 1999

FHWA (2000), *Roundabouts: An Informational Guide*. Federal Highway Administration. Turner Fairbank Highway Research Center. FHWA-RD-00-067. McLean, VA. 2000

FHWA, (2003), *Manual on Uniform Traffic Control Devices for Streets and Highways (MUTCD)*. US DOT, FHWA, Washington, DC. 2003. Available online at http://mutcd.fhwa.dot.gov, accessed January 2007.

FHWA (2003). *Surrogate Safety Measures From Traffic Simulation Models*, Publication No: FHWA-RD-03-050. Turner-Fairbank Highway Research Center, Federal Highway Administration, McLean, VA, 2003.

FHWA (2004-1), *NGSIM Task E.3: High-Level Data Plan,* Publication No. #FHWA-HOP-06-0111. Department of Transportation. Federal Highway Administration. Washington, DC. 2004

FHWA (2004-2), *NGSIM Task E.1: Core Algorithm Assessment.,* Publication No. #FHWA-HOP-06-0009. Department of Transportation. Federal Highway Administration. Washington, DC. 2004

Fitzpatrick, Kay, et al. (2006), *Improving Pedestrian Safety at Unsignalized Intersections*. TCRP Report 112/NCHRP Report 562. Transportation Research Board. http://onlinepubs.trb.org Accessed February 2008. Washington, D.C. 2006.

Gates, Tim J., Steven D. Schrock, and James A. Bonneson (2004), *Comparison of Portable Speed Measurement Devices*. Transportation Research Records: Journal of the Transportation Research Board, No. 1870, TRB, National Research Council, Washington, D.C., 2004, pp. 139-146

Geruschat, Duane R. and Shirin E. Hassan (2005), *Driver Behavior in Yielding to Sighted and Blind Pedestrians at Roundabouts.* Journal of Visual Impairment and Blindness. Volume 99, Number 5, May 2005.

Guth et al. (2005), *Blind and Sighted Pedestrians' Judgment of Gaps in Traffic at Roundabouts.* Human Factors, Vol. 47, No. 2, Summer 2005. pp. 314-331.

Harrel, W.A. (1993), *The Impact of Pedestrian Visibility and Assertiveness on Motorist Yielding;* Journal of Social Psychology, Vol. 133(3), pp. 353-360.

Hauer, Ezra (1997), *Observational before-after Studies in Road Safety: Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety,* Elsevier Science & Technology Books, January 1997.

Holden, R. and A. Cangelosi (2003), *Cellular Automata Models of Human Traffic.* Submitted to: First Conference of the European Social Simulation Association, Groningen, The Netherlands.

Institute of Transportation Engineers, (ITE 1982). Transportation and Traffic Engineering Handbook. Englewood Cliffs, NJ, USA: Prentice- Hall, 1982

Institute of Transportation Engineers, ITE (1994), *Manual of Transportation Engineering Studies*. Washington, DC.

Kita, H (1993), *Effects of Merging Lane Length on Merging Behavior at Expressway On-Ramps,* Transportation and Traffic Theory, pp. 37-51. Referenced in Cambridge Systematics, *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

Kittelson and Associates, Roundabout / Traffic Circle Inventory Database. http://roundabouts.kittelson.com/InvMain.asp. Accessed December 31, 2007.

Laser Atlanta (2008), *SpeedLaser ® R Product Specifications,* Laser Atlanta, LLC, Atlanta, GA. http://www.laseratlanta.com/speedlaser_law.htm, Accessed February 2008.

Madanat, S.M et al. (1994), *A Probabilistic Model of Queuing Delay at Stop Controlled Intersection Approaches,* ASCE Journal of Transportation Engineering, Volume 120 (1), pp. 21-36. Referenced in Cambridge Systematics, *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

Mahmassani, H. and Y. Sheffi (1981), *Using Gap Sequences to Estimate Gap Acceptance Functions,* Transportation Research 15B, pp. 143-148. Referenced in Cambridge Systematics, *NGSIM Task E.1-1: Core Algorithm Assessment.* Prepared for Federal Highway Administration. Oakland, California. February 2004.

NCDOT (2007), *Preliminary Evaluation of 14 Roundabout Installations.* Prepared by Safety Evaluation Group, Traffic Safety Systems Management Section, Traffic Engineering and Safety Systems Branch, North Carolina Department of Transportation. Project Log # 200706083. Raleigh, NC. September 2007.

NIH/NEI Bioengineering Research Partnership Grant R01 EY12894-03

NHTSA (2006), *Traffic Safety Facts: 2006 Data,* Nation Highway Traffic Safety Administration (NHTSA), US Department of Transportation. Publication Number DOT HS 810 803. Washington, DC. 2006.

Pedestrian Safety Guide and Countermeasure Selection System (PEDSAFE). Improved Right-Turn Slip-Lane Design. http://www.walkinginfo.org/pedsafe

Polus, Abishai, Sitvanit Shmueli Lazar, and Moshe Libneh (2003), *Critical Gap as a Function of Waiting Time in Determining Roundabout Capacity.* Journal of Transportation Engineering. American Society of Civil Engineers. Washington, DC. September/October 2003.

PTV (2005), *VISSIM 4.10 User Manual.* Karlsruhe, Germany. March 2005.

Pushkarev, B. and J. Zupan (1975), *Urban Space for Pedestrians*. MIT Press, Cambridge, MA. 1975.

Rodegerdts, Lee, et al. (2007), *Roundabouts in the United States*. NCHRP Report 572. Transportation Research Board. http://onlinepubs.trb.org. Accessed February 2008, Washington, D.C. 2007

Quadstone (2005). Paramics Webpage, http://paramics-online.com. Last visited November 3, 2005

Quadstone (2005). *Paramics V5.1 Release Notes.* Paramics Webpage. http://paramics-online.com. May 2005. Last visited November 3, 2005

Ramsey, J.B.H. and I.W. Routledge (1973), *A New Approach to Analysis of Gap Acceptance Times,* Traffic Engineering Control, Vol. 15, No.7.

Rouphail, Nagui M. and Brian S. Eads (1997), *Pedestrian Impedance of Turning Movement Saturation Flow Rates – Comparison of Simulation, Analytical and Field Observations,* Transportation Research Record 1578, Transportation Research Board, Washington, DC. pp. 56-63

Rouphail, Nagui, Ron Hughes and Kosok Chae (2005), *Exploratory Simulation of Pedestrian Crossings at Roundabouts.* ASCE Journal of Transportation Engineering. March 2005. pp. 211-218

SAS Institute (1999), SAS OnlineDoc®, Version 8, http://v8doc.sas.com, accessed February 2008. Cary, NC: SAS Institute Inc., 1999

Schroeder, Bastian J., Nagui M. Rouphail and Robert Wall Emerson(2006), *Exploratory Analysis of Crossing Difficulties for Blind and Sighed Pedestrians at Channelized Turn Lanes*. Journal of the Transportation Research Board, No. 1956. October 2006

Schroeder, Bastian J., Nagui M. Rouphail and Ron Hughes (2008). *Towards Roundabout Accessibility – Exploring the Operational Impact of Pedestrian Signalization Options at Modern Roundabouts*. ASCE Journal of Transportation Engineering. In press Summer 2008.

Schroeder, Bastian J. and Nagui M. Rouphail (2007). *A Framework for Evaluating Pedestrian-Vehicle Interactions at Unsignalized Crossing Facilities in a Microscopic Modeling Environment*. Presented at the 86th Annual Meeting of the Transportation Research Board, Washington, DC. 2007

SIDRA SOLUTIONS (2007), *SIDRA INTERSECTION USER MANUAL*, Greythorn Australia. 2007

Sun et Al (2002), *Modeling of Motorist-Pedestrian Interaction at Uncontrolled Mid-Block Crosswalks.* Submitted for Publication in Transportation Research Record. TRB 2003 Annual Meeting CD-ROM. Washington, DC.

Tiwari, Geetam, Shrikant Bangdiwala, Arvind Saraswat and Sushat Garurav, (2007) *Survival Analysis: Pedestrian Risk Exposure at Signalized Intersection.* Transportation Research Part F 10 (2007) 77–89

Trafficware (2004), *Synchro/SimTraffic 6 User Guide,* Trafficware, Albany, CA. 2004.

TRB (1985), National Cooperative Highway Research Program (NCHRP) Report 279. Intersection Channelization Guide. *Transportation Research Board (TRB)*. Washington, DC. November 1985.

TRB (2000), *Highway Capacity Manual (HCM),* Transportation Research Board (TRB), Washington, DC 2000.

TRB (2003), National Cooperative Highway Research Program (NCHRP) Project 3-72. Synthesis on Channelized Right Turns at Intersections on Urban and Suburban Arterials. *Midwest Research Institute*. Kansas City, Missouri. December 2003.

TRB (2006), National Cooperative Highway Research Program (NCHRP) Project 3-65. Applying Roundabouts in the United States. Kittelson & Associates Inc. http://www4.nationalacademies.org. Accessed July 26, 2006

TRB (2007), National Cooperative Highway Research Program (NCHRP) Project 3-78 (ongoing). Crossing Solutions at Roundabouts and Channelized Turn Lanes for Pedestrians with Vision Disabilities. Institute of Transportation Research and Education. Raleigh, North Carolina.

Troutbeck, R.J. (1992), *Estimating the Critical Acceptance Gap from Traffic Movements*. Physical Infrastructure Centre Research Report 92-5, Queensland University of Technology, Brisbane, Australia. 1992, Revised May 2001.

Troutbeck, Rod J. and Werner Brilon (2002), *Chapter 8: Unsignalized Intersection Theory*, Revised Monograph on Traffic Flow Theory. Turner-Fairbank Highway Research Center. http://www.tfhrc.gov/its/tft/tft.htm. 2002

TSS (2006), *AIMSUN NG User's Manual, Version 5.1.4,* TSS-Transportation Simulation Systems. December 2006.

Tucson DOT (2006), *Pedestrian Traffic Signal Operations*. City of Tucson Department of Transportation, http://dot.ci.tucson.az.us/traffic/tspedestrian.cfm. Accessed July 31, 2006

US Access Board (2006), *Revised Draft Guidelines for Accessible Public Rights-of-Way*. http://www.access-board.gov/prowac/draft.htm. Accessed July 29, 2006

Wall, R., Long, R., Guth, D., Ashmead, D., & Ponchillia, P. (2005), *Roundabouts: Problems of and strategies for access*. International Congress Series 1282, In Proceedings of Vision 2005, April 2005, London

Washington, S.P., M.G. Karlaftis, and F.L. Mannering (2003), *Statistical and Econometric Methods for Transportation Data Analysis.* Chapman & Hall/CRC. Boca Raton, Florida. 2003.

Zeeger, C.V., Stewart, R.J., Huang, H., Lagerwey, P. (2001), "Safety Effects of Marked versus Unmarked Crosswalk at Uncontrolled Locations: Analysis of Pedestrian Crashes in 30 cities, Transportation Research Record, 1773, pp.56-68 (2001).

10 APPENDIX

10.1 Appendix A: Yielding at Mid-Block Models

Table A-23: Correlation Matrix with Yield Response, MB-CLT *

	YIELD	ADY	AST	COM	FLASH	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	TRTMT	DECEL	DIST1	SPEED_FT
YIELD																		
ADY	0.24																	
	<.0001																	
AST	0.30	0.05																
	<.0001	0.2498																
COM	0.50	-0.07	0.21															
	<.0001	0.0885	**<.0001**															
FLASH	0.20	0.09	0.04	0.09														
	<.0001	**0.0204**	0.3393	**0.0232**														
FOLL	-0.06	0.01	-0.03	-0.04	-0.02													
	0.1718	0.7595	0.4746	0.3166	0.6908													
HEV	0.02	0.01	-0.01	0.03	0.03	0.10												
	0.6983	0.771	0.7886	0.3925	0.4119	**0.0156**												
MUP	0.09	0.06	0.03	0.04	0.20	-0.05	0.00											
	0.0319	0.1457	0.394	0.3404	**<.0001**	0.2288	0.9347											
NEAR	-0.06	-0.18	-0.29	0.00	0.03	-0.01	-0.04	-0.05										
	0.1551	**<.0001**	**<.0001**	0.9041	0.523	0.7233	0.2842	0.2177										
PLT	-0.16	0.00	-0.08	-0.18	0.00	0.62	-0.03	-0.08	0.01									
	<.0001	0.9443	0.0561	**<.0001**	0.997	**<.0001**	0.4582	0.059	0.7772									
PREV	-0.03	0.03	-0.06	-0.07	0.13	0.06	-0.09	0.02	0.03	0.28								
	0.4692	0.4461	0.1181	0.0829	**0.0013**	0.144	**0.0259**	0.6381	0.5324	**<.0001**								
PXW	0.35	0.34	0.67	0.14	0.05	-0.01	-0.01	0.06	-0.28	-0.03	-0.04							
	<.0001	**<.0001**	**<.0001**	**0.0008**	0.2062	0.7846	0.8508	0.1697	**<.0001**	0.4934	0.2798							
QUE	0.07	-0.02	0.03	-0.02	-0.03	0.00	-0.01	0.08	-0.08	0.01	0.01	0.03						
	0.084	0.5434	0.5362	0.6474	0.4376	0.9657	0.8056	0.0651	**0.0404**	0.7366	0.7567	0.4862						
TRIG	0.38	0.09	0.56	0.21	0.18	-0.03	0.01	0.05	-0.21	-0.08	-0.02	0.48	-0.02					
	<.0001	**0.0323**	**<.0001**	**<.0001**	**<.0001**	0.4555	0.7229	0.2456	**<.0001**	**0.0468**	0.6233	**<.0001**	0.5566					
TRTMT	0.08	-0.01	0.00	-0.05	0.47	0.03	0.04	0.05	0.02	-0.03	-0.06	-0.06	-0.07	0.16				
	0.0584	0.8656	0.9404	0.2375	**<.0001**	0.4444	0.349	0.2308	0.5761	0.51	0.1389	0.1258	0.0993	**<.0001**				
DECEL	-0.20	-0.14	-0.07	-0.09	-0.12	0.02	-0.04	-0.06	0.03	-0.03	-0.46	-0.13	-0.05	-0.11	0.17			
	<.0001	**0.0008**	0.0879	**0.0258**	**0.0028**	0.5779	0.3305	0.1672	0.3983	0.3987	**<.0001**	**0.0011**	0.1985	**0.0055**	**<.0001**			
DIST1	0.13	0.12	0.02	0.09	0.00	-0.04	-0.04	0.04	-0.05	0.03	0.39	0.06	-0.04	0.08	-0.22	-0.49		
	0.0017	**0.0022**	0.7065	**0.0351**	0.9663	0.3279	0.3309	0.3115	0.2599	0.428	**<.0001**	0.1619	0.277	**0.0412**	**<.0001**	**<.0001**		
SPEED_FT	-0.17	-0.12	-0.02	-0.01	-0.02	-0.08	-0.10	-0.01	0.00	-0.01	-0.02	-0.05	-0.21	-0.01	-0.07	0.25	0.26	
	<.0001	0.0041	0.6564	0.8974	0.6323	0.0586	0.0186	0.7355	0.9738	0.7583	0.5459	0.2293	<.0001	0.7496	0.0773	<.0001	<.0001	
TTC	0.20	0.16	0.03	0.09	0.00	-0.01	-0.02	0.04	-0.04	0.05	0.41	0.09	0.03	0.10	-0.22	-0.56	0.93	-0.04
	<.0001	<.0001	0.4066	0.0221	0.9542	0.8382	0.6424	0.3115	0.2949	0.2141	<.0001	0.0305	0.4074	0.0112	<.0001	<.0001	<.0001	0.304

Shaded cells have correlation > 0.30; bold values are significant at the 0.05 confidence level

Table A-24: DYM Results of Multi-Linear Regression, MB-CLT

a) Full Model

Parameter	Estimate	Standard Error	t-value	PR > |t|
Intercept	0.2611	0.1253	2.08	**0.0377**
ADY	0.1732	0.0565	3.07	**0.0023**
AST	0.0866	0.0636	1.36	0.1741
FLASH	0.1375	0.0502	2.74	**0.0064**
FOLL	0.0309	0.0372	0.83	0.4065
NEAR	0.0690	0.0314	2.19	**0.0286**
PLT	-0.1254	0.0421	-2.98	**0.003**
PREV	-0.0967	0.0406	-2.38	**0.0177**
PXW	0.1414	0.0630	2.25	**0.0251**
TRIG	0.2970	0.0662	4.48	**<.0001**
trtmt	0.0189	0.0374	0.51	0.6134
Decel	-0.0178	0.0130	-1.38	0.1688
DIST1	-0.0003	0.0003	-1.2	0.2316
SPEED_FT	-0.0017	0.0032	-0.53	0.5944
TTC_V	0.0197	0.0111	1.78	**0.0761**

Source	DF	Sum of Squares	Mean Squares	F-Value	pr > F
Model	14	24.24	1.732	15.07	<.0001
Error	525	60.34	0.114937		
Corr. Total	539	84.58			

R-Square	Coeff Var	Root MSE	Yield Mean
0.2866	174.355	0.3390	0.1944

Adj. R - Square
0.27

b) Restricted Model

Parameter	Estimate	Standard Error	t-value	PR > |t|
Intercept	0.4329	0.0699	6.19	**<.0001**
PLT	-0.1183	0.0298	-3.96	**<.0001**
NEAR	0.0195	0.2925	0.67	0.5054
AST	0.3028	0.0421	7.2	**<.0001**
SPEED_FT	-0.0054	0.0016	-3.51	**0.0005**
DECEL	-0.0082	0.0026	-3.19	**0.0015**
TRTMT	0.0043	0.0338	0.13	0.8983
FLASH	0.1862	0.0485	3.84	**0.0001**

Source	DF	Sum of Squares	Mean Squares	F-Value	pr > F
Model	7	16.33	2.333	19.77	<.0001
Error	597	70.45	0.118		
Corr. Total	604	86.78			

R-Square	Coeff Var	Root MSE	Yield Mean
0.1882	197.928	0.3435	0.1736

Adj. R - Square
0.18

Table A-25: DYM Results of Binary Logistic Regression, MB-CLT

a) Full Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.6762	1.0879	0.3863	0.5343	
ADY	1	1.1055	0.4104	7.256	**0.0071**	3.021
AST	1	0.7741	0.49	2.4958	0.1142	2.169
FLASH	1	0.8544	0.4046	4.4584	**0.0347**	2.35
FOLL	1	0.3369	0.3665	0.8452	0.3579	1.401
NEAR	1	0.6839	0.3102	4.8615	**0.0275**	1.982
PLT	1	-1.0534	0.3851	7.481	**0.0062**	0.349
PREV	1	-0.866	0.3415	6.4295	**0.0112**	0.421
PXW	1	0.8251	0.4576	3.2514	**0.0714**	2.282
TRIG	1	1.4267	0.4916	8.4219	**0.0037**	4.165
trtmt	1	0.3578	0.3473	1.0616	0.3028	1.43
Decel	1	-0.2967	0.1462	4.115	**0.0425**	0.743
DIST1	1	-0.00169	0.00253	0.4457	0.5044	0.998
SPEED_FT	1	-0.0121	0.0307	0.1543	0.6945	0.99
TTC_V	1	0.0988	0.096	1.0592	0.3034	1.10

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	534.012	413.251
SC	538.304	477.625
-2 Log L	532.012	383.251
R-Square		0.2408
Max-rescaled R-2		0.3843

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	148.7605	14	<.0001
Score	154.7637	14	<.0001
Wald	96.7286	14	<.0001

b) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
ADY	1	0.9669	0.3868	6.2507	**0.0124**	2.63
FLASH	1	1.0264	0.3265	9.8828	**0.0017**	2.791
NEAR	1	0.5902	0.295	4.0012	**0.0455**	1.804
PLT	1	-0.7543	0.2742	7.5657	**0.0059**	0.47
PREV	1	-1.0156	0.3308	9.4274	**0.0021**	0.36
PXW	1	1.1498	0.3708	9.6175	**0.0019**	3.16
TRIG	1	1.7988	0.4329	17.2634	**<.0001**	6.04
DECEL	1	-0.4349	0.0924	22.1535	**<.0001**	0.65

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	534.012	430.430
SC	538.304	448.488
-2 Log L	532.012	391.864
R-Square		0.2286
Max-rescaled R-2		0.3648

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	140.1484	8	<.0001
Score	145.4136	8	<.0001
Wald	91.8624	8	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
8.4954	6	0.204

c) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.4356	0.5505	0.626	0.4288	
AST	1	1.8823	0.3181	35.0159	**<.0001**	6.57
FLASH	1	0.9124	0.3729	5.9866	**0.0144**	2.49
NEAR	1	0.2637	0.2695	0.9574	0.3278	1.30
PLT	1	-0.9622	0.2502	14.7929	**0.0001**	0.38
trtmt	1	0.4073	0.3135	1.6884	0.1938	1.50
Decel	1	-0.3428	0.0859	15.9139	**<.0001**	0.71
SPEED_FT	1	-0.0308	0.0134	5.2726	**0.0217**	0.97

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	534.444	441.107
SC	538.737	475.455
-2 Log L	532.444	425.107
R-Square		0.1800
Max-rescaled R-2		0.2874

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	107.3368	7	<.0001
Score	106.1210	7	<.0001
Wald	77.5397	7	<.0001

d) Restricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.6781	0.5212	1.6931	0.1932	
AST	1	1.749	0.2897	36.4438	**<.0001**	5.75
FLASH	1	1.2118	0.3021	16.0853	**<.0001**	3.36
PLT	1	-0.9608	0.2489	14.9	**0.0001**	0.38
Decel	1	-0.3177	0.0829	14.6779	**0.0001**	0.73
SPEED_FT	1	-0.0318	0.0132	5.7528	**0.0165**	0.97

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	534.444	439.594
SC	538.737	465.355
-2 Log L	532.444	427.594
R-Square		0.1762
Max-rescaled R-2		0.2813

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	104.8499	5	<.0001
Score	105.1097	5	<.0001
Wald	77.3054	5	<.0001

e) Restricted Model 3*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.3776	0.2861	1.7418	0.1869	
AST	1	1.7206	0.2851	36.4131	**<.0001**	5.59
FLASH	1	1.1891	0.3004	15.6718	**<.0001**	3.28
PLT	1	-0.9551	0.2469	14.9664	**0.0001**	0.39
Decel	1	-0.3818	0.0818	21.7706	**<.0001**	0.68

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	534.444	443.418
SC	538.737	464.885
-2 Log L	532.444	433.418
R-Square		0.1673
Max-rescaled R-2		0.2671

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	99.0262	4	<.0001
Score	97.7912	4	<.0001
Wald	72.6737	4	<.0001

* Model was selected as preferred model in its category

Table A-26: DYM Results of Cumulative Logistic Regression, MB-CLT

a) Unrestricted Model**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.0622	0.3954	0.0247	0.8751	.
Intercept	1	0.5535	0.3991	1.9235	0.1655	.
ADY	1	-0.8153	0.3484	5.4751	0.0193	0.443
FLASH	1	-0.766	0.3085	6.1649	0.013	0.465
PLT	1	0.7067	0.2586	7.4707	0.0063	2.027
PREV	1	0.8638	0.3081	7.8586	0.0051	2.372
PXW	1	-0.8006	0.3376	5.6258	0.0177	0.449
TRIG	1	-1.127	0.3756	9.0034	0.0027	0.324
Decel	1	0.3793	0.0857	19.5974	<.0001	1.461

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and
AIC	669.68	568.757
SC	678.263	607.381
-2 Log L	665.680	550.757
R-Square		0.1917
Max-rescaled R-2		0.2706

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	114.923	7	<.0001
Score	133.119	7	<.0001
Wald	83.2733	7	<.0001

Residual Chi2 Test

Chi-Square	DF	PR > Chi2
12.8309	10	0.2333

b) Restricted Model 1**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.2414	0.533	0.2052	0.6506	
Intercept	1	0.3317	0.5344	0.3851	0.5349	
AST	1	-1.4959	0.2995	24.9429	**<.0001**	0.224
FLASH	1	-0.7793	0.3661	4.5313	**0.0333**	0.459
NEAR	1	-0.2161	0.2602	0.6894	0.4064	0.806
PLT	1	0.864	0.241	12.8535	**0.0003**	2.373
trtmt	1	-0.231	0.3081	0.5621	0.4534	0.794
Decel	1	0.306	0.0822	13.8595	**0.0002**	1.358
SPEED_FT	1	0.0256	0.0129	3.9679	**0.0464**	1.026

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	670.112	594.364
SC	678.699	633.005
-2 Log L	666.112	576.364
R-Square		0.1529
Max-rescaled R-2		0.2159

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	89.7475	7	<.0001
Score	96.5818	7	<.0001
Wald	67.4291	7	<.0001

c) Restricted Model 2**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.4254	0.5035	0.714	0.3981	
Intercept	1	0.1467	0.5046	0.0846	0.7712	
AST	1	-1.4007	0.2734	26.2518	**<.0001**	0.246
FLASH	1	-0.96	0.2899	10.9664	**0.0009**	0.383
PLT	1	0.8732	0.2403	13.2069	**0.0003**	2.395
Decel	1	0.292	0.0797	13.4126	**0.0002**	1.339
SPEED_FT	1	0.0263	0.0127	4.2832	**0.0385**	1.027

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	670.112	591.566
SC	678.699	621.62
-2 Log L	666.112	577.566
R-Square		0.1510
Max-rescaled R-2		0.2132

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	88.546	5	<.0001
Score	95.7918	5	<.0001
Wald	67.4935	5	<.0001

d) Restricted Model 3**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.4323	0.28	2.3843	0.1226	
Intercept	1	0.9993	0.2868	12.1425	0.0005	
AST	1	-1.3916	0.2709	26.3778	**<.0001**	0.249
FLASH	1	-0.9257	0.2892	10.2426	**0.0014**	0.396
PLT	1	0.8642	0.2389	13.084	**0.0003**	2.373
Decel	1	0.3508	0.0785	19.9575	**<.0001**	1.42

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	670.112	594.067
SC	678.699	619.827
-2 Log L	666.112	582.067
R-Square		0.1439
Max-rescaled R-2		0.2032

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	84.0454	4	<.0001
Score	89.1761	4	<.0001
Wald	63.3124	4	<.0001

Table A-27: DYM Results of Multinomial Logistic Regression, MB-CLT

a) Unrestricted Model

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
		Analysis of Maximum Likelihood Estimates				
Intercept-2	1	2.2846	1.2016	3.6148	0.0573	
Intercept-3	1	-1.0084	0.7479	1.818	0.1776	
ADY-2	1	0.9542	0.5501	3.0084	0.0828	2.597
ADY-3	1	1.2322	0.3761	10.7333	0.0011	3.429
AST-2	1	1.5514	0.5232	8.7942	0.003	4.718
AST-3	1	0.6397	0.4271	2.2433	0.1342	1.896
FLASH-2	1	1.6247	0.4748	11.7116	0.0006	5.077
FLASH-3	1	0.8271	0.3762	4.8349	0.0279	2.287
PLT-2	1	-0.9126	0.4511	4.0934	0.0431	0.401
PLT-3	1	-0.6768	0.2972	5.1858	0.0228	0.508
PREV-2	1	-1.1762	0.506	5.4026	0.0201	0.308
PREV-3	1	-0.9067	0.3562	6.4795	0.0109	0.404
TRIG-2	1	1.7517	0.5915	8.7702	0.0031	5.765
TRIG-3	1	1.4121	0.5017	7.9206	0.0049	4.105
DECEL-2	1	-1.2308	0.2809	19.1977	<.0001	0.292
DECEL-3	1	-0.244	0.1279	3.6382	0.0565	0.783
TTC_V-2	1	-0.1738	0.0679	6.5406	0.0105	0.84
TTC_V-3	1	0.0376	0.0325	1.34	0.247	1.038

* Estimates for SY=2 and HY=3 are relative to baseline response NY=1

Model Fit Statistics

Criterion	Intercept Only	Intercept and
AIC	669.680	540.955
SC	678.263	618.203
-2 Log L	665.680	504.955
R-Square		0.2574
Max-rescaled R-2		0.3633

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	160.725	16	<.0001
Score	169.053	16	<.0001
Wald	104.061	16	<.0001

Residual Chi2 Test

Chi-Square	DF	PR > Chi2
28.5359	18	0.0544

b) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept-2	1	0.0311	0.8045	0.0015	0.9692	
Intercept-3	1	0.0764	0.5829	0.0172	0.8957	
AST-2	1	2.5332	0.4244	35.6343	**<.0001**	12.594
AST-3	1	1.3971	0.33	17.9216	**<.0001**	4.043
FLASH-2	1	1.9417	0.4458	18.9692	**<.0001**	6.971
FLASH-3	1	0.8984	0.3477	6.6755	**0.0098**	2.456
PLT-2	1	-1.2522	0.4084	9.4004	0.0022	0.286
PLT-3	1	-0.8639	0.2757	9.8205	0.0017	0.422
DECEL-2	1	-0.4681	0.1722	7.3893	**0.0066**	0.626
DECEL-3	1	-0.2715	0.0884	9.4306	**0.0021**	0.762
SPEED_FT-2	1	-0.0474	0.0215	4.8741	**0.0273**	0.954
SPEED_FT-3	1	-0.0252	0.0147	2.9496	0.0859	0.975

* Estimates for SY=2 and HY=3 are relative to baseline response NY=1

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	670.112	570.576
SC	678.699	622.097
-2 Log L	666.112	546.576
R-Square		0.1982
Max-rescaled R-2		0.28

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	119.5357	10	<.0001
Score	125.1188	10	<.0001
Wald	81.7971	10	<.0001

c) Restricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept-2	2	-1.4458	0.4994	8.3817	**0.0038**	
Intercept-3	3	-0.7815	0.3166	6.0915	**0.0136**	
AST-2	2	2.5006	0.418	35.795	**<.0001**	12.19
AST-3	3	1.3646	0.3268	17.432	**<.0001**	3.914
FLASH-2	2	1.8793	0.4397	18.2628	**<.0001**	6.549
FLASH-3	3	0.8844	0.3466	6.511	**0.0107**	2.421
PLT-2	2	-1.2003	0.4022	8.9041	**0.0028**	0.301
PLT-3	3	-0.8684	0.2746	10.0021	**0.0016**	0.42
DECEL-2	2	-0.6037	0.1694	12.7066	**0.0004**	0.547
DECEL-3	3	-0.3144	0.0866	13.1672	**0.0003**	0.73

* Estimates for SY=2 and HY=3 are relative to baseline response NY=1

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	670.112	573.053
SC	678.699	615.988
-2 Log L	666.112	553.053
R-Square		0.1886
Max-rescaled R-2		0.2663

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	113.0584	8	<.0001
Score	116.4177	8	<.0001
Wald	77.7378	8	<.0001

Table A-28: DYM Results of Nested Logistic Regression, MB-CLT

a) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.6967	0.848	0.6749	0.4113	
AST	1	-1.7344	0.5438	10.1706	0.0014	0.177
COM***	1	-1.7923	0.6093	8.6537	0.0033	0.167
TRTMT	1	-2.2495	0.6146	13.3956	0.0003	0.105
SPEED_FT	1	0.0683	0.0253	7.2688	0.007	1.071

*** First level of nested logit model is identical with binary logistics model

**** COM was allowed to enter the P(HY|Y) model, but not the other models

Model Fit Statistics

Criterion	Intercept Only	Intercept and
AIC	135.668	113.838
SC	138.322	127.108
-2 Log L	133.668	103.838
R-Square		0.2473
Max-rescaled R-2		0.3435

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	29.83	4	<.0001
Score	25.8091	4	<.0001
Wald	19.5429	4	0.0006

Residual Chi2 Test

Chi-Square	DF	PR > Chi2
9.5619	11	0.5702

b) Restricted Model – 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.5539	0.9463	0.3426	0.5583	
AST	1	-1.9421	0.5986	10.5248	**0.0012**	0.143
FLASH	1	-0.2999	0.6462	0.2153	0.6426	0.741
NEAR	1	-0.4934	0.5448	0.8202	0.3651	0.611
PLT	1	0.596	0.4845	1.5135	0.2186	1.815
trtmt	1	-1.6901	0.6757	6.2558	**0.0124**	0.184
Decel	1	0.2262	0.1956	1.3374	0.2475	1.254
SPEED_FT	1	0.0378	0.0252	2.2516	0.1335	1.038

*** First level of nested logit model is identical with binary logistics model

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	135.668	125.531
SC	138.322	146.762
-2 Log L	133.668	109.531
R-Square		0.2054
Max-rescaled R-2		0.2852

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	24.1373	7	0.0011
Score	21.3125	7	0.0033
Wald	16.831	7	0.0185

c) Restricted Model – 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.6146	0.8316	0.5461	0.4599	
AST	1	-1.6594	0.5139	10.4266	**0.0012**	0.190
trtmt	1	-1.6087	0.5126	9.8482	**0.0017**	0.200
SPEED_FT	1	0.0444	0.0227	3.8297	**0.0504**	1.045

*** First level of nested logit model is identical with binary logistics model

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	135.668	121.558
SC	138.322	132.174
-2 Log L	133.668	113.558
R-Square		0.1743
Max-rescaled R-2		0.2421

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	20.11	3	0.0002
Score	18.54	3	0.0003
Wald	15.12	3	0.0017

d) Restricted Model – 3*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.5249	0.5468	7.7784	0.0053	
AST	1	-1.4754	0.4943	8.9093	**0.0028**	0.229
trtmt	1	-1.5803	0.5069	9.7214	**0.0018**	0.206
Decel	1	0.2873	0.1827	2.473	0.1158	1.333

*** First level of nested logit model is identical with binary logistics model

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	135.668	122.671
SC	138.322	133.287
-2 Log L	133.668	114.671
R-Square		0.1655
Max-rescaled R-2		0.2299

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	18.9968	3	0.0003
Score	17.1811	3	0.0006
Wald	14.1989	3	0.0026

* Model was selected as preferred model in its category

Table A-29: Correlation Matrix with Yield Response, MB-RAL *

	YIELD	ADY	AST	COM	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	TRTMT	DECEL	DIST1	SPEED_FT
YIELD																	
ADY	0.16																
	0.0007																
AST	0.29	-0.02															
	<.0001	0.5908															
COM	0.45	-0.05	0.03														
	<.0001	0.2375	0.5551														
FOLL	0.01	-0.07	-0.04	0.04													
	0.7614	0.1217	0.3491	0.3573													
HEV	-0.01	0.14	0.00	-0.05	-0.02												
	0.8072	**0.0025**	0.925	0.3114	0.7404												
MUP	0.14	0.06	-0.03	0.00	0.04	0.05											
	0.0029	0.2258	0.4834	0.9745	0.4159	0.3196											
NEAR	0.06	-0.18	-0.12	0.06	0.12	-0.04	0.05										
	0.2144	**<.0001**	**0.009**	0.1758	**0.0074**	0.4081	0.2488										
PLT	-0.06	-0.10	-0.11	-0.01	0.71	0.01	0.04	0.15									
	0.1917	**0.0248**	**0.0139**	0.8779	**<.0001**	0.9111	0.3402	**0.0015**									
PREV	-0.07	-0.02	-0.09	-0.11	-0.02	0.03	0.15	-0.03	0.34								
	0.1135	0.6537	**0.0483**	**0.0199**	0.6781	0.4563	**0.0009**	0.5463	**<.0001**								
PXW	0.24	0.07	0.21	0.05	-0.03	0.00	0.05	-0.04	-0.16	-0.26							
	<.0001	0.1227	**<.0001**	0.266	0.5186	0.9208	0.2488	0.3912	**0.0004**	**<.0001**							
QUE	0.08	-0.06	0.03	-0.01	0.21	-0.03	0.07	0.08	0.25	0.15	-0.07						
	0.0815	0.1822	0.5598	0.8872	**<.0001**	0.4595	0.1171	0.0846	**<.0001**	**0.0013**	0.1122						
TRIG	0.29	-0.02	0.60	0.03	-0.06	0.03	-0.01	-0.08	-0.12	-0.11	0.28	-0.05					
	<.0001	0.6235	**<.0001**	0.5598	0.1622	0.4784	0.8522	0.08	**0.0075**	**0.0202**	**<.0001**	0.2437					
TRTMT	0.16	0.03	0.08	0.08	0.06	-0.04	0.01	0.02	0.04	-0.12	0.07	0.05	0.05				
	0.0003	0.5804	0.091	0.091	0.2072	0.3812	0.841	0.6839	0.3914	**0.007**	0.1475	0.29	0.2857				
DECEL	-0.25	-0.13	0.00	-0.11	-0.02	-0.04	-0.15	0.06	-0.09	-0.28	0.06	0.00	-0.02	-0.08			
	<.0001	**0.0043**	0.9166	**0.0209**	0.6363	0.41	**0.0015**	0.2296	0.0506	**<.0001**	0.1752	0.9531	0.6267	0.0859			
DIST1	0.12	0.18	-0.04	0.06	-0.08	-0.02	0.19	-0.01	-0.05	0.38	-0.08	-0.22	0.01	-0.11	-0.49		
	0.0113	**<.0001**	0.3918	0.2097	0.072	0.6946	**<.0001**	0.7966	0.2699	**<.0001**	0.0839	**<.0001**	0.7899	**0.0127**	**<.0001**		
SPEED_FT	-0.14	-0.01	0.04	0.01	-0.19	-0.01	-0.05	0.03	-0.25	-0.10	-0.01	-0.43	0.07	-0.18	0.26	0.33	
	0.0029	0.9043	0.4218	0.7872	**<.0001**	0.8054	0.3295	0.5104	**<.0001**	**0.0285**	0.8842	**<.0001**	0.1165	**<.0001**	**<.0001**	**<.0001**	
TTC	0.19	0.20	-0.05	0.06	-0.01	-0.02	0.23	-0.02	0.04	0.43	-0.07	-0.10	-0.01	-0.06	-0.61	0.92	-0.02
	<.0001	**<.0001**	0.2369	0.2298	0.7533	0.6169	**<.0001**	0.6641	0.4049	**<.0001**	0.1236	**0.0257**	0.7933	0.2185	**<.0001**	**<.0001**	0.6481

* Shaded cells have correlation > 0.30; bold values are significant at the 0.05 confidence level

Table A-30: DYM Results of Multi-Linear Regression, MB-RAL

a) Full Model

Parameter	Estimate	Standard Error	t-value	PR > |t|
Intercept	0.1253	0.1966	0.64	0.5241
ADY	0.2215	0.0832	2.66	**0.0081**
AST	0.3230	0.0905	3.57	**0.0004**
FOLL	0.0377	0.0737	0.51	0.6095
NEAR	0.1215	0.0444	2.74	**0.0065**
PLT	-0.0736	0.0710	-1.04	0.3003
PREV	-0.0883	0.0596	-1.48	0.1389
PXW	0.1822	0.0552	3.3	**0.0011**
QUE	0.2158	0.1082	1.99	**0.0468**
TRIG	0.2255	0.1198	1.88	**0.0604**
trtmt	0.1042	0.0428	2.44	**0.0152**
Decel	-0.0610	0.0195	-3.13	**0.0019**
DIST1	-0.0012	0.0008	-1.54	0.1241
SPEED_FT	0.0077	0.0059	1.32	0.1878
TTC_V	0.0431	0.0275	1.57	0.1173

Source	DF	Sum of Squares	Mean Squares	F-Value	pr > F
Model	14	24.93	1.780	9.95	<.0001
Error	414	74.07	0.178916		
Corr. Total	428	99.00			

R-Square	Coeff Var	Root MSE	Yield Mean
0.2518	######	0.4230	0.3613

Adj. R - Square
0.23

b) Restricted Model

Parameter	Estimate	Standard Error	t-value	PR > |t|
Intercept	0.5082	0.1007	5.05	**<.0001**
AST	0.4895	0.0732	6.69	**<.0001**
NEAR	0.1166	0.0446	2.61	**0.0093**
PLT	-0.1021	0.0458	-2.23	**0.0264**
trtmt	0.1210	0.0435	2.78	**0.0056**
Decel	-0.0572	0.0115	-4.96	**<.0001**
SPEED_FT	-0.0021	0.0027	-0.78	0.4386

Source	DF	Sum of Squares	Mean Squares	F-Value	pr > F
Model	6	17.97	2.995	15.55	<.0001
Error	423	81.44	0.192522		
Corr. Total	429	99.40			

R-Square	Coeff Var	Root MSE	Yield Mean
0.1808	120.944	0.4388	0.3628

Adj. R - Square
0.17

Table A-31: DYM Results of Binary Logistic Regression, MB-RAL

a) Full Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-1.5824	1.1915	1.7639	0.1841	
ADY	1	1.0882	0.4458	5.9585	**0.0146**	2.97
AST	1	1.7324	0.5382	10.3636	**0.0013**	5.65
FOLL	1	0.0853	0.4295	0.0395	0.8425	1.09
NEAR	1	0.6693	0.2657	6.3425	**0.0118**	1.95
PLT	1	-0.328	0.4125	0.6322	0.4266	0.72
PREV	1	-0.5119	0.3431	2.2252	0.1358	0.60
PXW	1	0.9394	0.3084	9.2756	**0.0023**	2.56
QUE	1	1.1165	0.6078	3.3746	**0.0662**	3.05
TRIG	1	1.6034	0.8766	3.3459	**0.0674**	4.97
TRTMT	1	0.5553	0.2431	5.2177	**0.0224**	1.74
DECEL	1	-0.415	0.136	9.3076	**0.0023**	0.66
DIST1	1	-0.0059	0.00466	1.6083	0.2047	0.99
SPEED_FT	1	0.0449	0.036	1.5552	0.2124	1.05
TTC_V	1	0.1871	0.1623	1.3292	0.249	1.21

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	563.274	471.903
SC	567.336	532.825
-2 Log L	561.274	441.903
R-Square		0.2429
Max-rescaled R-2		0.3329

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	119.3707	14	<.0001
Score	108.0163	14	<.0001
Wald	76.6804	14	<.0001

b) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.3229	0.3992	0.6541	0.4187	.
ADY	1	1.0963	0.4386	6.2471	**0.0124**	2.99
AST	1	1.8089	0.5319	11.5658	**0.0007**	6.10
NEAR	1	0.7021	0.2593	7.3319	**0.0068**	2.02
PREV	1	-0.5755	0.2801	4.2229	**0.0399**	0.56
PXW	1	0.9257	0.3067	9.1104	**0.0025**	2.52
TRIG	1	1.6642	0.8765	3.6045	**0.0576**	5.28
TRTMT	1	0.5399	0.2344	5.3058	**0.0213**	1.72
DECEL	1	-0.3758	0.0756	24.6862	**<.0001**	0.69

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	563.274	465.024
SC	567.336	501.577
-2 Log L	561.274	447.024
R-Square		0.2338
Max-rescaled R-2		0.3204

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	114.2501	8	<.0001
Score	102.8855	8	<.0001
Wald	72.6349	8	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
5.0711	6	0.5347

c) Restricted Model 1

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.1324	0.5268	0.0632	0.8015	.
AST	1	2.4965	0.4475	31.1262	**<.0001**	12.14
NEAR	1	0.6249	0.242	6.6701	**0.0098**	1.87
PLT	1	-0.5153	0.2414	4.5552	**0.0328**	0.60
TRTMT	1	0.6221	0.2268	7.525	**0.0061**	1.86
DECEL	1	-0.3287	0.0702	21.9219	**<.0001**	0.72
SPEED_FT	1	-0.0085	0.0141	0.3608	0.5481	0.99

(Analysis of Maximum Likelihood Estimates)

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	565.306	493.258
SC	569.370	521.705
-2 Log L	563.306	479.258
R-Square		0.1775
Max-rescaled R-2		0.2431

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	84.0477	6	<.0001
Score	77.7245	6	<.0001
Wald	59.3376	6	<.0001

d) Restricted Model 2*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.124	0.3083	0.1619	0.6875	.
AST	1	2.4865	0.4468	30.9666	**<.0001**	12.02
NEAR	1	0.6165	0.2415	6.5179	**0.0107**	1.85
PLT	1	-0.4907	0.2377	4.2617	**0.039**	0.61
trtmt	1	0.6477	0.2228	8.4534	**0.0036**	1.91
Decel	1	-0.3441	0.0658	27.3609	**<.0001**	0.71

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	565.306	491.62
SC	569.37	516.002
-2 Log L	563.306	479.620
R-Square		0.1769
Max-rescaled R-2		0.2442

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	83.6863	5	<.0001
Score	77.2238	5	<.0001
Wald	59.0366	5	<.0001

* Model was selected as preferred model in its category

Table A-32: DYM Results of Cumulative Logistic Regression, MB-RAL

a) Unrestricted Model**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept 1	1	0.5806	0.2859	4.1237	0.0423	
Intercept 2	1	1.6216	0.2986	29.4908	**<.0001**	
AST	1	-1.114	0.3386	10.8228	**0.001**	0.328
NEAR	1	-0.606	0.2248	7.267	**0.007**	0.546
PXW	1	-0.9424	0.251	14.0995	**0.0002**	0.39
TRTMT	1	-0.5001	0.2099	5.6733	**0.0172**	0.606
DECEL	1	0.2854	0.0605	22.2684	**<.0001**	1.33

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and
AIC	779.988	719.41
SC	788.111	747.84
-2 Log L	775.988	705.410
R-Square		0.1517
Max.ReScaled R2		0.1814

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	70.5788	5	<.0001
Score	72.4797	5	<.0001
Wald	56.593	5	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
12.8996	9	0.1672

b) Restricted Model - 1**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept 1	1	-0.3355	0.4849	0.4789	0.4889	
Intercept 2	1	0.6791	0.4866	1.9476	0.1628	
AST	1	-1.3008	0.3299	15.5507	**<.0001**	0.272
NEAR	1	-0.6171	0.2245	7.5556	**0.006**	0.539
PLT	1	0.4626	0.2253	4.2181	**0.04**	1.588
TRTMT	1	-0.5225	0.2109	6.1407	**0.0132**	0.593
DECEL	1	0.2665	0.0646	17.0214	**<.0001**	1.305
SPEED_FT	1	0.0179	0.013	1.8868	0.1696	1.018

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	783.337	734.213
SC	791.465	766.723
-2 Log L	779.337	718.213
R-Square		0.1325
Max.ReScaled R2		0.1584

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	61.1241	6	<.0001
Score	62.5268	6	<.0001
Wald	49.7261	6	<.0001

c) Restricted Model - 2**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.1987	0.2902	0.4689	0.4935	
Intercept	1	1.2073	0.2988	16.326	**<.0001**	
AST	1	-1.2864	0.3284	15.3434	**<.0001**	0.276
NEAR	1	-0.5998	0.2242	7.1586	**0.0075**	0.549
PLT	1	0.4069	0.2212	3.3857	**0.0658**	1.502
trtmt	1	-0.5726	0.2073	7.6286	**0.0057**	0.564
Decel	1	0.3018	0.0607	24.7071	**<.0001**	1.352

** Proportional Odds Assumption was rejected at p<0.0001

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	783.337	734.05
SC	791.465	762.496
-2 Log L	779.337	720.050
R-Square		0.1288
Max.ReScaled R2		0.1539

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	59.2874	5	<.0001
Score	60.3726	5	<.0001
Wald	47.7022	5	<.0001

Table A-33: DYM Results of Multinomial Logistic Regression, MB-RAL

a) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept-2	1	-1.4179	0.7425	3.6469	**0.0562**	
Intercept-3	1	0.0845	0.6079	0.0193	0.8894	
ADY-2	1	1.4549	0.5189	7.8603	**0.0051**	4.284
ADY-3	1	0.6464	0.5628	1.319	0.2508	1.909
AST-2	1	2.6419	0.5933	19.831	**<.0001**	14.04
AST-3	1	1.1937	0.6346	3.5381	**0.06**	3.299
NEAR-2	1	0.614	0.364	2.8457	**0.0916**	1.848
NEAR-3	1	0.767	0.3057	6.2973	**0.0121**	2.153
PREV-2	1	-1.5586	0.4291	13.1929	**0.0003**	0.21
PREV-3	1	-0.1675	0.3185	0.2765	0.599	0.846
PXW-2	1	0.8391	0.3923	4.5742	**0.0325**	2.314
PXW-3	1	1.0286	0.3468	8.7954	**0.003**	2.797
TRIG-2	1	2.0856	0.9218	5.1185	**0.0237**	8.049
TRIG-3	1	0.3964	1.1299	0.1231	0.7257	1.486
DECEL-2	1	-0.7012	0.14	25.0835	**<.0001**	0.496
DECEL-3	1	-0.2122	0.0891	5.679	**0.0172**	0.809
SPEED_FT-2	1	0.0458	0.0222	4.2471	**0.0393**	1.047
SPEED_FT-3	1	-0.0396	0.017	5.3873	**0.0203**	0.961

* Estimates for SY=2 and HY=3 are relative to baseline response NY=1

Model Fit Statistics

Criterion	Intercept Only	Intercept and
AIC	779.988	653.088
SC	788.111	726.194
-2 Log L	775.988	617.088
R-Square		0.3095
Max.ReScaled R2		0.3702

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	158.9002	16	<.0001
Score	162.3283	16	<.0001
Wald	97.6017	16	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
16.2814	12	0.1787

b) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept-2	1	-2.0258	0.6686	9.1801	**0.0024**	
Intercept-3	1	0.2857	0.5467	0.273	0.6013	
AST-2	1	3.2498	0.4864	44.6405	**<.0001**	25.786
AST-3	1	1.3081	0.5652	5.3556	**0.0207**	3.699
TRTMT-2	1	0.7069	0.303	5.4426	**0.0197**	2.028
TRTMT-3	1	0.5383	0.2673	4.0539	**0.0441**	1.713
DECEL-2	1	-0.5036	0.1088	21.4318	**<.0001**	0.604
DECEL-3	1	-0.1917	0.0791	5.8809	**0.0153**	0.826
SPEED_FT-2	1	0.0461	0.0193	5.7196	**0.0168**	1.047
SPEED_FT-3	1	-0.0346	0.0163	4.4919	**0.0341**	0.966

* Estimates for SY=2 and HY=3 are relative to baseline response NY=1

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	783.337	692.779
SC	791.465	733.417
-2 Log L	779.337	672.779
R-Square		0.2195
Max.ReScaled R2		0.2623

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	106.5584	8	<.0001
Score	112.5071	8	<.0001
Wald	78.1988	8	<.0001

c) Restricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept-2	1	-0.7151	0.3388	4.4539	**0.0348**	
Intercept-3	1	-0.6684	0.3019	4.9012	**0.0268**	
AST-2	1	3.1928	0.4783	44.554	**<.0001**	24.357
AST-3	1	1.3702	0.5577	6.0355	**0.014**	3.936
TRTMT-2	1	0.5708	0.2943	3.7608	**0.0525**	1.77
TRTMT-3	1	0.6519	0.2612	6.2306	**0.0126**	1.919
DECEL-2	1	-0.3794	0.091	17.3732	**<.0001**	0.684
DECEL-3	1	-0.2669	0.0751	12.6297	**0.0004**	0.766

* Estimates for SY=2 and HY=3 are relative to baseline response NY=1

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	783.337	703.391
SC	791.465	735.901
-2 Log L	779.337	687.391
R-Square		0.1925
Max.ReScaled R2		0.2301

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	91.946	6	<.0001
Score	100.2206	6	<.0001
Wald	68.8904	6	<.0001

Table A-34: DYM Results of Nested Logistic Regression, MB-RAL

a) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.1088	0.2915	14.4729	**0.0001**	
ADY	1	-1.6782	0.5788	8.4065	**0.0037**	0.187
AST	1	-1.7366	0.628	7.6472	**0.0057**	0.176
COM	1	-1.5069	0.4318	12.1774	**0.0005**	0.222
QUE	1	2.4945	1.1978	4.3368	**0.0373**	12.116
TRIG	1	-1.8224	0.8804	4.2854	**0.0384**	0.162

*** First level of nested logit model is identical with binary logistics model

**** COM was allowed to enter the P(HY|Y) model, but not the other models

Model Fit Statistics

Criterion	Intercept Only	Intercept and
AIC	216.714	176.978
SC	219.758	195.238
-2 Log L	214.714	164.978
R-Square		0.2745
Max.ReScaled R2		0.3361

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	49.7367	5	<.0001
Score	42.0706	5	<.0001
Wald	30.1704	5	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
15.5569	10	0.1130

b) Restricted Model – 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.8814	0.8309	5.1268	**0.0236**	
AST	1	-2.0394	0.527	14.9782	**0.0001**	0.13
NEAR	1	0.413	0.3994	1.0693	0.3011	1.511
PLT	1	0.1007	0.4072	0.0611	0.8047	1.106
trtmt	1	-0.0629	0.3727	0.0285	0.866	0.939
Decel	1	0.4106	0.1424	8.3078	**0.0039**	1.508
SPEED_FT	1	-0.0871	0.0247	12.4599	**0.0004**	0.917

*** First level of nested logit model is identical with binary logistics model

**** COM was allowed to enter the P(HY|Y) model, but not the other models

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	218.031	194.699
SC	221.081	216.048
-2 Log L	216.031	180.699
R-Square		0.2027
Max.ReScaled R2		0.2704

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	35.3323	4	<.0001
Score	31.4568	4	<.0001
Wald	24.8845	4	0.0006

c) Restricted Model – 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	2.2316	0.6854	10.6003	**0.0011**	
AST	1	-2.0916	0.5186	16.2637	**<.0001**	0.123
Decel	1	0.4163	0.1421	8.5869	**0.0034**	1.516
SPEED_FT	1	-0.0895	0.024	13.8458	**0.0002**	0.914

*** First level of nested logit model is identical with binary logistics model

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	218.031	190.059
SC	221.081	202.259
-2 Log L	216.031	182.059
R-Square		0.1957
Max.ReScaled R2		0.261

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	33.9717	3	<.0001
Score	30.3735	3	<.0001
Wald	24.0929	3	<.0001

d) Restricted Model – 3

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	2.0496	0.6552	9.7843	**0.0018**	
AST	1	-1.7387	0.4794	13.1558	**0.0003**	0.176
SPEED_FT	1	-0.049	0.0185	6.9986	**0.0082**	0.952

*** First level of nested logit model is identical with binary logistics model

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	218.031	197.932
SC	221.081	207.081
-2 Log L	216.031	191.932
R-Square		0.1431
Max.ReScaled R2		0.191

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	24.0994	2	<.0001
Score	22.2893	2	<.0001
Wald	18.5429	2	<.0001

e) Restricted Model – 4*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.0965	0.3438	0.0788	**0.7789**	
AST	1	-1.8219	0.4775	14.5596	**0.0001**	0.162
Decel	1	0.1109	0.1032	1.1552	**0.2825**	1.117

*** First level of nested logit model is identical with binary logistics model

Model Fit Statistics

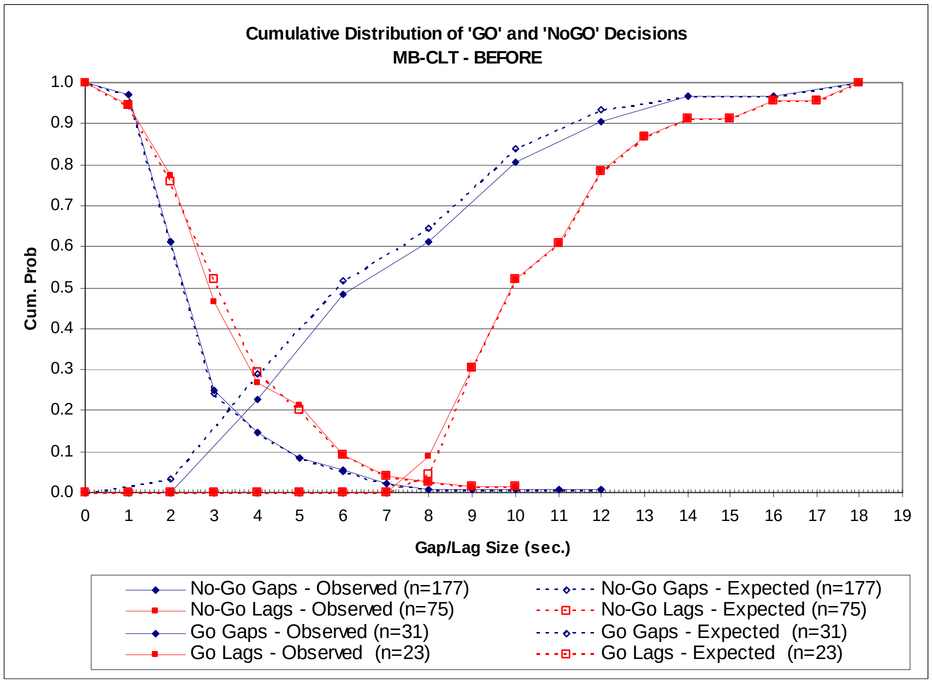
Criterion	Intercept Only	Intercept and Covariates
AIC	218.031	204.325
SC	221.081	213.474
-2 Log L	216.031	198.325
R-Square		0.1073
Max.ReScaled R2		0.1431

Testing Global Null Hypothesis: BETA=0

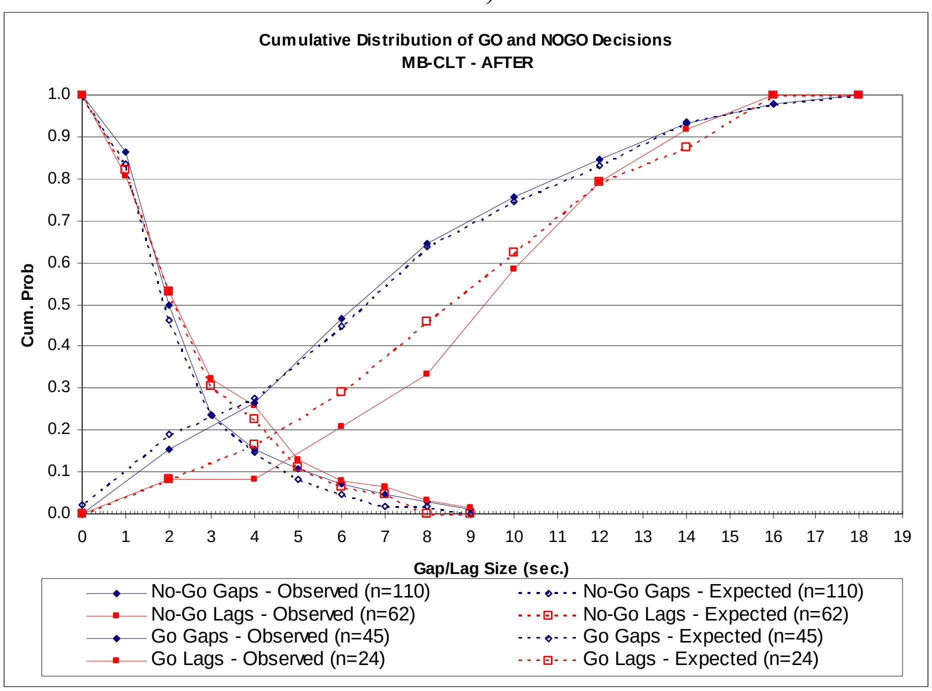
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	17.7064	2	0.0001
Score	16.8496	2	0.0002
Wald	14.617	2	0.0007

* Model was selected as preferred model in its category

10.2 Appendix B: Pedestrian Crossing at Mid-Block Models

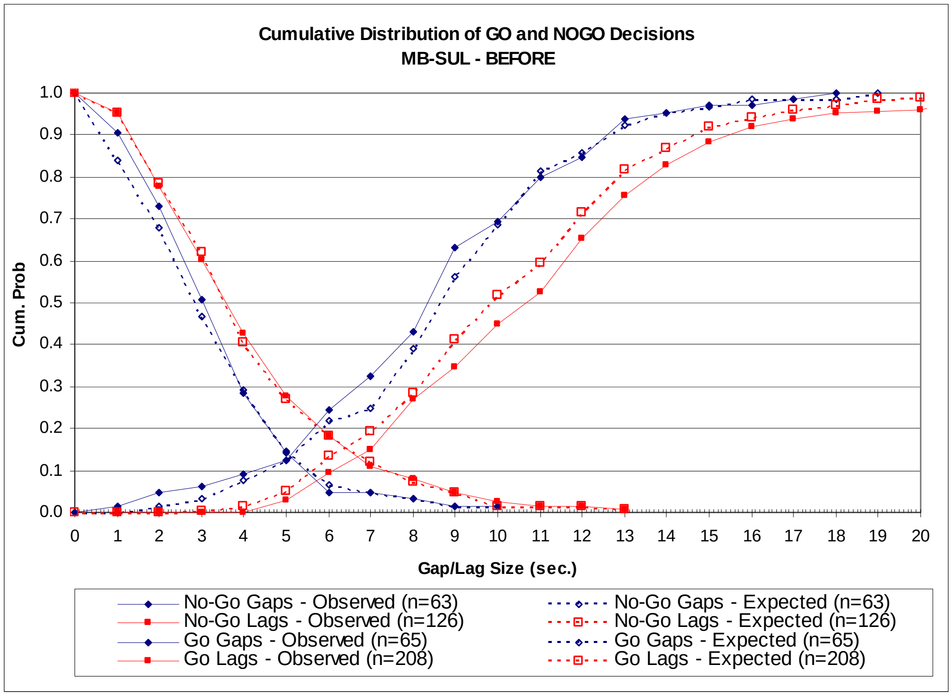


a) Before

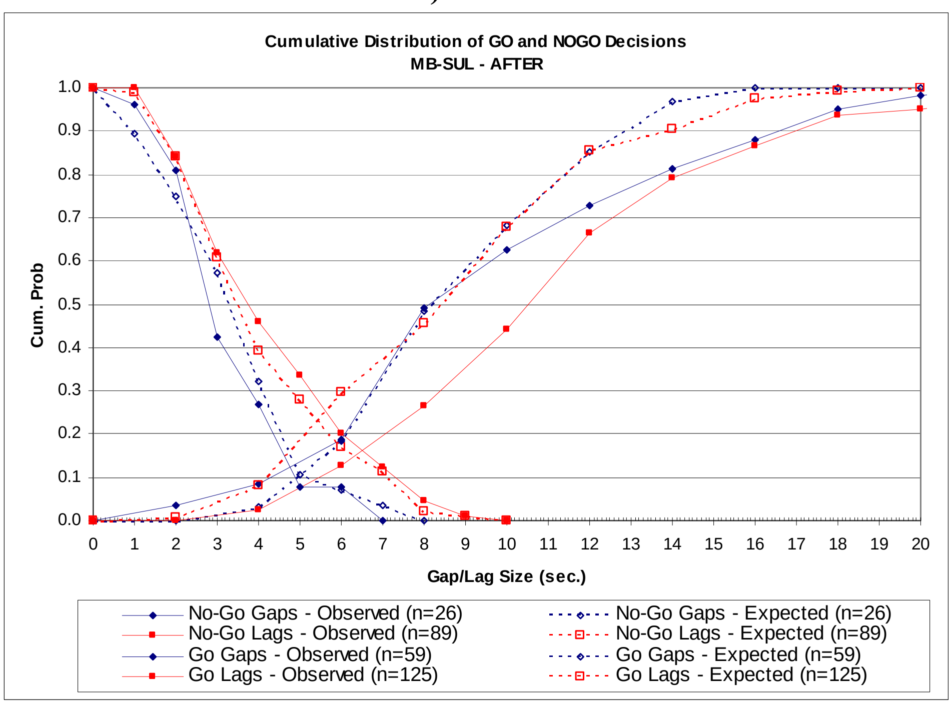


b) After

Figure B-55: Cumulative Prob. Plots for Ped. Crossing– MB-CLT



a) Before



b) ‘After’ Case

Figure B-56: Cumulative Prob. Plots for Ped. Crossing– MB-RAL

Table B-35: Correlation Matrix – MB-CLT - Gaps*

	GO	NoGo	ADY	AST	COM	FLASH	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	TRIG	trtmt	G_NEAR	G_FAR	G_COMBO	Decel	DIST1	D_WAIT	O_GAP	T_GAP	SPEED_FT
GO																								
NoGo	-1.00 **<.0001**																							
ADY	0.23 **<.0001**	-0.23 **<.0001**																						
AST	0.59 **<.0001**	-0.59 **<.0001**	0.08 0.1174																					
COM	0.10 0.0586	-0.10 0.0586	-0.01 0.8257	0.12 **0.021**																				
FLASH	0.21 **<.0001**	-0.21 **<.0001**	0.24 **<.0001**	0.04 0.4459	-0.02 0.649																			
FOLL	-0.09 0.0867	0.09 0.0867	-0.01 0.8223	-0.10 0.0503	0.05 0.3153	-0.05 0.3581																		
HEV	0.03 0.6303	-0.03 0.6303	-0.02 0.702	-0.04 0.4518	0.00 0.9277	-0.04 0.4291	0.09 0.0807																	
MUP	-0.05 0.3186	0.05 0.3186	0.03 0.5934	0.03 0.5553	0.08 0.1224	0.12 **0.0245**	-0.07 0.192	-0.06 0.2617																
NEAR	-0.03 0.5326	0.03 0.5326	-0.03 0.5865	-0.07 0.2021	0.04 0.4081	0.05 0.3052	-0.05 0.2977	-0.05 0.3595	-0.04 0.4806															
PLT	-0.39 **<.0001**	0.39 **<.0001**	-0.05 0.307	-0.30 **<.0001**	-0.08 0.1273	-0.03 0.534	0.57 **<.0001**	0.06 0.2555	-0.09 0.1026	-0.03 0.52														
PREV	-0.22 **<.0001**	0.22 **<.0001**	-0.35 **<.0001**	-0.09 0.075	0.01 0.8104	-0.08 0.1199	0.05 0.3723	0.02 0.6769	0.00 0.9606	-0.03 0.5941	0.18 **0.0004**													
PXW	0.07 0.1708	-0.07 0.1708	0.07 0.154	0.40 <.0001	0.24 <.0001	-0.03 0.5435	0.01 0.7867	-0.02 0.702	0.03 0.5934	-0.11 0.0393	0.00 0.953	-0.06 0.243												
TRIG	0.24 **<.0001**	-0.24 **<.0001**	0.20 **0.0001**	0.29 **<.0001**	-0.01 0.8672	0.19 **0.0003**	0.03 0.5113	-0.02 0.7714	-0.11 **0.0381**	-0.13 **0.0103**	-0.04 0.4881	-0.11 **0.0404**	0.12 **0.0193**											
trtmt	0.20 **0.0002**	-0.20 **0.0002**	0.12 **0.0181**	0.03 0.541	-0.05 0.3868	0.53 **<.0001**	0.00 0.9881	-0.02 0.7377	-0.02 0.7593	0.02 0.6815	-0.07 0.1814	-0.16 **0.0028**	-0.14 **0.0078**	0.16 **0.0022**										
G_NEAR	0.00 0.9582	0.00 0.9582	-0.11 **0.0293**	-0.10 0.068	-0.03 0.6064	-0.09 0.0746	-0.07 0.1758	0.03 0.601	-0.11 **0.0299**	0.43 **<.0001**	0.06 0.2478	0.09 0.0706	-0.02 0.7262	-0.09 0.0984	-0.15 **0.0042**									
G_FAR	-0.02 0.7043	0.02 0.7043	-0.10 0.0618	0.11 **0.0338**	-0.02 0.6585	-0.07 0.2143	0.00 0.9632	0.04 0.4275	0.02 0.6895	-0.53 **<.0001**	0.05 0.3517	0.04 0.4284	0.22 **<.0001**	0.02 0.7556	-0.13 **0.0126**	-0.23 **<.0001**								
G_COMBO	-0.14 **0.0089**	0.14 **0.0089**	-0.25 **<.0001**	-0.10 **0.0496**	-0.06 0.2544	0.03 0.5095	0.06 0.2866	-0.04 0.4165	0.07 0.1721	0.06 0.2592	-0.05 0.3852	0.06 0.2848	-0.23 **<.0001**	-0.06 0.2854	0.18 **0.0005**	-0.59 **<.0001**	-0.50524 **<.0001**							
Decel	-0.31 **<.0001**	0.31 **<.0001**	-0.12 **0.0276**	-0.12 **0.0221**	-0.02 0.6359	-0.06 0.2422	-0.03 0.5105	-0.05 0.3728	0.01 0.8425	0.00 0.9672	0.10 0.0625	-0.11 **0.0305**	0.00 0.9595	-0.08 0.1064	0.15 **0.0045**	-0.06 0.2512	-0.04 0.3928	0.14569 **0.0052**						
DIST1	0.38 **<.0001**	-0.38 **<.0001**	0.06 0.2206	0.15 **0.0033**	-0.03 0.624	-0.05 0.3608	-0.07 0.1979	0.05 0.3539	0.05 0.3201	-0.05 0.307	-0.17 **0.0013**	0.00 0.98	0.03 0.564	-0.02 0.6385	-0.14 **0.0062**	0.13 **0.0134**	0.08 0.1191	-0.21 <.0001	-0.39 <.0001					
D_WAIT	0.06 0.219	-0.06 0.219	0.13 **0.0121**	0.00 0.9802	-0.03 0.6155	-0.09 0.0834	-0.03 0.6215	0.00 0.9295	0.02 0.6402	0.04 0.396	0.01 0.8521	-0.03 0.5203	-0.04 0.4518	-0.02 0.7497	-0.20 **0.0001**	0.12 **0.0255**	-0.04 0.5018	-0.13 0.0168	-0.58 <.0001	0.76 **<.0001**				
O_GAP	0.73 **<.0001**	-0.73 **<.0001**	0.01 0.9108	0.33 **<.0001**	0.16 **0.0026**	0.16 **0.0022**	-0.05 0.3874	0.08 0.1144	-0.01 0.9104	-0.14 **0.0078**	-0.35 **<.0001**	0.01 0.9159	0.10 0.0658	0.12 **0.0245**	0.09 0.0818	0.03 0.5336	0.14 **0.0094**	-0.17 **0.0014**	-0.35 **<.0001**	0.47 **<.0001**	-0.03 0.5449			
T_GAP	0.75 **<.0001**	-0.75 **<.0001**	0.14 **0.0081**	0.33 **<.0001**	0.02 0.7217	0.15 **0.0052**	-0.06 0.2607	0.08 0.109	-0.03 0.5398	-0.14 **0.007**	-0.36 **<.0001**	-0.12 **0.0249**	0.07 0.1591	0.13 **0.0098**	0.11 **0.0302**	0.02 0.7511	0.14 **0.0077**	-0.20 **<.0001**	-0.37 **<.0001**	0.50 **<.0001**	0.01 0.8142	0.94 **<.0001**		
SPEED_FT	-0.04 0.4727	0.04 0.4727	-0.05 0.3295	0.03 0.5736	-0.05 0.3262	-0.07 0.2085	-0.11 **0.0308**	-0.01 0.8346	0.06 0.2588	-0.02 0.6881	-0.01 0.8178	0.05 0.306	0.10 **0.0481**	-0.13 **0.0145**	-0.08 0.1064	0.09 0.0822	0.10 0.0621	-0.13 0.0135	0.24 <.0001	0.30807 <.0001	-0.06 0.2312	0.01 0.8026	0.00 0.9883	
TTC_V	0.42 **<.0001**	-0.42 **<.0001**	0.10 0.0676	0.16 **0.0021**	-0.01 0.824	-0.01 0.8069	-0.05 0.3082	0.04 0.4063	0.01 0.8761	-0.04 0.4143	-0.17 **0.0008**	-0.02 0.6431	0.00 0.9685	0.04 0.4854	-0.14 **0.0092**	0.12 **0.0176**	0.05 0.3083	-0.19 0.0002	-0.69 <.0001	0.91 **<.0001**	0.85 **<.0001**	0.49 <.0001	0.52 **<.0001**	-0.05 0.3272

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table B-36: Correlation Matrix – MB-CLT - Lags*

	GO	NoGo	ADY	AST	COM	FLASH	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	TRIG	trtmt	G_NEAR	G_FAR	G_COMBO	Decel	DIST1	O_LAG	T_LAG	SPEED_FT	TTC_V
GO																								
NoGo	-1.00																							
	<.0001																							
ADY	0.14	-0.14																						
	0.0599	0.0599																						
AST	0.62	-0.62	0.05																					
	<.0001	**<.0001**	0.5105																					
COM	0.13	-0.13	-0.01	0.12																				
	0.0777	0.0777	0.8682	0.1005																				
FLASH	0.31	-0.31	0.20	0.19	0.26																			
	<.0001	**<.0001**	**0.0053**	**0.0081**	**0.0004**																			
FOLL	-0.14	0.14	0.05	-0.09	0.08	0.03																		
	0.0621	0.0621	0.509	0.2204	0.274	0.7213																		
HEV	0.11	-0.11	-0.03	0.09	-0.01	-0.05	0.08																	
	0.1376	0.1376	0.6801	0.1997	0.8553	0.4788	0.2901																	
MUP	-0.11	0.11	0.06	-0.11	0.13	0.03	-0.02	-0.03																
	0.1376	0.1376	0.3907	0.1316	0.0733	0.6637	0.7361	0.6792																
NEAR	0.02	-0.02	0.01	-0.12	-0.08	-0.07	-0.06	0.04	0.01															
	0.7458	0.7458	0.8446	0.1081	0.2635	0.3179	0.4134	0.5841	0.8622															
PLT	-0.27	0.27	0.04	-0.17	0.08	0.01	0.84	0.01	-0.06	-0.06														
	0.0002	**0.0002**	0.5919	**0.0193**	0.3003	0.8836	**<.0001**	0.9254	0.4565	0.4525														
PREV	-0.02	0.02	0.11	-0.09	-0.02	0.11	0.02	-0.04	-0.02	-0.03	0.10													
	0.7448	0.7448	0.145	0.2147	0.8118	0.1278	0.7657	0.5542	0.7741	0.7121	0.1559													
PXW	0.31	-0.31	0.27	0.32	-0.02	0.17	-0.06	-0.06	0.02	-0.02	-0.08	0.08												
	<.0001	<.0001	0.0002	<.0001	0.7361	0.0189	0.4314	0.4023	0.7858	0.7794	0.302	0.2999												
TRIG	0.15	-0.15	0.14	0.26	0.37	0.48	-0.01	-0.04	0.09	-0.05	-0.02	-0.05	0.03											
	0.0393	**0.0393**	0.0544	**0.0003**	**<.0001**	**<.0001**	0.8909	0.6237	0.2292	0.4891	0.7783	0.5217	0.723											
trtmt	0.02	-0.02	-0.02	0.01	0.08	0.30	0.08	0.07	0.03	-0.03	0.09	0.01	-0.10	0.15										
	0.7751	0.7751	0.7512	0.8727	0.2898	**<.0001**	0.3034	0.3298	0.653	0.6719	0.2238	0.8475	0.156	**0.0367**										
G_NEAR	0.07	-0.07	-0.10	-0.03	-0.04	-0.03	-0.09	0.10	-0.13	0.53	-0.05	-0.09	0.04	-0.05	-0.14									
	0.3663	0.3663	0.1816	0.7151	0.5553	0.6903	0.2032	0.1736	0.0827	**<.0001**	0.4852	0.2392	0.5568	0.4758	0.0616									
G_FAR	-0.02	0.02	-0.08	0.13	-0.04	-0.14	0.07	-0.01	-0.05	-0.55	0.07	0.00	0.01	0.05	-0.05	-0.29								
	0.7449	0.7449	0.2676	0.0749	0.6244	0.0562	0.3248	0.8615	0.4983	**<.0001**	0.3216	0.9648	0.8541	0.5373	0.4754	**<.0001**								
G_COMBO	-0.15	0.15	-0.16	-0.16	-0.07	0.00	-0.03	-0.06	0.11	-0.06	-0.02	0.05	-0.12	-0.14	0.16	-0.58	-0.48363							
	0.0356	**0.0356**	**0.0257**	**0.029**	0.3265	0.95	0.6987	0.4324	0.1338	0.4329	0.82	0.4847	0.1062	0.0602	**0.0339**	**<.0001**	**<.0001**							
Decel	-0.43	0.43	-0.12	-0.30	-0.03	-0.18	0.16	-0.11	0.07	0.03	0.22	0.03	-0.21	-0.12	0.16	-0.07	0.02	0.10632						
	<.0001	**<.0001**	0.1132	**<.0001**	0.6786	**0.013**	**0.0319**	0.1244	0.3589	0.6438	**0.0021**	0.7132	**0.0049**	0.1121	**0.0309**	0.3435	0.776	0.1498						
DIST1	0.79	-0.79	0.06	0.54	0.01	0.21	-0.15	0.14	-0.14	-0.04	-0.30	-0.08	0.31	0.06	-0.12	0.06	0.03	-0.12	-0.55					
	<.0001	**<.0001**	0.387	**<.0001**	0.8857	**0.0043**	**0.0449**	0.0584	0.0609	0.6118	**<.0001**	0.303	**<.0001**	0.3925	0.0982	0.4318	0.6689	0.1017	<.0001					
O_LAG	0.87	-0.87	0.11	0.58	0.09	0.31	-0.16	0.13	-0.14	-0.03	-0.29	-0.06	0.34	0.15	-0.05	0.07	0.00279	-0.142	-0.61518	0.9375				
	<.0001	**<.0001**	0.1409	**<.0001**	0.2372	**<.0001**	**0.0331**	0.0833	0.0527	0.6421	**<.0001**	0.4551	**<.0001**	**0.0391**	0.4905	0.3241	0.97	0.0538	<.0001	<.0001				
T_LAG	0.85	-0.85	0.12	0.56	0.00	0.24	-0.17	0.14	-0.15	-0.03	-0.31	-0.05	0.34	0.08	-0.08	0.07	0.01	-0.12521	-0.61619	0.94843	0.99			
	<.0001	**<.0001**	0.1135	**<.0001**	0.9785	**0.0009**	**0.0176**	0.064	**0.0364**	0.6533	**<.0001**	0.4707	**<.0001**	0.2723	0.3009	0.3775	0.8465	0.0895	<.0001	<.0001	**<.0001**			
SPEED_FT	0.03	-0.03	-0.09	0.06	0.06	-0.03	0.05	-0.01	0.04	-0.06	-0.06	-0.16	0.02	0.00	-0.16	-0.06	0.11	0.00	0.23	0.32062	0.08	0.08		
	0.6602	0.6602	0.2223	0.3819	0.4506	0.6836	0.4629	0.8766	0.5734	0.3814	0.4356	**0.033**	0.8223	0.9873	**0.0265**	0.449	0.1452	0.964	0.002	<.0001	0.2866	0.2749		
TTC_V	0.85	-0.85	0.12	0.56	0.00	0.24	-0.17	0.14	-0.15	-0.03	-0.31	-0.05	0.34	0.08	-0.08	0.07	0.01	-0.13	-0.62	0.95	0.99	1.00	0.08	
	<.0001	**<.0001**	0.1135	**<.0001**	0.9826	**0.0009**	**0.0176**	0.065	**0.0362**	0.6545	**<.0001**	0.4721	**<.0001**	0.27	0.3014	0.3744	0.8504	0.0893	<.0001	**<.0001**	<.0001	<.0001	0.2761	

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table B-37: Correlation Matrix – MB-RAL - Gaps*

	GO	NoGo	ADY	AST	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	trtmt	G_NEAR	G_FAR	G_COMBO	Decel	DIST1	D_WAIT	O_GAP	T_GAP	SPEED_FT
GO																							
NoGo	-1.00 **<.0001**																						
ADY	0.04 0.5754	-0.04 0.5754																					
AST	0.45 **<.0001**	-0.45 **<.0001**	0.02 0.8236																				
COM	. .	. .	. .	. .																			
FOLL	-0.05 0.4312	0.05 0.4312	0.00 0.9637	-0.01 0.8552																			
HEV	0.02 0.7536	-0.02 0.7536	0.05 0.4742	0.05 0.4535	0.01 0.831																		
MUP	-0.08 0.2358	0.08 0.2358	-0.02 0.7245	-0.02 0.8095	0.10 0.1437	0.12 0.0697																	
NEAR	0.10 0.1564	-0.10 0.1564	-0.13 **0.0479**	0.03 0.6644	0.11 0.1057	0.01 0.9173	-0.05 0.4243																
PLT	-0.44 **<.0001**	0.44 **<.0001**	-0.01 0.8345	-0.21 **0.0017**	0.65 **<.0001**	0.05 0.4924	0.09 0.1964	0.12 0.0892															
PREV	-0.15 **0.0265**	0.15 **0.0265**	-0.43 **<.0001**	-0.15 **0.0243**	-0.02 0.814	0.10 0.1558	0.10 0.1353	0.07 0.2801	0.18 **0.0086**														
PXW	-0.10 0.143	0.10 0.143	-0.05 0.4257	0.03 0.6119	-0.11 0.1055	-0.04 0.5529	-0.05 0.4894	-0.02 0.7468	-0.16 **0.0156**	-0.13 0.0561													
QUE	-0.16 0.0199	0.16 0.0199	-0.04 0.5998	-0.08 0.2331	0.18 0.0095	-0.03 0.6959	-0.02 0.7364	0.04 0.5574	0.17 0.0104	-0.10 0.124	-0.03 0.6777												
TRIG	0.18 **0.0077**	-0.18 **0.0077**	-0.05 0.4257	0.35 **<.0001**	-0.05 0.4259	-0.04 0.5529	0.05 0.4529	-0.02 0.7468	-0.12 0.0868	-0.07 0.2929	-0.04 0.5281	-0.03 0.6777											
trtmt	0.17 **0.0104**	-0.17 **0.0104**	0.09 0.1955	0.14 **0.0322**	0.10 0.1363	0.04 0.5849	0.03 0.6123	-0.04 0.5656	0.09 0.1704	-0.04 0.5993	-0.08 0.2527	-0.04 0.5226	0.06 0.3544										
G_NEAR	0.15 **0.0289**	-0.15 **0.0289**	-0.19 **0.0047**	0.00 0.9438	0.03 0.6469	-0.04 0.5591	0.00 0.9967	0.59 **<.0001**	0.06 0.4078	0.12 0.0792	-0.05 0.4241	0.04 0.5188	-0.01 0.9301	0.02 0.7488									
G_FAR	0.02 0.7495	-0.02 0.7495	-0.12 0.0819	-0.05 0.5051	0.00 0.9621	0.04 0.5353	0.05 0.4833	-0.56 **<.0001**	0.00 0.9436	0.16 **0.0167**	-0.03 0.6381	-0.06 0.3651	-0.03 0.6381	0.12 0.0689	-0.33 **<.0001**								
G_COMBO	-0.19 **0.0039**	0.19 **0.0039**	-0.22 **0.0011**	0.03 0.6238	-0.04 0.5687	-0.01 0.8341	-0.01 0.864	-0.09 0.1919	-0.05 0.4788	0.02 0.8175	0.11 0.1123	0.02 0.7164	0.06 0.3702	-0.14 **0.0343**	-0.61 **<.0001**	-0.37661 **<.0001**							
Decel	-0.18 **0.0068**	0.18 **0.0068**	-0.02 0.7361	0.08 0.2192	-0.04 0.5622	-0.02 0.7185	0.06 0.3628	-0.10 0.1347	-0.01 0.8328	0.02 0.7375	0.03 0.6328	-0.01 0.9074	-0.01 0.9411	-0.09 0.1867	-0.06 0.4054	-0.06 0.4179	0.10944 0.1063						
DIST1	0.60 **<.0001**	-0.60 **<.0001**	-0.04 0.5537	0.00 0.9955	-0.03 0.6498	-0.02 0.8078	0.02 0.8177	0.10 0.1595	-0.32 **<.0001**	0.01 0.8999	-0.08 0.26	-0.19 **0.004**	-0.09 0.1633	0.10 0.1255	0.14 **0.0415**	0.09 0.1651	-0.20 0.0034	-0.33 <.0001					
D_WAIT	0.03 0.6632	-0.03 0.6632	0.33 **<.0001**	-0.18 **0.0067**	-0.01 0.8823	-0.01 0.8501	0.12 0.0762	0.02 0.7823	-0.10 0.1298	-0.15 **0.0278**	0.02 0.7439	-0.10 0.1529	-0.10 0.1252	0.04 0.5766	-0.14 **0.0389**	0.01 0.8894	-0.05 0.4985	-0.17 0.0121	0.50 **<.0001**				
O_GAP	0.72 **<.0001**	-0.72 **<.0001**	-0.24 **0.0004**	0.25 **0.0002**	0.06 0.3723	0.14 **0.0352**	0.02 0.7326	0.07 0.2707	-0.23 **0.0006**	0.13 0.0567	-0.10 0.1522	-0.12 0.0807	0.02 0.7869	0.23 **0.0006**	0.21 **0.0014**	0.13 0.0641	-0.17 **0.0101**	-0.19 **0.0056**	0.64 **<.0001**	-0.09 0.2043			
T_GAP	0.79 **<.0001**	-0.79 **<.0001**	0.01 0.9287	0.17 **0.0115**	0.06 0.3618	0.02 0.7379	-0.01 0.8501	0.03 0.6947	-0.29 **<.0001**	-0.02 0.7909	-0.09 0.2103	-0.13 **0.0476**	-0.07 0.3261	0.20 **0.0024**	0.15 **0.032**	0.10 0.1287	-0.23 **0.0008**	-0.25 **0.0003**	0.74 **<.0001**	0.07 0.3018	0.86 **<.0001**		
SPEED_FT	0.24 **0.0004**	-0.24 **0.0004**	-0.11 0.1119	0.08 0.2209	-0.10 0.1276	-0.06 0.3727	-0.10 0.1381	0.10 0.156	-0.21 **0.0023**	-0.03 0.6592	-0.03 0.6615	-0.28 **<.0001**	0.01 0.8823	-0.03 0.6351	0.17 **0.0103**	0.01 0.8611	-0.15 0.0259	0.20 0.002	0.4026 <.0001	-0.05 0.4592	0.16 0.015	0.17 **0.0114**	
TTC_V	0.60 **<.0001**	-0.60 **<.0001**	0.00 0.9639	-0.02 0.7843	0.02 0.7355	0.03 0.648	0.06 0.386	0.07 0.3364	-0.27 **<.0001**	0.02 0.7326	-0.05 0.4825	-0.16 **0.0168**	-0.11 0.0983	0.13 0.061	0.08 0.2542	0.10 0.1231	-0.16 0.0194	-0.30 <.0001	0.92 **<.0001**	0.60 **<.0001**	0.67 <.0001	0.78 **<.0001**	0.13 0.049

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table B-38: Correlation Matrix – MB-RAL - Lags*

	GO	NoGo	ADY	AST	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	trtmt	G_NEAR	G_FAR	G_COMBO	Decel	DIST1	O_LAG	T_LAG	SPEED_FT
GO																						
NoGo	-1.00																					
	<.0001																					
ADY	-0.02	0.02																				
	0.6565	0.6565																				
AST	0.66	-0.66	0.01																			
	<.0001	**<.0001**	0.875																			
FOLL	-0.04	0.04	0.11	0.00																		
	0.3283	0.3283	**0.008**	0.9238																		
HEV	0.02	-0.02	-0.01	0.05	0.02																	
	0.6398	0.6398	0.7371	0.2738	0.5951																	
MUP	-0.10	0.10	0.00	-0.07	0.00	0.01																
	0.0195	**0.0195**	0.9293	0.0837	0.9673	0.7426																
NEAR	-0.01	0.01	0.02	-0.05	0.10	-0.04	0.06															
	0.8033	0.8033	0.6598	0.2731	**0.0258**	0.3612	0.1332															
PLT	-0.12	0.12	0.10	-0.07	0.92	0.01	0.02	0.09														
	0.0034	**0.0034**	**0.0167**	0.1171	**<.0001**	0.81	0.5603	**0.0392**														
PREV	-0.13	0.13	-0.02	-0.12	0.00	-0.03	0.06	-0.03	0.17													
	0.0017	**0.0017**	0.7045	**0.007**	0.9934	0.4581	0.1498	0.5424	**<.0001**													
PXW	0.12	-0.12	0.05	0.10	0.02	0.05	-0.05	-0.06	-0.02	-0.09												
	0.0065	**0.0065**	0.2694	**0.0238**	0.6344	0.2056	0.2632	0.182	0.6259	**0.0369**												
QUE	-0.12	0.12	-0.01	-0.08	0.12	-0.02	0.01	-0.04	0.18	0.31	-0.07											
	0.0047	0.0047	0.8076	0.055	0.0038	0.6337	0.8998	0.3895	<.0001	<.0001	0.0927											
TRIG	0.22	-0.22	-0.03	0.33	-0.06	-0.01	-0.08	-0.07	-0.08	-0.06	0.16	-0.04										
	<.0001	**<.0001**	0.5399	**<.0001**	0.1424	0.7908	0.0782	0.0911	0.0587	0.1753	**0.0001**	0.3842										
trtmt	-0.04	0.04	0.06	-0.10	0.10	0.05	-0.06	-0.02	0.10	-0.05	0.01	-0.03	0.14									
	0.3527	0.3527	0.1387	**0.0168**	**0.0208**	0.2486	0.1777	0.7167	**0.018**	0.2501	0.7424	0.415	**0.0008**									
G_NEAR	0.11	-0.11	-0.08	0.04	0.06	0.00	-0.01	0.70	0.04	-0.04	-0.02	-0.02	-0.01	-0.03								
	0.0084	**0.0084**	0.0589	0.2959	0.1749	0.9795	0.7334	**<.0001**	0.3211	0.3677	0.5944	0.5886	0.7402	0.5324								
G_FAR	0.06	-0.06	-0.05	0.05	-0.09	-0.04	-0.13	-0.72	-0.10	-0.05	0.06	-0.03	0.07	0.01	-0.50							
	0.1546	0.1546	0.2841	0.2348	**0.0273**	0.402	**0.0029**	**<.0001**	**0.025**	0.2127	0.1313	0.5061	0.095	0.7616	**<.0001**							
G_COMBO	-0.18	0.18	-0.05	-0.10	-0.01	0.04	0.14	-0.10	0.00	0.10	-0.03	0.06	-0.08	0.01	-0.60	-0.34281						
	<.0001	**<.0001**	0.1987	**0.0164**	0.8531	0.3491	**0.0008**	**0.0169**	0.9075	**0.0218**	0.4688	0.1916	0.056	0.9033	**<.0001**	**<.0001**						
Decel	-0.56	0.56	-0.01	-0.31	0.01	-0.06	0.02	0.06	0.08	0.13	-0.02	0.17	-0.04	-0.01	-0.04	-0.03	0.07411					
	<.0001	**<.0001**	0.8083	**<.0001**	0.7524	0.1488	0.7025	0.1609	0.0755	**0.0028**	0.6557	**<.0001**	0.3796	0.807	0.3553	0.4877	0.0828					
DIST1	0.66	-0.66	-0.02	0.29	-0.07	-0.02	-0.04	0.00	-0.14	-0.14	-0.04	-0.16	-0.08	-0.10	0.09	0.02	-0.11	-0.55				
	<.0001	**<.0001**	0.6658	**<.0001**	0.1144	0.6266	0.3644	0.9805	**0.0011**	**0.0012**	0.3655	**0.0002**	0.0531	**0.0253**	**0.0354**	0.5869	0.0096	<.0001				
O_LAG	0.68	-0.68	-0.01	0.34	-0.01	0.07	-0.02	-0.04	-0.08	-0.12	0.04	-0.13	0.01	0.02	0.07	0.05526	-0.1224	-0.57132	0.88454			
	<.0001	**<.0001**	0.7374	**<.0001**	0.7718	0.1159	0.5883	0.3508	**0.0483**	**0.0044**	0.3678	**0.0015**	0.792	0.6976	0.1129	0.1961	0.0041	<.0001	<.0001			
T_LAG	0.67	-0.67	-0.01	0.30	-0.01	0.01	-0.02	-0.02	-0.09	-0.14	-0.03	-0.13	-0.10	-0.07	0.08	0.04	-0.11943	-0.60769	0.95433	0.93		
	<.0001	**<.0001**	0.7767	**<.0001**	0.7669	0.748	0.6467	0.6518	**0.0436**	**0.0009**	0.4987	**0.0031**	**0.0186**	0.0953	0.0546	0.3139	**0.0051**	<.0001	<.0001	**<.0001**		
SPEED_FT	0.17	-0.17	-0.03	0.12	-0.19	-0.09	-0.06	0.07	-0.23	-0.13	-0.01	-0.31	0.09	-0.10	0.06	-0.04	-0.04	0.05	0.3203	0.08	0.08	
	<.0001	**<.0001**	0.5539	**0.0067**	**<.0001**	**0.0263**	0.1381	0.084	**<.0001**	**0.0021**	0.7974	**<.0001**	**0.039**	**0.0179**	0.1454	0.4	0.386	0.1987	<.0001	0.0749	0.0754	
TTC_V	0.67	-0.67	-0.01	0.30	-0.01	0.01	-0.02	-0.02	-0.09	-0.14	-0.03	-0.13	-0.10	-0.07	0.08	0.04	-0.12	-0.61	0.95	0.93	1.00	0.08
	<.0001	**<.0001**	0.7763	**<.0001**	0.764	0.749	0.6439	0.6558	**0.0432**	**0.0009**	0.496	**0.0031**	**0.0185**	0.0942	0.0537	0.3159	0.005	<.0001	**<.0001**	<.0001	<.0001	0.0738

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table B-39: PCM Results of <u>Multi-Linear Regression</u> for Lags – MB-CLT

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0024	0.1473	-0.02	0.9873
ADY	-0.0612	0.1490	-0.41	0.6818
AST	0.1621	0.0438	3.7	**0.0003**
FLASH	0.0728	0.0777	0.94	0.3503
FOLL	0.0237	0.0587	0.4	0.6871
HEV	0.0260	0.0878	0.3	0.7675
MUP	0.0159	0.0359	0.44	0.6576
NEAR	0.0559	0.0415	1.35	0.1799
PLT	-0.0601	0.0602	-1	0.3195
PREV	0.0360	0.0683	0.53	0.5993
PXW	-0.0205	0.0554	-0.37	0.7124
TRIG	-0.1762	0.0999	-1.76	**0.0795**
trtmt	0.0160	0.0335	0.48	0.6338
G_NEAR	-0.2229	0.1134	-1.96	**0.0511**
G_FAR	-0.1957	0.1214	-1.61	0.1088
G_COMBO	-0.2227	0.1139	-1.95	**0.0523**
Decel	0.0084	0.0024	3.43	**0.0008**
DIST1	0.0000	0.0004	-0.08	0.9373
O_LAG	0.1058	0.0333	3.18	**0.0018**
T_LAG	-1.3288	1.2464	-1.07	0.288
SPEED_FT	-0.0030	0.0027	-1.1	0.2734
TTC_V	1.3108	1.2508	1.05	0.2962

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	21	27.6720	1.3177	33.65	<.0001
Error	163	6.3821	0.0392		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean
0.8126	81.3481	0.1979	0.2432

Adj. R-Square
0.79

b) Unrestricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.1871	0.0378	-4.95	**<.0001**
AST	0.1689	0.0441	3.83	**0.0002**
TRIG	-0.0274	0.0844	-0.32	0.7461
G_NEAR	0.0055	0.0441	0.12	0.9008
G_COMBO	-0.0141	0.0391	-0.36	0.7188
O_LAG	0.0777	0.0045	17.29	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	26.2863	5.2573	121.15	<.0001
Error	179	7.7678	0.0434		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean
0.7719	85.6410	0.2083	0.2432

Adj. R-Square
0.77

c) Unrestricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.2567	0.0331	-7.76	**<.0001**
AST	0.1741	0.0419	4.15	**<.0001**
NEAR	0.0636	0.0304	2.09	**0.0381**
trtmt	0.0520	0.0301	1.73	**0.0862**
O_LAG	0.0780	0.0044	17.79	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	26.5665	6.6416	159.66	<.0001
Error	180	7.4876	0.0416		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean
0.7801	83.8480	0.2040	0.2432

Adj. R-Square
0.78

d) Unrestricted Model 3

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.1942	0.0237	-8.18	**<.0001**
AST	0.1671	0.0421	3.97	**0.0001**
O_LAG	0.0779	0.0044	17.57	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	26.2690	13.1345	307.06	<.0001
Error	182	7.7850	0.0428		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean	Adj. R-Square
0.7714	85.0264	0.2068	0.2432	0.77

e) Restricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.2376	0.0414	-5.74	**<.0001**
AST	0.2006	0.0428	4.68	**<.0001**
FLASH	0.1517	0.0646	2.35	**0.02**
NEAR	0.0688	0.0317	2.17	**0.0311**
PLT	-0.013976564	0.03293767	-0.42	0.6718
trtmt	0.041659113	0.03320465	1.25	0.2113
T_LAG	0.072927595	0.00480405	15.18	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	26.0906	4.3484	97.2	<.0001
Error	178	7.9634	0.0447		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean	Adj. R-Square
0.7662	86.9560	0.2115	0.2432	0.76

f) Restricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.2471	0.0348	-7.1	**<.0001**
AST	0.2009	0.0427	4.7	**<.0001**
FLASH	0.1498	0.0643	2.33	**0.021**
NEAR	0.0697	0.0315	2.21	**0.0284**
trtmt	0.041070623	0.03309961	1.24	0.2163
T_LAG	0.073452766	0.00463125	15.86	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	26.0826	5.2165	117.14	<.0001
Error	179	7.9715	0.0445		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean	Adj. R-Square
0.7659	86.7567	0.2110	0.2432	0.76

g) Restricted Model 3

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.2257	0.0302	-7.46	**<.0001**
AST	0.2032	0.0428	4.75	**<.0001**
FLASH	0.1760	0.0608	2.89	**0.0043**
NEAR	0.0694	0.0316	2.2	**0.0292**
T_LAG	0.0725	0.0046	15.84	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	26.0140	6.5035	145.6	<.0001
Error	180	8.0401	0.0447		
Corrected Total	184	34.0541			

R-Square	Coeff Var	Root MSE	GO Mean	Adj. R-Square
0.7639	86.8866	0.2113	0.2432	0.76

Table B-40: PCM Results of Multi-Linear Regression for Gaps – MB-CLT

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.1400	0.1588	0.88	**0.3785**
ADY	0.0000	0.1126	0	**0.9997**
AST	0.4532	0.0373	12.15	**<.0001**
FLASH	0.0454	0.0366	1.24	**0.2164**
FOLL	0.00174206	0.02731511	0.06	**0.9492**
HEV	-0.0154635	0.11898811	-0.13	0.8967
MUP	-0.0480533	0.02447942	-1.96	**0.0505**
NEAR	-0.0107032	0.02853613	-0.38	**0.7078**
PLT	-0.0206	0.0329	-0.63	**0.5317**
PREV	-0.1586	0.0591	-2.68	**0.0077**
PXW	-0.2788	0.0586	-4.75	**<.0001**
TRIG	-0.0092	0.0727	-0.13	**0.8998**
TRTMT	0.04009227	0.02786424	1.44	**0.1511**
G_NEAR	-0.0887849	0.10227201	-0.87	0.3859
G_FAR	-0.2153705	0.10196793	-2.11	**0.0354**
G_COMBO	-0.1273432	0.1000128	-1.27	**0.2038**
D_WAIT	0.0613	0.0213	2.88	**0.0042**
Decel	-0.0025	0.0077	-0.32	**0.7507**
DIST1	-0.0001	0.0002	-0.43	**0.6693**
O_GAP	0.0711	0.0133	5.33	**<.0001**
T_GAP	0.05654382	0.01583366	3.57	**0.0004**
SPEED_FT	0.00042321	0.00284193	0.15	0.8817
TTC_V	-0.0546069	0.02280692	-2.39	**0.0172**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	22	47.9449	2.1793	53.4	<.0001
Error	342	13.9565	0.0408		
Corrected Total	364	61.9014			

R-Square	Coeff Var	Root MSE	GO Mean
0.7745	93.3343	0.2020	0.2164

Adj. R - Square
0.76

b) Unrestricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.1804	0.0581	3.11	**0.002**
AST	0.4906	0.0348	14.11	**<.0001**
MUP	-0.0448	0.0240	-1.87	**0.0626**
PREV	-0.2994	0.0501	-5.97	**<.0001**
PXW	-0.2794011	0.0588076	-4.75	**<.0001**
TRTMT	0.07935562	0.02347586	3.38	**0.0008**
D_WAIT	0.00567787	0.00202368	2.81	**0.0053**
G_FAR	-0.1574022	0.03468908	-4.54	**<.0001**
G_COMBO	-0.0760984	0.02661151	-2.86	**0.0045**
O_GAP	0.06935184	0.00330991	20.95	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	46.6261	5.1807	120.4	<.0001
Error	355	15.2753	0.0430		
Corrected Total	364	61.9014			

R-Square	Coeff Var	Root MSE	GO Mean
0.7532	95.8399	0.2074	0.2164

Adj. R - Square
0.75

c) Unrestricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.1265	0.0576	2.2	**0.0286**
AST	0.4876	0.0357	13.67	**<.0001**
MUP	-0.0535	0.0244	-2.19	**0.0292**
PREV	-0.3205	0.0511	-6.27	**<.0001**
PXW	-0.2958008	0.05903033	-5.01	**<.0001**
TRTMT	0.0814769	0.02377428	3.43	**0.0007**
D_WAIT	0.00689056	0.0020516	3.36	**0.0009**
O_GAP	0.06912312	0.00334367	20.67	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	45.7132	6.5305	144.02	<.0001
Error	357	16.1882	0.0453		
Corrected Total	364	61.9014			

R-Square	Coeff Var	Root MSE	GO Mean
0.7385	98.3854	0.2129	0.2164

Adj. R - Square
0.73

d) Restricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.1849	0.0414	-4.47	**<.0001**
AST	0.4088	0.0346	11.82	**<.0001**
MUP	-0.0476	0.0259	-1.84	**0.0664**
FLASH	0.0729	0.0370	1.97	**0.0493**
NEAR	0.05001844	0.02397018	2.09	**0.0376**
PLT	-0.0491422	0.02799097	-1.76	**0.08**
TRTMT	0.07301434	0.02801906	2.61	**0.0095**
D_WAIT	0.00593476	0.00211711	2.8	**0.0053**
T_GAP	0.0706958	0.00379922	18.61	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	44.6013	5.5752	114.73	<.0001
Error	356	17.3001	0.0486		
Corrected Total	364	61.9014			

R-Square	Coeff Var	Root MSE	GO Mean
0.7205	101.8509	0.2204	0.2164

Adj. R - Square
0.71

e) Restricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.1729	0.0382	-4.53	**<.0001**
AST	0.4056	0.0350	11.59	**<.0001**
FLASH	0.1130	0.0318	3.56	**0.0004**
NEAR	0.0530	0.0242	2.19	**0.0293**
PLT	-0.0468481	0.0281184	-1.67	**0.0966**
D_WAIT	0.00476059	0.00210757	2.26	**0.0245**
T_GAP	0.07176602	0.00382397	18.77	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	44.0598	7.3433	147.35	<.0001
Error	358	17.8416	0.0498		
Corrected Total	364	61.9014			

R-Square	Coeff Var	Root MSE	GO Mean
0.7118	103.1432	0.2232	0.2164

Adj. R - Square
0.71

Table B-41: PCM Results of Binary Logistic Regression for Lags - MB-CLT

a) Full Model

Analysis of Maximum Likelihood Estimates / **Odds Ratio***

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-22.4369	44.707	0.2519	0.6158	
ADY	1	-4.8284	56.4921	0.0073	0.9319	0.008
AST	1	12.0454	12.3403	0.9528	0.329	>999.999
FLASH	1	4.8146	16.6803	0.0833	0.7729	123.295
FOLL	1	0.0309	27.1737	0	0.9991	1.031
HEV	1	-10.6359	85.9784	0.0153	0.9015	<0.001
MUP	1	-10.343	16.4479	0.3954	0.5295	<0.001
NEAR	1	3.4262	20.7868	0.0272	0.8691	30.76
PLT	1	-5.2912	31.7677	0.0277	0.8677	0.005
PREV	1	10.887	44.7093	0.0593	0.8076	>999.999
PXW	1	-1.2939	11.8434	0.0119	0.913	0.274
TRIG	1	-16.244	15.3796	1.1156	0.2909	<0.001
trtmt	1	6.1195	11.0825	0.3049	0.5808	454.638
G_NEAR	1	-11.8375	26.4207	0.2007	0.6541	<0.001
G_FAR	1	-19.9952	28.875	0.4795	0.4886	<0.001
G_COMBO	1	-15.4466	23.5635	0.4297	0.5121	<0.001
Decel	1	0.4786	0.8761	0.2984	0.5849	1.614
DIST1	1	0.0131	0.1145	0.0131	0.9087	1.013
O_LAG	1	3.9011	5.4976	0.5035	0.478	49.459
SPEED_FT	1	-0.142	0.9883	0.0207	0.8857	0.868

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	40.361
SC	210.493	104.768
-2 Log L	205.272	0.361
R-Square		0.6697
Max-rescaled R-2		0.9990

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	204.9114	19	<.0001
Score	150.0154	19	<.0001
Wald	3.4129	19	1.0000

b) Unrestricted Model - 1

Analysis of Maximum Likelihood Estimates / **Odds Ratio***

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-15.4961	4.6991	10.8745	**0.001**	
AST	1	3.4797	1.743	3.9854	**0.0459**	32.45
G_FAR	1	-4.7526	2.2164	4.5982	**0.032**	0.009
O_LAG	1	1.8552	0.5779	10.3044	**0.0013**	6.393

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	24.602
SC	210.493	37.483
-2 Log L	205.272	16.602
R-Square		0.6393
Max-rescaled R-2		0.9538

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	188.6702	3	<.0001
Score	143.1621	3	<.0001
Wald	10.8359	3	0.0126

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
5.4639	14	0.9783

c) Unrestricted Model - 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-16.333	5.6641	8.3152	**0.0039**	
AST	1	4.7736	2.0464	5.4416	**0.0197**	118.341
FLASH	1	2.7573	1.6374	2.8355	**0.0922**	15.757
G_FAR	1	-5.7795	2.8437	4.1306	**0.0421**	0.003
T_LAG	1	1.9115	0.6914	7.6444	**0.0057**	6.763

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	28.458
SC	210.493	44.559
-2 Log L	205.272	18.458
R-Square		0.6357
Max-rescaled R-2		0.9484

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	186.8145	4	<.0001
Score	140.5577	4	<.0001
Wald	8.9443	4	0.0625

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
7.5801	12	0.8170

d) Restricted Model - 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-19.6822	7.3521	7.1668	**0.0074**	
AST	1	3.206	1.9762	2.6319	**0.1047**	24.68
FLASH	1	0.1606	1.8706	0.0074	0.9316	1.174
NEAR	1	2.334	1.7657	1.7474	0.1862	10.319
PLT	1	-2.2319	1.8733	1.4196	0.2335	0.107
trtmt	1	3.0373	2.1956	1.9136	0.1666	20.85
O_LAG	1	1.8225	1.1594	2.4709	0.116	6.187
T_LAG	1	0.1229	1.0895	0.0127	0.9102	1.131

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	31.86
SC	210.493	57.622
-2 Log L	205.272	15.860
R-Square		0.6408
Max-rescaled R-2		0.9560

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	189.4126	7	<.0001
Score	144.8761	7	<.0001
Wald	9.6123	7	0.2116

e) Restricted Model - 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-15.9573	4.8945	10.6293	**0.0011**	
AST	1	3.9209	1.6864	5.4055	**0.0201**	50.444
FLASH	1	2.269	1.7401	1.7002	0.1923	9.669
NEAR	1	1.9819	1.4584	1.8468	0.1742	7.257
PLT	1	-0.8211	1.3948	0.3465	0.5561	0.44
trtmt	1	2.6432	1.7118	2.3843	0.1226	14.058
T_LAG	1	1.4653	0.4242	11.9343	**0.0006**	4.329

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	35.491
SC	210.493	58.033
-2 Log L	205.272	21.491
R-Square		0.6297
Max-rescaled R-2		0.9394

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	183.7814	6	<.0001
Score	141.7383	6	<.0001
Wald	14.7635	6	0.0222

f) Restricted Model - 3

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-16.7192	5.1252	10.6416	**0.0011**	
AST	1	3.8314	1.6958	5.1047	**0.0239**	46.128
FLASH	1	2.2371	1.7013	1.7292	0.1885	9.367
NEAR	1	2.0399	1.4593	1.9540	0.1622	7.69
trtmt	1	2.5820	1.7117	2.2754	0.1314	13.223
T_LAG	1	1.5344	0.4425	12.0265	**0.0005**	4.639

Analysis of Maximum Likelihood Estimates

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	33.846
SC	210.493	53.168
-2 Log L	205.272	21.846
R-Square		0.6290
Max-rescaled R-2		0.9384

Model Fit Statistics

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	183.4266	5	<.0001
Score	141.6945	5	<.0001
Wald	13.3946	5	0.0199

Testing Global Null Hypothesis: BETA=0

g) Restricted Model - 4

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-16.9345	4.9323	11.7883	**0.0006**	
AST	1	4.0323	1.5542	6.7313	**0.0095**	56.393
NEAR	1	2.0941	1.3202	2.5159	0.1127	8.118
trtmt	1	3.4168	1.6322	4.3822	**0.0363**	30.472
T_LAG	1	1.5414	0.4231	13.2733	**0.0003**	4.671

Analysis of Maximum Likelihood Estimates

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	33.787
SC	210.493	49.889
-2 Log L	205.272	23.787
R-Square		0.6251
Max-rescaled R-2		0.9325

Model Fit Statistics

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	181.4852	4	<.0001
Score	140.3825	4	<.0001
Wald	14.0657	4	0.0071

Testing Global Null Hypothesis: BETA=0

h) Restricted Model – 5*

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-12.9303	3.155	16.7962	**<.0001**	
AST	1	3.0924	1.3402	5.3242	**0.021**	22.031
FLASH	1	3.2393	1.5245	4.515	**0.0336**	25.517
NEAR	1	1.941	1.2937	2.2511	0.1335	6.966
T_LAG	1	1.2516	0.3017	17.2146	**<.0001**	3.496

Analysis of Maximum Likelihood Estimates

Criterion	Intercept Only	Intercept and Covariates
AIC	207.272	34.874
SC	210.493	50.976
-2 Log L	205.272	24.874
R-Square		0.6229
Max-rescaled R-2		0.9292

Model Fit Statistics

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	180.3981	4	<.0001
Score	141.3220	4	<.0001
Wald	18.6450	4	0.0009

Testing Global Null Hypothesis: BETA=0

* Model was selected as preferred model in its category

Table B-42: PCM Results of Binary Logistic Regression for Gaps - MB-CLT

a) Full Model

Analysis of Maximum Likelihood Estimates / Odds Ratio*

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	8.8012	221.1	0.0016	0.9682	
ADY	1	-15.8883	221	0.0052	0.9427	<0.001
AST	1	7.0697	1.6713	17.8932	**<.0001**	>999.999
FLASH	1	0.1645	1.6594	0.0098	0.921	1.179
FOLL	1	-0.9087	1.9812	0.2104	0.6465	0.403
ADY	1	-15.8883	221	0.0052	0.9427	<0.001
AST	1	7.0697	1.6713	17.8932	**<.0001**	>999.999
FLASH	1	0.1645	1.6594	0.0098	0.921	1.179
FOLL	1	-0.9087	1.9812	0.2104	0.6465	0.403
PREV	1	-5.4786	2.1798	6.3171	**0.012**	0.004
PXW	1	-9.2855	2.9824	9.6937	**0.0018**	<0.001
TRIG	1	1.3154	2.577	0.2606	0.6097	3.726
TRTMT	1	0.9784	1.1491	0.725	0.3945	2.66
G_NEAR	1	-16.9828	221	0.0059	0.9387	<0.001
G_FAR	1	-21.4843	221	0.0094	0.9226	<0.001
G_COMBO	1	-17.0238	221	0.0059	0.9386	<0.001
D_WAIT	1	0.4291	0.367	1.3669	0.2424	1.536
DECEL	1	-2.5276	1.6514	2.3427	0.1259	0.08
DIST1	1	-0.0179	0.0111	2.5805	0.1082	0.982
O_GAP	1	1.0898	0.4192	6.7566	**0.0093**	2.974
T_GAP	1	0.9284	0.5798	2.5637	0.1093	2.53
SPEED_FT	1	0.2769	0.2151	1.6566	0.1981	1.319

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	90.748
SC	387.225	176.546
-2 Log L	381.325	46.748
R-Square		0.6001
Max-rescaled R-Square		0.9258

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	334.5765	21	<.0001
Score	281.3263	21	<.0001
Wald	26.2080	21	0.1986

b) Unrestricted Model -1

Analysis of Maximum Likelihood Estimates / Odds Ratio*

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-4.6478	1.1828	15.4407	**<.0001**	
AST	1	4.7976	0.8251	33.8068	**<.0001**	121.218
PREV	1	-3.7751	1.1426	10.9151	**0.0010**	0.023
G_FAR	1	-3.3314	0.9502	12.2916	**0.0005**	0.036
T_GAP	1	1.2422	0.1999	38.6242	**<.0001**	3.463

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	82.604
SC	387.225	102.104
-2 Log L	381.325	72.604
R-Square		0.5708
Max-rescaled R-Square		0.8806

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	308.7206	4	<.0001
Score	262.9994	4	<.0001
Wald	47.2831	4	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
16.7368	17	0.4723

c) Unrestricted Model -2

Analysis of Maximum Likelihood Estimates / **Odds Ratio***

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-3.9435	1.0190	14.9753	**0.0001**	
AST	1	5.3618	0.9209	33.8981	**<.0001**	213.102
PREV	1	-5.1016	1.1356	20.1834	**<.0001**	0.006
TRTMT	1	1.4364	0.6744	4.5366	**0.0332**	4.205
G_FAR	1	-3.2508	0.9743	11.1339	**0.0008**	0.039
O_GAP	1	1.1653	0.1896	37.7593	**<.0001**	3.207

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	82.090
SC	387.225	105.490
-2 Log L	381.325	70.090
R-Square		0.5737
Max-rescaled R-Square		0.8851

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	311.2348	5	<.0001
Score	263.3704	5	<.0001
Wald	44.4158	5	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
15.3152	15	0.4290

d) Restricted Model - 1

Analysis of Maximum Likelihood Estimates / **Odds Ratio***

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.1246	1.5903	32.9214	**<.0001**	
AST	1	4.0192	0.7252	30.7141	**<.0001**	55.657
MUP	1	-0.2566	0.6707	0.1464	0.7020	0.774
FLASH	1	1.1575	0.8416	1.8916	0.1690	3.182
NEAR	1	1.3292	0.7054	3.5506	**0.0595**	3.778
PLT	1	-0.1969	0.6513	0.0914	0.7624	0.821
TRTMT	1	0.6898	0.7489	0.8485	0.3570	1.993
D_WAIT	1	0.0777	0.0552	1.9790	0.1595	1.081
T_GAP	1	1.0009	0.1569	40.6779	**<.0001**	2.721

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	102.526
SC	387.225	137.625
-2 Log L	381.325	84.526
R-Square		0.5565
Max-rescaled R-Square		0.8586

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	296.7993	8	<.0001
Score	262.9904	8	<.0001
Wald	61.0349	8	<.0001

e) Restricted Model - 2

Analysis of Maximum Likelihood Estimates / **Odds Ratio***

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.1698	1.2788	51.4196	**<.0001**	
AST	1	4.1648	0.7011	35.2839	**<.0001**	64.377
FLASH	1	1.5477	0.6722	5.3008	**0.0213**	4.701
NEAR	1	1.4032	0.6561	4.5740	**0.0325**	4.068
D_WAIT	1	0.0618	0.0535	1.3375	0.2475	1.064
T_GAP	1	1.0307	0.1504	46.9732	**<.0001**	2.803

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	97.709
SC	387.225	121.109
-2 Log L	381.325	85.709
R-Square		0.5551
Max-rescaled R-Square		0.8564

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	295.6159	5	<.0001
Score	258.9819	5	<.0001
Wald	59.7785	5	<.0001

f) Restricted Model – 3*

Analysis of Maximum Likelihood Estimates / **Odds Ratio***

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-8.5109	1.1308	56.6455	**<.0001**	
AST	1	4.3601	0.7006	38.732	**<.0001**	78.267
FLASH	1	1.726	0.6437	7.1905	**0.0073**	5.618
NEAR	1	1.4537	0.6361	5.2233	**0.0223**	4.279
T_GAP	1	0.9739	0.1391	49.0126	**<.0001**	2.648

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	386.376	101.337
SC	390.279	120.85
-2 Log L	384.376	91.337
R-Square		0.5510
Max-rescaled R-Square		0.8475

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	293.0390	4	<.0001
Score	256.8958	4	<.0001
Wald	61.0654	4	<.0001

g) Restricted Model – 4

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-9.5640	1.3649	49.1001	**<.0001**	
AST	1	4.0359	0.6949	33.7318	**<.0001**	56.593
trtmt	1	1.2857	0.6029	4.5476	**0.0330**	3.617
NEAR	1	1.4941	0.6630	5.0780	**0.0242**	4.455
D_WAIT	1	0.0825	0.0537	2.3620	0.1243	1.086
T_GAP	1	1.0214	0.1464	48.6918	**<.0001**	2.777

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	98.543
SC	387.225	121.942
-2 Log L	381.325	86.543
R-Square		0.5541
Max-rescaled R-Square		0.8548

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	294.7821	5	<.0001
Score	260.5981	5	<.0001
Wald	61.8203	5	<.0001

h) Restricted Model – 5

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-8.6058	1.1434	56.6475	**<.0001**	
AST	1	4.2397	0.6931	37.4219	**<.0001**	69.384
TRTMT	1	1.1945	0.5578	4.5858	**0.0322**	3.302
NEAR	1	1.5762	0.6324	6.2118	**0.0127**	4.837
T_GAP	1	0.955	0.1333	51.3424	**<.0001**	2.599

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	386.376	104.277
SC	390.279	123.79
-2 Log L	384.376	94.277
R-Square		0.5473
Max-rescaled R-Square		0.8419

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	290.0989	4	<.0001
Score	257.4806	4	<.0001
Wald	64.1412	4	<.0001

i) Restricted Model – 6

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-8.2814	1.087	58.0383	**<.0001**	
AST	1	3.8296	0.6352	36.3498	**<.0001**	46.045
TRTMT	1	1.3541	0.5817	5.4181	**0.0199**	3.873
D_WAIT	1	0.0877	0.0512	2.9409	**0.0864**	1.092
T_GAP	1	0.9603	0.1364	49.5876	**<.0001**	2.613

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	102.276
SC	387.225	121.775
-2 Log L	381.325	92.276
R-Square		0.5470
Max-rescaled R-Square		0.8439

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	289.0493	4	<.0001
Score	258.8463	4	<.0001
Wald	63.8192	4	<.0001

j) Restricted Model – 7

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio* Point Estimate
Intercept	1	-8.0518	1.0542	58.3353	**<.0001**	
AST	1	4.0271	0.655	37.8027	**<.0001**	56.099
FLASH	1	1.7552	0.6748	6.7653	**0.0093**	5.784
D_WAIT	1	0.0663	0.0512	1.6761	0.1954	1.069
T_GAP	1	0.9805	0.1421	47.6097	**<.0001**	2.666

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	383.325	100.798
SC	387.225	120.297
-2 Log L	381.325	90.798
R-Square		0.5489
Max-rescaled R-Square		0.8467

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	290.5274	4	<.0001
Score	257.3398	4	<.0001
Wald	60.2710	4	<.0001

* Model was selected as preferred model in its category

Table B-43: PCM Results of Multi-Linear Regression for Lags – MB-RAL

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0259	0.1642	-0.16	0.8749
ADY	-0.2698	0.1794	-1.5	0.1332
AST	0.4188	0.0264	15.85	**<.0001**
FOLL	0.0873	0.0779	1.12	0.2632
HEV	-0.033752325	0.07000652	-0.48	0.6299
MUP	-0.037960614	0.02699329	-1.41	0.1602
NEAR	0.051572358	0.04127467	1.25	0.212
PLT	-0.113123456	0.07626338	-1.48	0.1386
PREV	0.130598191	0.06983349	1.87	**0.062**
PXW	0.078510633	0.02637112	2.98	**0.003**
TRIG	0.128017608	0.0462881	2.77	**0.0059**
trtmt	0.030745083	0.024366	1.26	0.2076
G_NEAR	-0.164204826	0.12420297	-1.32	0.1867
G_FAR	-0.136061075	0.12378523	-1.1	0.2722
G_COMBO	-0.212592765	0.12305603	-1.73	**0.0846**
Decel	-0.01788501	0.0035895	-4.98	**<.0001**
DIST1	-0.000254235	0.00032483	-0.78	0.4342
O_LAG	0.006873926	0.00535419	1.28	0.1998
T_LAG	-0.420711686	0.28965905	-1.45	0.147
SPEED_FT	0.007007493	0.00275654	2.54	**0.0113**
TTC_V	0.465418729	0.28981758	1.61	0.1089

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	95.1001	4.7550	70.32	<.0001
Error	528	35.7014	0.0676		
Corrected Total	548	130.8015			

R-Square	Coeff Var	Root MSE	GO Mean
0.7271	42.7417	0.2600	0.6084

Adj. R-Square
0.72

b) Unrestricted Model - 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.2490	0.0709	3.51	**0.0005**
AST	0.4905	0.0299	16.38	**<.0001**
PREV	0.0203	0.0742	0.27	0.7844
PXW	0.0643	0.0307	2.09	**0.0368**
TRIG	0.01632934	0.05079004	0.32	0.748
G_COMBO	-0.102634365	0.02940749	-3.49	**0.0005**
Decel	-0.048464464	0.00348281	-13.92	**<.0001**
SPEED_FT	0.0086871	0.0017762	4.89	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	78.9456	11.2779	117.66	<.0001
Error	541	51.8559	0.0959		
Corrected Total	548	130.8015			

R-Square	Coeff Var	Root MSE	GO Mean
0.6036	50.8893	0.3096	0.6084

Adj. R-Square
0.60

c) Unrestricted Model - 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.2503	0.0699	3.58	**0.0004**
AST	0.4931	0.0283	17.4	**<.0001**
PXW	0.0650	0.0303	2.15	**0.0324**
G_COMBO	-0.1025	0.0292	-3.51	**0.0005**
Decel	-0.048284718	0.00344832	-14	**<.0001**
SPEED_FT	0.008651456	0.00175616	4.93	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	78.9286	15.7857	165.24	<.0001
Error	543	51.8728	0.0955		
Corrected Total	548	130.8015			

R-Square	Coeff Var	Root MSE	GO Mean
0.6034	50.8038	0.3091	0.6084

Adj. R-Square
0.60

d) Restricted Model – 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0474	0.0310	-1.53	0.1271
AST	0.4967	0.0249	19.97	**<.0001**
NEAR	0.0293	0.0247	1.19	0.2362
PLT	-0.0623	0.0279	-2.23	**0.026**
trtmt	0.05481888	0.0243878	2.25	**0.025**
T_LAG	0.048645202	0.00238831	20.37	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	89.5318	17.9064	235.6	<.0001
Error	543	41.2696	0.0760		
Corrected Total	548	130.8015			

R-Square	Coeff Var	Root MSE	GO Mean
0.6845	45.3149	0.2757	0.6084

Adj. R-Square
0.68

e) Restricted Model – 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0443	0.0255	-1.74	**0.0829**
AST	0.4974	0.0249	19.95	**<.0001**
trtmt	0.0492	0.0244	2.02	**0.044**
T_LAG	0.0490	0.0024	20.48	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	89.0776	29.6925	387.85	<.0001
Error	545	41.7238	0.0766		
Corrected Total	548	130.8015			

R-Square	Coeff Var	Root MSE	GO Mean
0.6810	45.4799	0.2767	0.6084

Adj. R-Square
0.68

Table B-44: PCM Results of Multi-Linear Regression for Gaps – MB-RAL

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.2755	0.3357	0.82	0.4129
ADY	-0.1690	0.2517	-0.67	0.5029
AST	0.2830	0.0440	6.43	**<.0001**
FOLL	0.0429	0.0570	0.75	0.4527
HEV	-0.000342477	0.09179649	0	0.997
MUP	-0.045947156	0.03559406	-1.29	0.1983
NEAR	0.0949	0.0490	1.93	**0.0545**
PLT	-0.2143	0.0537	-3.99	**<.0001**
PREV	-0.0718	0.0508	-1.41	0.1595
PXW	-0.184639282	0.08492561	-2.17	**0.0309**
QUE	-0.044825385	0.13617036	-0.33	0.7424
TRIG	0.2822	0.0884	3.19	**0.0017**
trtmt	0.0081	0.0359	0.23	0.8211
G_NEAR	-0.3176	0.2560	-1.24	0.2161
G_FAR	-0.2887	0.2627	-1.1	0.2731
G_COMBO	-0.3424	0.2567	-1.33	0.1839
D_WAIT	-0.0168	0.0150	-1.12	0.2647
Decel	-0.001502739	0.0027065	-0.56	0.5794
DIST1	-4.17034E-05	0.00044805	-0.09	0.9259
O_GAP	0.0052	0.0084	0.61	0.5395
T_GAP	0.0496	0.0141	3.52	**0.0005**
SPEED_FT	0.0024	0.0057	0.42	0.6763
TTC_V	0.021550071	0.02374117	0.91	0.3652

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	22	42.7240	1.9420	35.25	<.0001
Error	195	10.7439	0.0551		
Corrected Total	217	53.4679			

R-Square	Coeff Var	Root MSE	GO Mean
0.7991	41.2666	0.2347	0.5688

Adj. R-Square
0.78

b) Unrestricted Model – 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0217	0.0419	-0.52	0.6051
AST	0.2883	0.0398	7.25	**<.0001**
NEAR	0.0909	0.0327	2.78	**0.006**
PLT	-0.2043	0.0357	-5.72	**<.0001**
PXW	-0.18582075	0.08186574	-2.27	**0.0242**
TRIG	0.281236869	0.08647746	3.25	**0.0013**
T_GAP	0.076762356	0.00385505	19.91	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	41.9206	6.9868	127.67	<.0001
Error	211	11.5473	0.0547		
Corrected Total	217	53.4679			

R-Square	Coeff Var	Root MSE	GO Mean
0.7840	41.1276	0.2339	0.5688

Adj. R-Square
0.78

c) Restricted Model – 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0376	0.0491	-0.77	0.4449
AST	0.3328	0.0401	8.3	**<.0001**
NEAR	0.0891	0.0341	2.61	**0.0096**
PLT	-0.2004	0.0373	-5.37	**<.0001**
trtmt	0.018272022	0.03527044	0.52	0.605
D_WAIT	0.001676171	0.00438781	0.38	0.7028
T_GAP	0.075486541	0.00402654	18.75	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	41.0053	6.8342	115.71	<.0001
Error	211	12.4626	0.0591		
Corrected Total	217	53.4679			

R-Square	Coeff Var	Root MSE	GO Mean
0.7669	42.7265	0.2430	0.5688

Adj. R-Square
0.76

d) Restricted Model – 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0252	0.0417	-0.6	0.5462
AST	0.3325	0.0385	8.64	**<.0001**
NEAR	0.0884	0.0339	2.61	**0.0097**
PLT	-0.1984	0.0361	-5.5	**<.0001**
T_GAP	0.076075272	0.00389651	19.52	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	40.9789	10.2447	174.72	<.0001
Error	213	12.4890	0.0586		
Corrected Total	217	53.4679			

R-Square	Coeff Var	Root MSE	GO Mean
0.7664	42.5705	0.2421	0.5688

Adj. R-Square
0.76

Table B-45: PCM Results of Binary Logistic Regression for Lags - MB-RAL +*

a) Full Model

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	2.9548	139	0.0005	0.983	
ADY	1	-10.5779	140.9	0.0056	0.9401	<0.001
AST	1	5.865	1.0524	31.0557	**<.0001**	352.483
FOLL	1	12.6478	203.6	0.0039	0.9505	>999.999
HEV	1	-0.8298	1.7175	0.2334	0.629	0.436
MUP	1	-1.3378	0.7963	2.8227	**0.0929**	0.262
NEAR	1	0.3117	1.1809	0.0696	0.7919	1.366
PLT	1	-12.3998	203.6	0.0037	0.9514	<0.001
PREV	1	2.0531	4.1091	0.2496	0.6173	7.792
PXW	1	0.8708	0.6571	1.7561	0.1851	2.389
QUE	1	2.6486	4.3594	0.3691	0.5435	14.135
TRIG	1	1.1947	1.2724	0.8816	0.3478	3.302
trtmt	1	0.2283	0.6561	0.1211	0.7279	1.256
G_NEAR	1	-9.955	138.9	0.0051	0.9429	<0.001
G_FAR	1	-10.7214	138.9	0.006	0.9385	<0.001
G_COMBO	1	-11.1504	138.9	0.0064	0.936	<0.001
Decel	1	-1.4376	0.7938	3.2802	**0.0701**	0.237
DIST1	1	0.00769	0.0202	0.1442	0.7041	1.008
O_LAG	1	0.978	0.4373	5.0013	**0.0253**	2.659
T_LAG	1	-0.5986	0.8066	0.5508	0.458	0.55
SPEED_FT	1	0.1066	0.2014	0.2804	0.5965	1.113

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	123.044
SC	741.384	213.514
-2 Log L	735.076	81.044
R-Square		0.6962
Max-rescaled R-Square		0.9435

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	654.0315	20	<.0001
Score	399.3122	20	<.0001
Wald	53.6392	20	<.0001

b) Unrestricted Model – 1

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.7659	1.3139	55.2463	**<.0001**	
AST	1	5.3687	0.7119	56.8747	**<.0001**	214.579
MUP	1	-1.3478	0.6513	4.2828	**0.0385**	0.26
O_LAG	1	1.0893	0.1456	55.9645	**<.0001**	2.972

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	107.523
SC	741.384	124.755
-2 Log L	735.076	99.523
R-Square		0.6858
Max-rescaled R-Square		0.9294

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	635.5526	3	<.0001
Score	366.8087	3	<.0001
Wald	69.9017	3	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
14.5862	17	0.6253

c) Unrestricted Model – 2

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.2288	1.1689	62.3332	**<.0001**	
AST	1	5.8661	0.7245	65.5580	**<.0001**	352.878
MUP	1	-1.2546	0.6082	4.2558	**0.0391**	0.285
T_LAG	1	1.0669	0.1340	63.4325	**<.0001**	2.906

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	119.139
SC	741.384	136.372
-2 Log L	735.076	111.139
R-Square		0.6791
Max-rescaled R-Square		0.9203

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	623.9363	3	<.0001
Score	374.0784	3	<.0001
Wald	76.2924	3	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
17.5115	16	0.3533

d) Restricted Model – 1

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-10.2396	1.3348	58.8511	**<.0001**	
AST	1	6.0352	0.7421	66.1355	**<.0001**	417.903
NEAR	1	0.6312	0.5336	1.3995	0.2368	1.880
PLT	1	0.1037	0.6829	0.0231	0.8792	1.109
trtmt	1	0.7879	0.5218	2.2798	0.1311	2.199
T_LAG	1	1.0535	0.1315	64.1423	**<.0001**	2.868

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	123.704
SC	741.384	149.553
-2 Log L	735.076	111.704
R-Square		0.6787
Max-rescaled R-Square		0.9198

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	623.3713	5	<.0001
Score	375.7830	5	<.0001
Wald	78.8375	5	<.0001

e) Restricted Model – 2*

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-10.2150	1.3224	59.6736	**<.0001**	
AST	1	6.0194	0.7330	67.4360	**<.0001**	411.332
NEAR	1	0.6420	0.5285	1.4753	0.2245	1.900
trtmt	1	0.7861	0.5214	2.2736	0.1316	2.195
T_LAG	1	1.0525	0.1313	64.2699	**<.0001**	2.865

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	121.727
SC	741.384	143.268
-2 Log L	735.076	111.727
R-Square		0.6787
Max-rescaled R-Square		0.9198

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	623.3482	4	<.0001
Score	374.1924	4	<.0001
Wald	78.8825	4	<.0001

f) Restricted Model – 3

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.7433	1.2262	63.1361	**<.0001**	
AST	1	5.9535	0.7223	67.9400	**<.0001**	385.117
trtmt	1	0.7711	0.5206	2.1938	0.1386	2.162
T_LAG	1	1.0480	0.1300	64.9734	**<.0001**	2.852

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	121.223
SC	741.384	138.455
-2 Log L	735.076	113.223
R-Square		0.6778
Max-rescaled R-Square		0.9186

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	621.8528	3	<.0001
Score	373.8768	3	<.0001
Wald	79.3445	3	<.0001

g) Restricted Model – 4

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.6982	1.2183	63.3688	**<.0001**	
AST	1	5.897	0.7151	67.998	**<.0001**	363.941
NEAR	1	0.6128	0.5184	1.3973	0.2372	1.846
T_LAG	1	1.0376	0.1269	66.8336	**<.0001**	2.823

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	122.09
SC	741.384	139.323
-2 Log L	735.076	114.090
R-Square		0.6773
Max-rescaled R-Square		0.9179

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	620.9851	3	<.0001
Score	372.8564	3	<.0001
Wald	80.4507	3	<.0001

h) Restricted Model – 5

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.2648	1.1326	66.9105	**<.0001**	
AST	1	5.8287	0.7047	68.4060	**<.0001**	339.908
T_LAG	1	1.0338	0.1260	67.3381	**<.0001**	2.812

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	737.076	121.505
SC	741.384	134.430
-2 Log L	735.076	115.505
R-Square		0.6765
Max-rescaled R-Square		0.9168

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	619.5702	2	<.0001
Score	372.5670	2	<.0001
Wald	80.6969	2	<.0001

* Model was selected as preferred model in its category

Table B-46: PCM Results of Binary Logistic Regression for Gaps - MB-RAL

a) Full Model

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-73.3202	175	0.1756	0.6752	
ADY	1	30.1471	177	0.029	0.8647	>999.999
AST	1	19.1788	18.0012	1.1351	0.2867	>999.999
FOLL	1	-16.7172	11.9972	1.9416	0.1635	<0.001
HEV	1	3.805	5.8428	0.4241	0.5149	44.924
MUP	1	-23.7572	13.0311	3.3238	**0.0683**	<0.001
NEAR	1	12.1391	6.9127	3.0837	**0.0791**	>999.999
PLT	1	2.8976	9.6229	0.0907	0.7633	18.131
PREV	1	-16.0108	12.6858	1.5929	0.2069	<0.001
PXW	1	-9.8444	11.6034	0.7198	0.3962	<0.001
QUE	1	-5.4908	68.017	0.0065	0.9357	0.004
TRIG	1	15.6245	29.6548	0.2776	0.5983	>999.999
trtmt	1	-15.3408	14.8254	1.0707	0.3008	<0.001
G_NEAR	1	8.5423	167.7	0.0026	0.9594	>999.999
G_FAR	1	22.4357	168.7	0.0177	0.8942	>999.999
G_COMBO	1	-3.0103	167.3	0.0003	0.9856	0.049
D_WAIT	1	1.1258	1.5423	0.5328	0.4654	3.083
Decel	1	-4.6609	8.0543	0.3349	0.5628	0.009
DIST1	1	-0.0919	0.0574	2.5665	0.1091	0.912
O_GAP	1	5.929	3.5961	2.7184	**0.0992**	375.769
T_GAP	1	4.8769	2.7659	3.1091	**0.0779**	131.229
SPEED_FT	1	1.5264	0.9934	2.3607	0.1244	4.602

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	300.071	50.223
SC	303.455	124.682
-2 Log L	298.071	6.223
R-Square		0.7378
Max-rescaled R-Square		0.9901

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	291.8479	21	<.0001
Score	174.0097	21	<.0001
Wald	6.4761	21	0.9990

b) Unrestricted Model – 1

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-16.4264	4.1249	15.8581	**<.0001**	
AST	1	9.3082	2.9025	10.2849	**0.0013**	>999.999
MUP	1	-3.4151	1.5566	4.8133	**0.0282**	0.033
NEAR	1	5.2463	1.8619	7.9391	**0.0048**	189.858
PXW	1	-9.2712	3.0865	9.0227	**0.0027**	<0.001
G_FAR	1	3.9974	2.0660	3.7436	**0.0530**	54.454
T_GAP	1	1.9754	0.4627	18.2291	**<.0001**	7.209

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	300.071	42.037
SC	303.455	65.729
-2 Log L	298.071	28.037
R-Square		0.7102
Max-rescaled R-Square		0.9531

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	270.0334	6	<.0001
Score	161.1539	6	<.0001
Wald	20.2006	6	0.0026

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
13.2453	15	0.5834

c) Unrestricted Model - 2

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-3.9936	1.3294	9.0243	**0.0027**	
ADY	1	2.9265	1.7350	2.8451	**0.0917**	18.662
AST	1	4.7599	1.3116	13.1697	**0.0003**	116.730
FOLL	1	-3.5851	1.5651	5.2472	**0.0220**	0.028
PREV	1	-5.7384	1.8154	9.9921	**0.0016**	0.003
PXW	1	-4.2132	1.5921	7.0035	**0.0081**	0.015
O_GAP	1	1.4469	0.2857	25.6416	**<.0001**	4.250

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	301.196	58.366
SC	304.585	82.090
-2 Log L	299.196	44.366
R-Square		0.7102
Max-rescaled R-Square		0.9531

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	254.8292	6	<.0001
Score	144.1770	6	<.0001
Wald	28.6961	6	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
13.7716	14	0.4669

d) Restricted Model – 1

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.7605	2.3459	17.3115	**<.0001**	
AST	1	4.7209	1.2990	13.2082	**0.0003**	112.272
NEAR	1	2.5723	1.1103	5.3677	**0.0205**	13.096
PLT	1	-1.2773	1.1590	1.2146	0.2704	0.279
trtmt	1	0.1155	1.0571	0.0119	0.9130	1.122
D_WAIT	1	-0.0483	0.1142	0.1786	0.6725	0.953
T_GAP	1	1.2629	0.2648	22.7503	**<.0001**	3.536

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	300.071	59.449
SC	303.455	83.141
-2 Log L	298.071	45.449
R-Square		0.6861
Max-rescaled R-Square		0.9207

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	252.6214	6	<.0001
Score	167.1874	6	<.0001
Wald	32.3576	6	<.0001

e) Restricted Model - 2

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-9.8237	2.2930	18.3541	**<.0001**	
AST	1	4.7805	1.2734	14.0941	**0.0002**	119.161
NEAR	1	2.4900	1.0674	5.4424	**0.0197**	12.062
PLT	1	-1.3033	1.0992	1.4058	0.2358	0.272
T_GAP	1	1.2388	0.2475	25.0570	**<.0001**	3.452

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	300.071	55.649
SC	303.455	72.571
-2 Log L	298.071	45.649
R-Square		0.6859
Max-rescaled R-Square		0.9204

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	252.4216	4	<.0001
Score	167.0797	4	<.0001
Wald	32.6554	4	<.0001

f) Restricted Model – 3*

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-10.9378	2.2697	23.2224	**<.0001**	
AST	1	5.2675	1.2678	17.2619	**<.0001**	193.935
NEAR	1	2.7576	1.0967	6.3229	**0.0119**	15.762
T_GAP	1	1.3350	0.2493	28.6733	**<.0001**	3.800

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	300.071	55.096
SC	303.455	68.634
-2 Log L	298.071	47.096
R-Square		0.6838
Max-rescaled R-Square		0.9175

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	250.9745	3	<.0001
Score	159.8575	3	<.0001
Wald	34.2771	3	<.0001

g) Restricted Model – 4

Analysis of Maximum Likelihood Estimates / **Odds Ratio**

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate
Intercept	1	-10.8702	2.3021	22.2967	**<.0001**	
AST	1	5.2338	1.2747	16.8587	**<.0001**	187.506
NEAR	1	2.8567	1.1323	6.3646	**0.0116**	17.403
D_WAIT	1	-0.0597	0.1144	0.272	0.602	0.942
T_GAP	1	1.368	0.2653	26.5803	**<.0001**	3.927

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	300.071	56.827
SC	303.455	73.75
-2 Log L	298.071	46.827
R-Square		0.6842
Max-rescaled R-Square		0.9181

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	251.2436	4	<.0001
Score	160.1626	4	<.0001
Wald	33.5419	4	<.0001

* Model was selected as preferred model in its category

10.3 Appendix C: RBT-RAL Roundabout Models

Table C-47: Correlation Matrix, RBT-RAL, Yielding Model*

	YIELD	Y_ORDERED	Y_TYPE	ADY	AST	COM	DECEL_TAU	DSC	ENTRY	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	TTC_Tau	DECEL	DIST1	SPEED_FT
YIELD																						
Y_ORDERED	0.91																					
	<.0001																					
Y_TYPE	.	1.00																				
	.	**<.0001**																				
ADY	0.05	0.03	-0.05																			
	0.6104	0.7525	0.7463																			
AST	0.02	-0.03	-0.18	-0.12																		
	0.8372	0.7847	0.2746	0.2252																		
COM	0.17	0.17	0.03	-0.04	-0.07																	
	0.0817	0.084	0.8312	0.7215	0.494																	
DECEL_TAU	-0.27	-0.23	0.19	-0.10	0.02	-0.06																
	0.0065	**0.0242**	0.2498	0.3129	0.8052	0.5689																
DSC	0.25	0.38	0.39	-0.05	-0.10	-0.03	-0.08															
	0.0121	**<.0001**	**0.0134**	0.6104	0.3278	0.7733	0.4153															
ENTRY	0.01	0.01	-0.01	-0.24	-0.15	0.01	0.20	0.11														
	0.9356	0.9567	0.9629	**0.0171**	0.1373	0.9324	**0.0489**	0.2566														
FOLL	0.17	0.19	0.14	-0.01	0.01	-0.01	-0.02	0.09	0.02													
	0.0878	0.0549	0.3766	0.9204	0.9518	0.955	0.8733	0.3524	0.8245													
HEV	0.14	0.20	0.22	-0.06	-0.12	0.26	-0.10	-0.05	-0.24	-0.01												
	0.1724	**0.0494**	0.1743	0.5281	0.2252	**0.0078**	0.3129	0.6104	**0.0171**	0.9204												
MUP	0.04	0.06	0.08	0.10	-0.09	-0.07	-0.11	0.30	-0.13	0.14	-0.12											
	0.6746	0.5584	0.6418	0.3182	0.3511	0.5082	0.2587	**0.0022**	0.2033	0.1724	0.2408											
NEAR	-0.04	0.01	0.18	-0.23	-0.28	0.01	0.21	0.23	0.36	0.02	-0.14	0.10										
	0.6852	0.9276	0.2621	**0.0222**	**0.0041**	0.8873	**0.0322**	**0.024**	**0.0003**	0.8116	0.1532	0.3251										
PLT	0.07	0.13	0.26	-0.02	-0.03	-0.07	-0.06	0.13	0.03	0.67	-0.02	0.13	0.05									
	0.4767	0.1956	0.1014	0.8117	0.7857	0.5134	0.5552	0.1958	0.7835	**<.0001**	0.8117	0.2067	0.6459									
PREV	-0.14	-0.14	-0.06	-0.13	-0.25	0.17	-0.04	-0.07	0.03	0.07	-0.04	0.03	0.02	0.31								
	0.1614	0.1566	0.7283	0.2153	**0.0128**	0.0882	0.6684	0.5116	0.769	0.4991	0.6973	0.7459	0.8243	**0.0018**								
PXW	0.26	0.21	-0.08	0.23	0.29	0.08	-0.24	-0.12	-0.19	0.07	0.14	0.02	-0.40	0.08	-0.26							
	0.0088	**0.0325**	0.6124	**0.019**	**0.003**	0.4395	**0.0166**	0.2305	0.0547	0.5044	0.1702	0.8513	**<.0001**	0.4442	**0.0084**							
QUE	0.18	0.26	0.29	-0.07	-0.13	-0.04	0.00	0.14	0.06	0.26	-0.07	-0.03	0.07	0.18	0.25	-0.16						
	0.0798	**0.0099**	0.0729	0.4932	0.1875	0.6986	0.9822	0.1529	0.5817	**0.0081**	0.4932	0.7934	0.508	0.081	**0.0123**	0.106						
TRIG	-0.12	-0.11	.	-0.04	0.29	-0.02	-0.06	-0.03	0.15	-0.15	-0.04	-0.07	0.01	-0.22	-0.12	0.08	-0.04					
	0.2478	0.2918	.	0.7215	**0.0029**	0.8403	0.5689	0.7733	0.1319	0.1398	0.7215	0.5082	0.8873	**0.0254**	0.238	0.4395	0.6986					
TTC_Tau	-0.26	-0.11	0.58	-0.10	-0.20	0.04	0.55	0.17	0.19	-0.05	-0.10	-0.02	0.39	-0.04	-0.01	-0.29	0.05	-0.10				
	0.0099	0.2836	**<.0001**	0.3365	0.0518	0.6572	**<.0001**	0.0886	0.0568	0.6188	0.3365	0.8716	**<.0001**	0.6981	0.8829	**0.0032**	0.6552	0.2993				
DECEL	-0.29	-0.22	0.35	-0.10	0.00	-0.05	0.83	-0.04	0.26	-0.08	-0.15	-0.02	0.27	-0.03	-0.06	-0.26	-0.07	-0.03	0.63			
	0.0038	**0.0246**	**0.0264**	0.341	0.9817	0.5967	**<.0001**	0.6828	**0.0094**	0.434	0.1446	0.849	**0.0067**	0.7742	0.5411	**0.0088**	0.5023	0.7337	**<.0001**			
DIST1	0.11	-0.02	-0.51	-0.08	0.01	-0.03	-0.40	-0.05	0.16	0.03	-0.06	0.11	-0.16	0.06	0.21	0.12	-0.12	0.05	-0.65	-0.47		
	0.2657	0.824	**0.0007**	0.4281	0.9531	0.8039	**<.0001**	0.6034	0.1144	0.7386	0.5256	0.262	0.1199	0.5595	**0.0394**	0.2264	0.2409	0.5952	**<.0001**	**<.0001**		
SPEED_FT	-0.26	-0.29	-0.22	-0.13	0.04	-0.05	0.36	-0.19	0.65	-0.09	-0.30	-0.12	0.20	-0.18	-0.04	-0.17	-0.27	0.11	0.14	0.40	0.27	
	0.0097	**0.003**	0.1737	0.1825	0.7132	0.6352	**0.0003**	0.0591	**<.0001**	0.3796	**0.0027**	0.251	**0.0448**	0.0785	0.6652	0.0855	**0.0061**	0.2595	0.1674	**<.0001**	**0.0072**	
TTC	0.26	0.13	-0.37	-0.03	0.01	-0.03	-0.45	0.00	-0.26	0.08	0.14	0.22	-0.30	0.11	0.18	0.23	-0.04	-0.02	-0.69	-0.58	0.77	-0.28
	0.0101	0.2013	**0.0184**	0.7797	0.9347	0.7349	**<.0001**	0.9647	**0.0079**	0.4053	0.1656	**0.0252**	**0.0024**	0.2765	0.0756	**0.0227**	0.7245	0.8574	**<.0001**	**<.0001**	**<.0001**	**0.0044**

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table C-48: Correlation Matrix, RBT-RAL, Yielding Model – EXIT only*

	YIELD	Y_ORDERED	Y_TYPE	ADY	AST	COM	DECEL_TAU	DSC	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TTC_Tau	DECEL	DIST1	SPEED_FT
YIELD																				
Y_ORDERED	0.91																			
	<.0001																			
Y_TYPE	.	1.00																		
	.	**<.0001**																		
ADY	0.08	0.05	-0.08																	
	0.5895	0.7382	0.735																	
AST	0.08	0.04	-0.12	-0.20																
	0.588	0.7938	0.5992	0.1435																
COM	0.17	0.26	0.26	-0.05	-0.08															
	0.2204	0.0602	0.2585	0.7246	0.5736															
DECEL_TAU	-0.09	-0.02	0.26	-0.10	0.00	-0.04														
	0.5431	0.8608	0.2585	0.467	0.9822	0.7782														
DSC	0.17118	0.25993	0.2582	**-0.0496**	**-0.0791**	**-0.0192**	**-0.0396**													
	0.2204	0.0602	0.2585	0.7246	0.5736	0.8913	0.7782													
FOLL	0.18	0.18	0.08	-0.01	0.03	0.14	-0.15	0.14												
	0.2032	0.1887	0.7144	0.9618	0.814	0.3312	0.2893	0.3312												
HEV	0.20	0.28	0.32	-0.13	-0.20	0.39	-0.10	-0.05	-0.01											
	0.1562	**0.0419**	0.1642	0.3623	0.1435	**0.0041**	0.467	0.7246	0.9618											
MUP	0.02	0.01	-0.03	0.09	-0.10	-0.08	-0.15	0.26	0.17	-0.19										
	0.8723	0.9307	0.8895	0.5157	0.4813	0.5934	0.2691	0.0639	0.2232	0.1655										
NEAR	-0.25	-0.19	0.20	-0.22	-0.26	-0.09	0.14	0.22	0.03	-0.09	0.16									
	0.0686	0.1704	0.3935	0.1061	0.0592	0.535	0.3258	0.1122	0.8309	0.511	0.2509									
PLT	0.03	0.11	0.33	-0.02	-0.01	0.09	-0.12	0.09	0.67	-0.02	0.06	0.14								
	0.8393	0.4309	0.138	0.8619	0.9591	0.5161	0.3791	0.5161	**<.0001**	0.8619	0.6636	0.3193								
PREV	-0.10	-0.04	0.20	-0.17	-0.37	0.17	0.06	0.17	0.10	-0.05	0.21	0.18	0.28							
	0.4579	0.7505	0.3748	0.23	**0.0061**	0.2204	0.6663	0.2204	0.4742	0.7439	0.137	0.2071	**0.0418**							
PXW	0.32	0.30	0.06	0.25	0.24	0.19	-0.20	-0.10	-0.01	0.12	-0.20	-0.45	0.04	-0.34						
	0.0216	**0.0276**	0.8127	0.0749	0.0843	0.1653	0.1411	0.4786	0.9234	0.3881	0.1562	**0.0007**	0.7889	**0.0137**						
QUE	0.14	0.25	0.37	-0.09	-0.14	-0.03	-0.07	0.57	0.24	-0.09	0.06	0.03	0.16	0.30	-0.18					
	0.3336	0.0762	0.0943	0.5332	0.3186	0.8092	0.6185	**<.0001**	0.083	0.5332	0.6562	0.8458	0.2492	**0.0278**	0.2083					
TTC_Tau	-0.31	-0.22	0.37	-0.08	-0.24	0.23	0.48	-0.08	-0.18	-0.08	-0.12	0.38	-0.17	0.13	-0.25	0.04				
	0.0237	0.1142	0.0943	0.5739	0.0807	0.0954	**0.0003**	0.5542	0.1908	0.5739	0.3936	**0.0046**	0.2368	0.3644	0.0723	0.7847				
DECEL	-0.23	-0.17	0.27	-0.06	-0.05	-0.02	0.87	-0.08	-0.19	-0.15	-0.10	0.25	-0.12	0.01	-0.23	-0.09	0.62			
	0.1	0.2243	0.2311	0.674	0.7013	0.9071	**<.0001**	0.5872	0.1727	0.2983	0.4811	0.0711	0.3963	0.9685	0.0961	0.4991	**<.0001**			
DIST1	0.23	0.12	-0.31	-0.08	0.09	-0.14	-0.35	0.42	0.17	-0.05	0.45	-0.07	0.07	0.17	0.12	0.06	-0.62	-0.50		
	0.0982	0.3824	0.17	0.5865	0.5336	0.3012	**0.0098**	**0.002**	0.2119	0.7344	**0.0008**	0.6056	0.627	0.2242	0.3826	0.693	**<.0001**	**0.0001**		
SPEED_FT	-0.28	-0.26	-0.02	0.05	0.29	-0.11	0.47	0.01	-0.18	-0.32	0.16	0.20	-0.28	-0.12	-0.13	-0.25	0.31	0.48	-0.09	
	0.0443	0.0616	0.9366	0.7413	**0.0344**	0.449	**0.0004**	0.9683	0.1923	**0.0188**	0.255	0.1561	**0.0424**	0.38	0.3673	0.067	**0.0241**	**0.0002**	0.5344	
TTC	0.35	0.24	-0.28	-0.12	-0.05	-0.12	-0.36	0.32	0.19	0.10	0.33	-0.15	0.15	0.17	0.15	0.07	-0.62	-0.54	0.88	-0.46
	0.0103	0.081	0.2235	0.4085	0.7147	0.4049	**0.0072**	**0.0212**	0.1707	0.4866	**0.0144**	0.2802	0.2862	0.2233	0.2935	0.6357	**<.0001**	**<.0001**	**<.0001**	**0.0005**

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table C-49: Correlation Matrix, RBT-RAL, Yielding Model – ENTRY only*

	YIELD	Y_ORDERED	Y_TYPE	AST	COM	DECEL_TAU	DSC	FOLL	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	TTC_Tau	DECEL	DIST1	SPEED_FT
YIELD																			
Y_ORDERED	0.91																		
	<.0001																		
Y_TYPE	.	1.00																	
	.	**<.0001**																	
AST	-0.06	-0.12	-0.29																
	0.7121	0.4193	0.2243																
COM	0.18	0.08	-0.20	-0.06															
	0.2287	0.5835	0.4093	0.7065															
DECEL_TAU	-0.43	-0.39	.	0.11	-0.08														
	0.0027	**0.0067**	.	0.4507	0.6086														
DSC	0.31698	0.48672	0.50775	**-0.0999**	**-0.0385**	**-0.1358**													
	0.0299	**0.0005**	**0.0265**	0.5041	0.7972	0.3629													
FOLL	0.16	0.20	0.21	-0.02	-0.16	0.07	0.07												
	0.2691	0.1715	0.3897	0.8703	0.2914	0.6356	0.6376												
MUP	0.07	0.13	0.22	-0.15	-0.06	-0.04	0.42	0.10											
	0.6181	0.3857	0.3758	0.3263	0.7065	0.7737	**0.0032**	0.4895											
NEAR	0.17	0.22	0.27	-0.24	0.11	0.17	0.20	0.00	0.16										
	0.2563	0.1409	0.2681	0.1001	0.4577	0.2395	0.1854	0.9799	0.2973										
PLT	0.12	0.15	0.18	-0.05	-0.24	-0.03	0.16	0.66	0.24	-0.07									
	0.4152	0.3029	0.4637	0.746	0.1065	0.856	0.2783	**<.0001**	0.1094	0.6425									
PREV	-0.18	-0.25	-0.35	-0.07	0.17	-0.13	-0.22	0.03	-0.20	-0.16	0.34								
	0.2186	0.0867	0.1418	0.6337	0.2496	0.3765	0.1288	0.8351	0.1771	0.2883	**0.0195**								
PXW	0.20	0.10	-0.27	0.34	-0.07	-0.24	-0.12	0.20	0.34	-0.25	0.15	-0.16							
	0.1696	0.4868	0.2681	**0.0211**	0.6556	0.1111	0.4285	0.1823	**0.0211**	0.0926	0.303	0.2803							
QUE	0.21	0.27	0.22	-0.12	-0.04	0.03	-0.08	0.29	-0.12	0.07	0.19	0.20	-0.14						
	0.1469	0.0671	0.3758	0.4348	0.7641	0.8531	0.5946	0.0512	0.4348	0.6358	0.2042	0.1774	0.3545						
TRIG	-0.17	-0.16	.	0.55	-0.03	-0.11	-0.06	-0.22	-0.08	-0.06	-0.34	-0.18	0.19	-0.06					
	0.243	0.2877	.	**<.0001**	0.8357	0.4633	0.7132	0.1288	0.59	0.6854	**0.019**	0.2222	0.2132	0.6676					
TTC_Tau	-0.22	0.00	0.80	-0.09	-0.13	0.58	0.29	0.07	0.17	0.32	0.08	-0.17	-0.29	0.03	-0.19				
	0.1427	0.981	**<.0001**	0.5595	0.3746	**<.0001**	**0.0476**	0.6345	0.2556	**0.0282**	0.6053	0.2602	**0.0455**	0.8276	0.2021				
DECEL	-0.36	-0.29	0.59	0.14	-0.09	0.79	-0.07	0.00	0.14	0.16	0.03	-0.14	-0.23	-0.08	-0.10	0.61			
	0.0119	**0.0455**	**0.0079**	0.3413	0.5406	**<.0001**	0.6213	0.9873	0.3602	0.2955	0.827	0.3531	0.123	0.5991	0.5085	**<.0001**			
DIST1	0.03	-0.13	-0.70	-0.02	0.06	-0.49	-0.28	-0.08	-0.14	-0.35	0.05	0.24	0.21	-0.25	0.04	-0.77	-0.56		
	0.8478	0.3679	**0.0008**	0.8863	0.7088	**0.0004**	0.06	0.6097	0.3388	**0.0164**	0.7505	0.109	0.1636	0.0969	0.8038	**<.0001**	**<.0001**		
SPEED_FT	-0.41	-0.51	-0.43	0.08	-0.05	0.22	-0.51	-0.10	-0.25	-0.22	-0.25	-0.05	-0.01	-0.51	0.03	-0.18	0.21	0.38	
	0.0042	**0.0003**	0.0683	0.5851	0.7625	0.1362	**0.0002**	0.4877	0.093	0.13	0.0952	0.718	0.9671	**0.0002**	0.8672	0.2153	0.1547	**0.0083**	
TTC	0.15	-0.03	-0.69	0.01	0.09	-0.55	-0.23	-0.06	-0.08	-0.36	0.08	0.24	0.27	-0.14	0.04	-0.80	-0.63	0.96	0.19
	0.3272	0.8183	**0.001**	0.9653	0.5277	**<.0001**	0.1175	0.6729	0.5947	**0.0128**	0.5946	0.1042	0.0662	0.3342	0.7776	**<.0001**	**<.0001**	**<.0001**	0.2052

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table C-50: DYM Multilinear Regression Models - RBT-RAL

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.5866	0.3948	1.49	0.1421
ADY	0.1174	0.2333	0.5	0.6167
AST	-0.0281	0.1620	-0.17	0.8628
entry	0.5087	0.1717	2.96	**0.0042**
FOLL	0.1720	0.1485	1.16	0.2508
MUP	-0.0205	0.1423	-0.14	0.8859
NEAR	0.0617	0.1388	0.44	0.6581
PLT	-0.1527	0.1755	-0.87	0.3872
PREV	-0.1600	0.1355	-1.18	0.242
PXW	0.2100	0.1363	1.54	0.1283
Decel	-0.0410	0.0533	-0.77	0.4445
DIST1	-0.0022	0.0027	-0.81	0.4214
SPEED_FT	-0.0119	0.0189	-0.63	0.5326
ttc_v	0.0534	0.0487	1.1	0.2769

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	5.1107	0.3931	1.8	0.062
Error	66	14.4393	0.2188		
Corrected Total	79	19.5500			

R-Square	Coeff Var	Root MSE	yield Mean
0.2614	110.0556	0.4677	0.4250

Adj. R - Square
0.12

b) Unrestricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.5879	0.2237	2.63	**0.0104**
entry	0.4374	0.1509	2.9	**0.0049**
FOLL	0.0770	0.1045	0.74	0.4634
PXW	0.2617	0.1132	2.31	**0.0236**
SPEED_FT	-0.0241	0.0090	-2.67	**0.0092**
ttc_v	0.0181	0.0175	1.03	0.3055

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	3.7950	0.7590	3.56	0.0061
Error	74	15.7550	0.2129		
Corrected Total	79	19.5500			

R-Square	Coeff Var	Root MSE	yield Mean
0.1941	108.5686	0.4614	0.4250

Adj. R - Square
0.14

c) Unrestricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.7472	0.1855	4.03	**0.0001**
entry	0.4319	0.1506	2.87	**0.0053**
PXW	0.2841	0.1117	2.54	**0.013**
SPEED_FT	-0.0253	0.0089	-2.84	**0.0057**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	3.4186	1.1395	5.37	0.0021
Error	76	16.1314	0.2123		
Corrected Total	79	19.5500			

R-Square	Coeff Var	Root MSE	yield Mean
0.1749	108.4028	0.4607	0.4250

Adj. R - Square
0.14

d) Restricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.5101	0.2975	1.71	**0.0908**
AST	0.0080	0.1536	0.05	**0.9587**
MUP	0.0450	0.1496	0.3	0.7643
entry	0.1900	0.1345	1.41	**0.162**
Decel	-0.0565	0.0458	-1.23	**0.2209**
NEAR	0.0007	0.1354	0.01	0.9959
PLT	-0.0235	0.1257	-0.19	**0.8524**
ttc_v	0.0031	0.0298	0.1	0.9173

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	1.1938	0.1705	0.67	0.6975
Error	72	18.3562	0.2549		
Corrected Total	79	19.5500			

R-Square	Coeff Var	Root MSE	yield Mean
0.0611	118.8053	0.5049	0.4250

Adj. R - Square
-0.03

e) Restricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.9099	0.1835	4.96	**<.0001**
entry	0.4310	0.1557	2.77	**0.0071**
Decel	-0.0395	0.0287	-1.38	0.1726
SPEED_FT	-0.0231	0.0095	-2.42	**0.0179**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	2.4720	0.8240	3.67	0.0159
Error	76	17.0780	0.2247		
Corrected Total	79	19.5500			

R-Square	Coeff Var	Root MSE	yield Mean
0.1264	111.5378	0.4740	0.4250

Adj. R - Square
0.09

Table C-51: DYM Binary Logit Regression Models - RBT-RAL

a) Full Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.4016	2.0114	0.0399	0.8417	
ADY	1	0.7066	1.2193	0.3358	0.5623	2.027
AST	1	-0.1606	0.7967	0.0406	0.8402	0.852
entry	1	2.8184	0.9973	7.9861	**0.0047**	16.749
FOLL	1	1.0184	0.8095	1.5825	0.2084	2.769
MUP	1	-0.4732	0.832	0.3235	0.5695	0.623
NEAR	1	0.2941	0.7139	0.1698	0.6803	1.342
PLT	1	-0.8337	0.9503	0.7695	0.3804	0.434
PREV	1	-0.8091	0.6929	1.3637	0.2429	0.445
PXW	1	1.0619	0.6919	2.3558	0.1248	2.892
Decel	1	-0.2499	0.3243	0.5941	0.4408	0.779
DIST1	1	-0.0135	0.016	0.7093	0.3997	0.987
SPEED_FT	1	-0.0562	0.1075	0.2735	0.601	0.945
ttc_v	1	0.3238	0.2726	1.4102	0.235	1.382

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	111.097	113.231
SC	113.479	146.58
-2 Log L	109.097	85.231
R-Square		0.2579
Max-rescaled R-2		0.3465

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	23.8653	13	0.0324
Score	20.9134	13	0.0747
Wald	15.8169	13	0.2592

b) Unrestricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-0.6931	0.2887	5.7648	**0.0164**	
PXW	1	1.1631	0.4958	5.5030	**0.0190**	3.200

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	111.097	107.390
SC	113.479	112.154
-2 Log L	109.097	103.390
R-Square		0.0688
Max-rescaled R-2		0.0925

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.7067	1	0.0169
Score	5.7132	1	0.0168
Wald	5.5030	1	0.0190

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
16.4378	12	0.1720

c) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.7917	1.8494	0.1833	0.6686	
AST	1	0.1944	0.6618	0.0863	0.769	1.215
MUP	1	0.0732	0.6993	0.011	0.9166	1.076
entry	1	2.5131	0.9088	7.6473	**0.0057**	12.343
NEAR	1	-0.1042	0.5938	0.0308	0.8608	0.901
PLT	1	-0.1887	0.5732	0.1084	0.742	0.828
DIST1	1	-0.0183	0.014	1.7089	0.1911	0.982
Decel	1	-0.3556	0.291	1.4929	0.2218	0.701
ttc_v	1	0.2957	0.242	1.4929	0.2218	1.344
SPEED_FT	1	-0.0157	0.0918	0.0294	0.8639	0.984

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	111.097	115.368
SC	113.479	139.188
-2 Log L	109.097	95.368
R-Square		0.1577
Max-rescaled R-2		0.2119

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	13.7291	9	0.1323
Score	12.4726	9	0.188
Wald	10.3033	9	0.3265

d) Restricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.1853	0.4279	0.1875	0.665	
ENTRY	1	0.8451	0.5418	2.4335	0.1188	2.328
DECEL	1	-0.2812	0.1416	3.9432	**0.0471**	0.755

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	111.097	109.982
SC	113.479	117.128
-2 Log L	109.097	103.982
R-Square		0.0619
Max-rescaled R-2		0.0832

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.1152	2	0.0775
Score	4.7333	2	0.0938
Wald	4.3899	2	0.1114

e) Restricted Model 3

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.8099	0.9606	3.5495	**0.0596**	
ENTRY	1	1.9744	0.8287	5.6763	**0.0172**	7.202
DIST1	1	0.00315	0.00387	0.6635	0.4153	1.003
SPEED_FT	1	-0.1418	0.052	7.4268	**0.0064**	0.868

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	111.097	107.338
SC	113.479	116.866
-2 Log L	109.097	99.338
R-Square		0.1148
Max-rescaled R-2		0.1543

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	9.7588	3	0.0207
Score	9.0661	3	0.0284
Wald	7.6842	3	0.053

f) Restricted Model 4*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.9461	0.9593	4.1153	**0.0425**	
ENTRY	1	2.0022	0.8353	5.7447	**0.0165**	7.405
SPEED_FT	1	-0.1317	0.0507	6.747	**0.0094**	0.877

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	111.097	106.002
SC	113.479	113.148
-2 Log L	109.097	100.002
R-Square		0.1075
Max-rescaled R-2		0.1444

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	9.0949	2	0.0106
Score	8.3729	2	0.0152
Wald	6.9826	2	0.0305

* Model was selected as preferred model in its category

Table C-52: DYM Cumulative Logit Regression Models - RBT-RAL

a) Unrestricted Model 1**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept 1	1	0.6756	0.2855	5.5978	**0.018**	
Intercept 2	1	2.1896	0.3841	32.5042	**<.0001**	
PXW	1	-1.0849	0.466	5.4193	**0.0199**	0.338

** Proportional Odds Assumption was rejected at p<0.0572

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	153.705
SC	162.01	160.851
-2 Log L	153.246	147.705
R-Square		0.0669
Max-rescaled R-Square		0.0785

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.5408	1	0.0186
Score	5.6587	1	0.0174
Wald	5.4193	1	0.0199

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
16.2732	12	0.179

b) Restricted Model 1**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept 1	1	-2.9237	1.4888	3.8565	**0.0496**	
Intercept 2	1	-1.2712	1.4643	0.7536	0.3853	
AST	1	0.059	0.6199	0.0091	0.9241	1.061
MUP	1	-0.17	0.6301	0.0728	0.7873	0.844
ENTRY	1	-2.3511	0.7999	8.6395	**0.0033**	0.095
NEAR	1	0.274	0.5605	0.239	0.6249	1.315
PLT	1	0.2271	0.5179	0.1924	0.661	1.255
DECEL	1	0.1108	0.2115	0.2746	0.6003	1.117
TTC_V	1	0.0475	0.123	0.149	0.6995	1.049
SPEED_FT	1	0.144	0.0478	9.0696	**0.0026**	1.155

** Proportional Odds Assumption was rejected at p=0.0035

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	159.649
SC	162.01	183.47
-2 Log L	153.246	139.649
R-Square		0.1563
Max-rescaled R-Square		0.1833

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	13.5963	8	0.0929
Score	11.9506	8	0.1534
Wald	11.2189	8	0.1896

c) Restricted Model 2**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.0351	0.4105	0.0073	0.9319	
Intercept	1	1.4984	0.458	10.7027	**0.0011**	
entry	1	-0.6296	0.5032	1.5652	0.2109	0.533
Decel	1	0.1846	0.1277	2.0894	0.1483	1.203

** Proportional Odds Assumption was rejected at p=0.0006

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	158.472
SC	162.01	168
-2 Log L	153.246	150.472
R-Square		0.0341
Max-rescaled R-Square		0.04

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2.7737	2	0.2499
Score	2.6608	2	0.2644
Wald	2.5225	2	0.2833

d) Restricted Model 3**

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept 1	1	-2.1843	0.856	6.5111	**0.0107**	
Intercept 2	1	-0.5445	0.8272	0.4333	0.5104	
entry	1	-2.139	0.7378	8.4057	**0.0037**	0.118
SPEED_FT	1	0.144	0.0447	10.3666	**0.0013**	1.155

**** Proportional Odds Assumption was NOT rejected (p=0.9214)**

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	148.363
SC	162.01	157.892
-2 Log L	153.246	140.363
R-Square		0.1487
Max-rescaled R-Square		0.1744

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	12.8822	2	0.0016
Score	11.2808	2	0.0036
Wald	10.7483	2	0.0046

Table C-53: DYM Multinomial Logit Regression Models - RBT-RAL

a) Unrestricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point
Intercept - 2	1	-1.9669	0.6508	9.1341	**0.0025**	
Intercept - 3	1	0.2356	0.7699	0.0936	0.7596	
PXW - 2	1	1.1201	0.5685	3.8814	**0.0488**	3.065
PXW - 3	1	1.7712	0.7794	5.1642	**0.0231**	5.878
DIST1 - 2	1	0.00641	0.0039	2.7108	**0.0997**	1.006
DIST1 - 3	1	-0.0252	0.00964	6.8444	**0.0089**	0.975

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	143.781
SC	162.01	158.073
-2 Log L	153.246	131.781
R-Square		0.2353
Max-rescaled R-		0.276

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	21.465	4	0.0003
Score	16.4097	4	0.0025
Wald	15.2094	4	0.0043

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
24.5	22	0.3216

b) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point
Intercept - 2	1	0.6836	2.1475	0.1013	0.7502	
Intercept - 3	1	3.2953	2.3599	1.9498	0.1626	
AST - 2	1	0.5128	0.7325	0.49	0.4839	1.67
AST - 3	1	-0.6796	1.2227	0.3089	0.5783	0.507
MUP - 2	1	-0.0859	0.8571	0.01	0.9202	0.918
MUP - 3	1	0.2037	0.975	0.0437	0.8345	1.226
ENTRY - 2	1	1.7701	1.1148	2.5209	0.1123	5.871
ENTRY - 3	1	2.6359	1.3063	4.0716	**0.0436**	13.956
NEAR - 2	1	-0.0513	0.6876	0.0056	0.9405	0.95
NEAR - 3	1	-0.6802	0.9234	0.5425	0.4614	0.507
PLT - 2	1	-0.7683	0.6427	1.4291	0.2319	0.464
PLT - 3	1	0.2854	0.9408	0.092	0.7617	1.33
DECEL - 2	1	-0.4981	0.4268	1.3621	0.2432	0.608
DECEL - 3	1	-0.0354	0.311	0.013	0.9093	0.965
TTC_V - 2	1	0.0827	0.1794	0.2128	0.6446	1.086
TTC_V - 3	1	-0.22	0.2231	0.9722	0.3241	0.803
SPEED_FT - 2	1	-0.0378	0.0704	0.288	0.5915	0.963
SPEED_FT - 3	1	-0.1992	0.084	5.628	**0.0177**	0.819

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	160.632
SC	162.01	203.508
-2 Log L	153.246	124.632
R-Square		0.3007
Max-rescaled R-		0.3526

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	28.614	16	0.0267
Score	28.6477	16	0.0264
Wald	18.1047	16	0.3178

c) Restricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point
Intercept - 2	1	0.3582	0.5269	0.4622	0.4966	
Intercept - 3	1	-1.5491	0.6212	6.2191	**0.0126**	
ENTRY - 2	1	1.3006	0.6678	3.7928	**0.0515**	3.672
ENTRY - 3	1	0.4354	0.7263	0.3593	0.5489	1.546
DECEL - 2	1	-0.6152	0.2254	7.4456	**0.0064**	0.541
DECEL - 3	1	0.00323	0.1602	0.0004	0.9839	1.003

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	153.355
SC	162.01	167.648
-2 Log L	153.246	141.355
R-Square		0.1381
Max-rescaled R-		0.162

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	11.8902	4	0.0182
Score	9.1372	4	0.0578
Wald	8.287	4	0.0816

d) Restricted Model 3

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point
Intercept - 2	1	0.8877	1.0784	0.6776	0.4104	
Intercept - 3	1	2.1166	1.2509	2.8633	**0.0906**	
ENTRY - 2	1	1.5072	0.9221	2.6719	0.1021	4.514
ENTRY - 3	1	2.9818	1.1349	6.9035	**0.0086**	19.724
SPEED_FT - 2	1	-0.0937	0.056	2.7976	**0.0944**	0.911
SPEED_FT - 3	1	-0.2103	0.0702	8.9732	**0.0027**	0.81

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	157.246	152.249
SC	162.01	166.541
-2 Log L	153.246	140.249
R-Square		0.1500
Max-rescaled R-		0.1758

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	12.9970	4	0.0113
Score	13.1864	4	0.0104
Wald	9.3168	4	0.0537

Table C-54: DYM Nested Logit Models, Level 2 - RBT-RAL

a) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	3.2349	1.2871	6.3169	**0.012**	
DIST1	1	-0.0366	0.0124	8.7914	**0.003**	0.964

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	46.149	31.186
SC	47.675	34.239
-2 Log L	44.149	27.186
R-Square		0.3928
Max-rescaled R-2		0.5403

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	16.9627	1	<.0001
Score	12.6269	1	0.0004
Wald	8.7914	1	0.003

b) Restricted Model – 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.1964	3.3673	0.1262	0.7224	
AST	1	-1.1976	1.7019	0.4952	0.4816	0.302
MUP	1	-0.8665	1.5476	0.3135	0.5755	0.42
entry	1	-0.4499	2.5292	0.0316	0.8588	0.638
NEAR	1	-0.4351	2.2182	0.0385	0.8445	0.647
PLT	1	0.8451	1.2849	0.4325	0.5107	2.328
Decel	1	1.9124	1.0941	3.0553	**0.0805**	6.769
ttc_v	1	-0.0268	0.3158	0.0072	0.9323	0.974
SPEED_FT	1	-0.3066	0.1411	4.7212	**0.0298**	0.736

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	46.149	40.87
SC	47.675	54.607
-2 Log L	44.149	22.87
R-Square		0.4652
Max-rescaled R-2		0.6398

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	21.2789	8	0.0064
Score	15.7443	8	0.0462
Wald	8.2353	8	0.4108

c) Restricted Model – 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.3697	1.7238	0.6313	0.4269	
AST	1	-0.8939	1.429	0.3914	0.5316	0.409
MUP	1	-0.7762	1.4897	0.2715	0.6023	0.46
PLT	1	0.7146	1.2389	0.3327	0.5641	2.043
Decel	1	1.9145	0.7414	6.6674	**0.0098**	6.783
SPEED_FT	1	-0.3345	0.1279	6.8389	**0.0089**	0.716

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	46.149	35.029
SC	47.675	44.187
-2 Log L	44.149	23.029
R-Square		0.4627
Max-rescaled R-2		0.6364

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	21.1202	5	0.0008
Score	15.0546	5	0.0101
Wald	7.9293	5	0.1602

d) Restricted Model – 3*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	1.6143	1.3568	1.4155	0.2341	
Decel	1	1.9268	0.7295	6.9769	**0.0083**	6.867
SPEED_FT	1	-0.3377	0.1262	7.1631	**0.0074**	0.713

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	46.149	30.028
SC	47.675	34.607
-2 Log L	44.149	24.028
R-Square		0.4467
Max-rescaled R-2		0.6143

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	20.1207	2	<.0001
Score	14.3465	2	0.0008
Wald	7.4575	2	0.024

e) Restricted Model - 4

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	0.4703	0.9461	0.2471	0.6191	
SPEED_FT	1	-0.0502	0.0419	1.437	**0.2306**	0.951

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	46.149	46.629
SC	47.675	49.681
-2 Log L	44.149	42.629
R-Square		0.0437
Max-rescaled R-2		0.0601

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1.5203	1	0.2176
Score	1.4853	1	0.2229
Wald	1.437	1	0.2306

f) Restricted Model - 5

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-1.9007	0.7465	6.4835	0.0109	
Decel	1	0.4573	0.2217	4.2548	**0.0391**	1.58

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	46.149	43.026
SC	47.675	46.079
-2 Log L	44.149	39.026
R-Square		0.1399
Max-rescaled R-2		0.1924

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5.1231	1	0.0236
Score	5.0616	1	0.0245
Wald	4.2548	1	0.0391

* Model was selected as preferred model in its category

Table C-55: Correlation Matrix, RBT-RAL, Pedestrian Crossing Model – Lags Only*

	GO	NoGo	ADY	AST	FOLL	HEV	MUP	NEAR	PLT	PREV	PXW	QUE	TRIG	Decel	DIST1	O_LAG	T_LAG
GO																	
NoGo	-1.00																
	<.0001																
ADY	0.23	-0.23															
	0.0768	0.0768															
AST	0.48	-0.48	0.09														
	<.0001	**<.0001**	0.5058														
FOLL	-0.03	0.03	-0.10	0.05													
	0.8017	0.8017	0.4308	0.7078													
HEV	0.09	-0.09	-0.07	0.23	0.30												
	0.4693	0.4693	0.591	0.0796	**0.02**												
MUP	0.00	0.00	0.11	0.06	0.09	-0.10											
	0.9896	0.9896	0.3884	0.6247	0.4742	0.4647											
NEAR	-0.29	0.29	-0.33	-0.05	-0.09	-0.19	0.08										
	0.0249	**0.0249**	**0.0096**	0.69	0.4758	0.1354	0.543										
PLT	-0.22	0.22	-0.15	-0.07	0.85	0.25	0.14	-0.03									
	0.084	0.084	0.2627	0.5907	**<.0001**	**0.0499**	0.2933	0.8331									
PREV	-0.24	0.24	-0.14	-0.15	-0.02	0.01	-0.20	-0.28	0.21								
	0.0635	0.0635	0.2663	0.2508	0.906	0.9213	0.1291	**0.0297**	0.1089								
PXW	0.09	-0.09	-0.07	0.09	0.16	0.20	0.11	0.08	0.12	-0.14							
	0.4693	0.4693	0.591	0.5058	0.2068	0.1273	0.3884	0.5513	0.3587	0.2663							
QUE	-0.21	0.21	-0.05	-0.13	0.21	-0.05	-0.07	-0.04	0.18	0.34	-0.05						
	0.0983	0.0983	0.7089	0.3054	0.1101	0.7089	0.6117	0.7586	0.1767	**0.0078**	0.7089						
TRIG	0.14	-0.14	0.16	0.29	-0.03	-0.08	0.08	0.12	-0.07	-0.16	0.16	-0.06					
	0.2935	0.2935	0.2115	0.0251	0.8445	0.5443	0.5404	0.3638	0.568	0.2092	0.2115	0.6737					
Decel	-0.58	0.58	-0.16	-0.28	-0.09	-0.15	0.17	0.25	0.17	0.08	-0.06	0.03	-0.12				
	<.0001	**<.0001**	0.2241	**0.027**	0.5047	0.2346	0.1976	0.0537	0.1779	0.5321	0.6236	0.8031	0.3567				
DIST1	0.70	-0.70	-0.04	0.21	-0.22	-0.11	0.07	-0.06	-0.36	-0.10	0.02	-0.19	-0.04	-0.49			
	<.0001	**<.0001**	0.7348	0.1039	0.0913	0.3799	0.6154	0.6478	**0.004**	0.4576	0.9016	0.1443	0.7585	**<.0001**			
O_LAG	0.85	-0.85	0.13	0.32	-0.07	0.16	0.03	-0.23	-0.25	-0.13	0.00	-0.23	0.08	-0.65	0.84		
	<.0001	**<.0001**	0.3085	**0.0127**	0.5762	0.2062	0.8431	0.0688	0.0504	0.325	0.9977	0.0742	0.5363	**<.0001**	**<.0001**		
T_LAG	0.82	-0.82	0.15	0.31	-0.08	0.07	0.01	-0.23	-0.27	-0.15	-0.01	-0.21	0.01	-0.66	0.89	0.95	
	<.0001	**<.0001**	0.2381	**0.0168**	0.5164	0.5835	0.9546	0.0768	**0.036**	0.2387	0.9293	0.1015	0.9123	**<.0001**	**<.0001**	<.0001	
speed_ft	0.17	-0.17	-0.29	0.03	-0.27	-0.37	0.15	0.21	-0.30	-0.04	0.07	-0.23	-0.05	0.14	0.55	0.19	0.19
	0.1923	0.1923	**0.0228**	0.7939	**0.0342**	**0.0035**	0.2586	0.1027	**0.0197**	0.7421	0.6179	0.0746	0.7003	0.2962	**<.0001**	0.1396	0.1394

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table C-56: Correlation Matrix, RBT-RAL, Pedestrian Crossing Model – Gaps Only*

	GO	NoGo	ADY	AST	FOLL	MUP	NEAR	PLT	PREV	PXW	TRIG	Decel	DIST1	D_WAIT	O_GAP	T_GAP
GO																
NoGo	-1.00															
	<.0001															
ADY	0.19	-0.19														
	0.3451	0.3451														
AST	0.52	-0.52	-0.10													
	0.006	**0.006**	0.6028													
FOLL	-0.26	0.26	-0.19	0.02												
	0.1934	0.1934	0.3451	0.9219												
MUP	-0.11	0.11	-0.12	0.09	0.28											
	0.597	0.597	0.5644	0.654	0.164											
NEAR	0.28	-0.28	0.12	0.32	-0.11	0.16										
	0.164	0.164	0.5644	0.1081	0.597	0.4338										
PLT	-0.68	0.68	-0.28	-0.19	0.68	0.24	-0.06									
	<.0001	**<.0001**	0.1613	0.3451	**<.0001**	0.2298	0.7672									
PREV	-0.34	0.34	0.07	-0.38	-0.13	-0.06	-0.21	0.00								
	0.082	0.082	0.7311	0.0519	0.5147	0.7672	0.2951	1								
PXW	0.19	-0.19	-0.04	-0.10	-0.19	0.33	0.12	-0.28	0.07							
	0.3451	0.3451	0.8489	0.6028	0.3451	0.0912	0.5644	0.1613	0.7311							
TRIG	0.19	-0.19	-0.04	0.37	-0.19	-0.12	0.12	-0.28	0.07	-0.04						
	0.3451	0.3451	0.8489	0.0598	0.3451	0.5644	0.5644	0.1613	0.7311	0.8489						
Decel	-0.28	0.28	-0.20	0.08	-0.15	-0.15	0.24	0.19	-0.07	-0.20	0.24					
	0.1636	0.1636	0.3225	0.6835	0.4637	0.4659	0.2288	0.3326	0.7432	0.3272	0.2378					
DIST1	0.43	-0.43	0.03	-0.06	0.04	-0.28	-0.13	-0.18	-0.16	-0.18	-0.17	-0.38				
	0.0236	**0.0236**	0.8754	0.7836	0.8328	0.1612	0.5028	0.3763	0.4384	0.3677	0.3927	0.0511				
D_WAIT	0.06	-0.06	0.52	-0.25	-0.01	-0.03	-0.14	-0.12	-0.03	-0.10	-0.17	-0.53	0.55			
	0.781	0.781	**0.0055**	0.2146	0.9645	0.8945	0.5015	0.5644	0.8969	0.618	0.3939	**0.0041**	**0.0029**			
O_GAP	0.53	-0.53	-0.40	0.28	0.15	0.12	-0.02	-0.11	-0.17	0.33	-0.04	-0.24	0.24	-0.46		
	0.0046	**0.0046**	**0.0395**	0.1544	0.4568	0.5574	0.924	0.5862	0.4101	0.0909	0.8412	0.2202	0.2335	**0.0162**		
T_GAP	0.67	-0.67	0.26	0.03	-0.07	-0.11	-0.10	-0.43	0.03	0.10	-0.11	-0.47	0.50	0.02	0.65259	
	0.0001	**0.0001**	0.1947	0.8739	0.746	0.5979	0.6113	**0.0243**	0.8677	0.6338	0.5759	**0.014**	**0.008**	0.9277	**0.0002**	
speed_ft	0.24	-0.24	-0.16	0.15	0.05	-0.47	0.08	-0.02	-0.34	-0.33	0.01	0.33	0.63	0.05	0.08	0.10
	0.2334	0.2334	0.4267	0.4577	0.8057	**0.0125**	0.6888	0.9143	0.0816	0.0922	0.9414	0.0974	**0.0004**	0.8163	0.7001	0.6215

* Shaded cells have correlation > 0.30 or <-0.30; bold values are significant at the 0.05 confidence level

Table C-57: PCM Multilinear Regression Models - RBT-RAL – Lags Only

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.2193	0.2770	-0.79	0.4326
ADY	0.1742	0.1556	1.12	0.2688
AST	0.2329	0.0736	3.16	**0.0028**
FOLL	-0.0810	0.1476	-0.55	0.5859
MUP	-0.1501	0.1091	-1.38	0.1758
NEAR	-0.1299	0.0812	-1.6	0.1166
PLT	0.1342	0.1565	0.86	0.396
PREV	-0.1917	0.0981	-1.95	0.0569
PXW	0.1407	0.1314	1.07	0.2901
TRIG	0.0081	0.1273	0.06	0.9497
entry	-0.1242	0.1115	-1.11	0.2714
Decel	-0.0023	0.0068	-0.34	0.7389
DIST1	-0.0003	0.0011	-0.23	0.8206
O_LAG	0.0736	0.0265	2.78	**0.0078**
T_LAG	0.0164	0.0500	0.33	0.7441
SPEED_FT	0.0132	0.0101	1.31	0.1972

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	12.3314	0.8221	14.3	<.0001
Error	45	2.5866	0.0575		
Corrected Total	60	14.9180			

R-Square	Coeff Var	Root MSE	GO Mean
0.8266	41.7853	0.2398	0.5738

Adj. R - Square
0.77

b) Unrestricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0503	0.1045	0.48	0.6322
ADY	0.1388	0.1406	0.99	0.328
AST	0.2329	0.0671	3.47	**0.0011**
MUP	-0.1085	0.0997	-1.09	0.2818
NEAR	-0.1305	0.0739	-1.77	**0.0834**
PLT	0.0275	0.0660	0.42	0.6786
PREV	-0.1852	0.0810	-2.29	**0.0263**
entry	0.0314	0.0680	0.46	0.6463

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	12.0671	1.5084	27.51	<.0001
Error	52	2.8509	0.0548		
Corrected Total	60	14.9180			

R-Square	Coeff Var	Root MSE	GO Mean
0.8089	40.8089	0.2341	0.5738

Adj. R - Square
0.78

c) Unrestricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0925	0.0824	1.12	0.2663
AST	0.2340	0.0657	3.56	**0.0008**
NEAR	-0.1506	0.0654	-2.3	**0.025**
PREV	-0.1815	0.0749	-2.42	**0.0187**
O_LAG	0.0853	0.0077	11.07	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	11.9648	2.9912	56.72	<.0001
Error	56	2.9532	0.0527		
Corrected Total	60	14.9180			

R-Square	Coeff Var	Root MSE	GO Mean
0.8020	40.0235	0.2296	0.5738

Adj. R - Square
0.79

d) Restricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0203	0.1034	0.2	0.845
AST	0.2716	0.0745	3.65	**0.0006**
MUP	-0.0192	0.1077	-0.18	0.8595
entry	-0.0104	0.0726	-0.14	0.8863
NEAR	-0.1076	0.0747	-1.44	0.1556
PLT	-0.0143	0.0714	-0.2	0.8417
T_LAG	0.0887	0.0095	9.34	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	11.1922	1.8654	27.04	<.0001
Error	54	3.7259	0.0690		
Corrected Total	60	14.9180			

R-Square	Coeff Var	Root MSE	GO Mean
0.7502	45.7803	0.2627	0.5738

Adj. R - Square
0.7225

e) Restricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0046	0.0806	0.06	0.9544
AST	0.2704	0.0724	3.73	**0.0004**
NEAR	-0.1106	0.0689	-1.61	**0.114**
T_LAG	0.0891	0.0088	10.08	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	11.1849	3.7283	56.93	<.0001
Error	57	3.7331	0.0655		
Corrected Total	60	14.9180			

R-Square	Coeff Var	Root MSE	GO Mean
0.7498	44.6026	0.2559	0.5738

Adj. R - Square
0.7366

Table C-58: PCM Multilinear Regression Models - RBT-RAL – Gaps Only

a) Full Model

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.1366	1.2867	-0.11	0.9175
ADY	-0.3188	1.0379	-0.31	0.7651
AST	0.3867	0.1844	2.1	**0.0623**
FOLL	0.0813	0.1507	0.54	0.6012
MUP	-0.1377	0.1760	-0.78	0.4523
NEAR	0.2397	0.1218	1.97	**0.0774**
PLT	-0.4347	0.2424	-1.79	**0.1032**
PREV	-0.2533	0.2086	-1.21	0.2524
PXW	0.1859	0.4532	0.41	0.6903
TRIG	0.0466	0.2902	0.16	0.8755
entry	0.0584	0.2768	0.21	0.837
Decel	0.1082	0.1200	0.9	0.3886
DIST1	-0.0001	0.0027	-0.02	0.984
D_WAIT	0.0604	0.1100	0.55	0.5954
O_GAP	0.0372	0.0659	0.57	0.5844
T_GAP	0.1027	0.1085	0.95	0.366
SPEED_FT	-0.0093	0.0283	-0.33	0.7486

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	6.2678	0.3917	8.28	0.0009
Error	10	0.4730	0.0473		
Corrected Total	26	6.7407			

R-Square	Coeff Var	Root MSE	GO Mean
0.9298	41.9419	0.2175	0.5185

Adj. R - Square
0.82

b) Unrestricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.0293	0.1668	0.18	0.8621
AST	0.4413	0.1079	4.09	**0.0005**
NEAR	0.2165	0.1016	2.13	**0.0444**
PLT	-0.4000	0.1005	-3.98	**0.0006**
T_GAP	0.1061	0.0193	5.5	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	5.7003	1.4251	30.13	<.0001
Error	22	1.0405	0.0473		
Corrected Total	26	6.7407			

R-Square	Coeff Var	Root MSE	GO Mean
0.8456	41.9409	0.2175	0.5185

Adj. R - Square
0.82

c) Unrestricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.4198	0.1516	2.77	**0.0112**
AST	0.2851	0.1351	2.11	**0.0464**
NEAR	0.1979	0.1215	1.63	0.1176
PLT	-0.6171	0.1085	-5.69	**<.0001**
O_GAP	0.0616	0.0162	3.8	**0.001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	5.2471	1.3118	19.32	<.0001
Error	22	1.4937	0.0679		
Corrected Total	26	6.7407			

R-Square	Coeff Var	Root MSE	GO Mean
0.7784	50.2515	0.2606	0.5185

Adj. R - Square
0.74

d) Restricted Model 1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0102	0.1691	-0.06	0.9526
AST	0.3916	0.1149	3.41	**0.0028**
MUP	0.0564	0.1186	0.48	0.6398
entry	0.1478	0.1072	1.38	0.1832
NEAR	0.2057	0.1032	1.99	**0.06**
PLT	-0.4465	0.1111	-4.02	**0.0007**
T_GAP	0.1022	0.0195	5.24	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	5.7947	0.9658	20.42	<.0001
Error	20	0.9461	0.0473		
Corrected Total	26	6.7407			

R-Square	Coeff Var	Root MSE	GO Mean
0.8596	41.9456	0.2175	0.5185

Adj. R - Square
0.82

e) Restricted Model 2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.1699	0.1556	1.09	0.2868
AST	0.4743	0.1126	4.21	**0.0004**
entry	0.1235	0.0961	1.29	0.2117
PLT	-0.4390	0.1083	-4.05	**0.0005**
GAP	0.0977	0.0204	4.79	**<.0001**

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	5.5732	1.3933	26.25	<.0001
Error	22	1.1676	0.0531		
Corrected Total	26	6.7407			

R-Square	Coeff Var	Root MSE	GO Mean
0.8268	44.4292	0.2304	0.5185

Adj. R - Square
0.80

Table C-59: PCM Binary Logit Regression Models - RBT-RAL – Lags Only

a) Full Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-31.0908	101.6	0.0937	0.7595	
AST	1	7.6167	19.5574	0.1517	0.6969	>999.999
FOLL	1	3.645	42.1732	0.0075	0.9311	38.281
MUP	1	-9.379	110.9	0.0072	0.9326	<0.001
NEAR	1	-7.0669	22.1379	0.1019	0.7496	<0.001
PLT	1	-2.2839	42.3923	0.0029	0.957	0.102
PREV	1	-2.7106	19.2949	0.0197	0.8883	0.066
entry	1	-13.1969	43.536	0.0919	0.7618	<0.001
Decel	1	0.2253	2.6254	0.0074	0.9316	1.253
DIST1	1	0.0228	0.4484	0.0026	0.9594	1.023
O_LAG	1	5.082	8.5873	0.3502	0.554	161.089
T_LAG	1	-2.3214	19.2037	0.0146	0.9038	0.098
SPEED_FT	1	0.7603	3.1438	0.0585	0.8089	2.139

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	85.231	26.065
SC	87.342	53.506
-2 Log L	83.231	0.065
R-Square		0.7442
Max-rescaled R-2		0.9996

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	83.1661	12	<.0001
Score	49.8448	12	<.0001
Wald	1.1307	12	1.0000

b) Unrestricted Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-44.3366	44.0002	1.0154	0.3136	
AST	1	12.5505	13.0493	0.925	0.3362	>999.999
O_LAG	1	6.9639	6.8807	1.0243	0.3115	>999.999

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	85.231	9.403
SC	87.342	15.735
-2 Log L	83.231	3.403
R-Square		0.7298
Max-rescaled R-2		0.9803

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	79.8285	2	<.0001
Score	47.0968	2	<.0001
Wald	1.0248	2	0.5990

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
2.5932	10	0.9894

d) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-7.2762	3.5030	4.3146	**0.0378**	
AST	1	3.3665	1.7636	3.6437	**0.0563**	28.977
MUP	1	0.4432	7.6040	0.0034	0.9535	1.558
entry	1	-0.2819	1.5070	0.0350	0.8516	0.754
NEAR	1	-0.0878	1.5742	0.0031	0.9555	0.916
PLT	1	-0.7387	1.5191	0.2365	0.6268	0.478
T_LAG	1	1.2804	0.4782	7.1679	**0.0074**	3.598

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	85.231	28.994
SC	87.342	43.770
-2 Log L	83.231	14.994
R-Square		0.6733
Max-rescaled R-2		0.9044

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	68.2373	6	<.0001
Score	45.7649	6	<.0001
Wald	9.5482	6	0.1450

e) Restricted Model 2*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-7.6989	2.6391	8.5102	**0.0035**	
AST	1	3.0943	1.5209	4.1395	**0.0419**	22.073
T_LAG	1	1.2723	0.4192	9.2105	**0.0024**	3.569

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	85.231	21.240
SC	87.342	27.573
-2 Log L	83.231	15.240
		0.6720
Max-rescaled R-2		0.9026

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	67.9912	2	<.0001
Score	45.0454	2	<.0001
Wald	10.1663	2	0.0062

* Model was selected as preferred model in its category

Table C-60: PCM Binary Logit Regression Models - RBT-RAL – Gaps Only

a) Full Model

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-126.7	245.3	0.2666	0.6056	
FOLL	1	-9.6916	25.9388	0.1396	0.7087	<0.001
MUP	1	-8.9939	54.3604	0.0274	0.8686	<0.001
NEAR	1	10.117	77.7565	0.0169	0.8965	>999.999
entry	1	-7.8338	114.2	0.0047	0.9453	<0.001
Decel	1	10.1223	49.6649	0.0415	0.8385	>999.999
DIST1	1	-0.2382	0.5339	0.1991	0.6555	0.788
D_WAIT	1	10.6151	17.931	0.3505	0.5539	>999.999
O_GAP	1	6.7425	23.0353	0.0857	0.7697	847.707
T_GAP	1	11.8412	22.4534	0.2781	0.5979	>999.999
SPEED_FT	1	1.5255	5.3207	0.0822	0.7743	4.598

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39.393	22.043
SC	40.689	36.297
-2 Log L	37.393	0.043
R-Square		0.7493
Max-rescaled R-2		0.9995

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	37.3498	10	<.0001
Score	19.9553	10	0.0297
Wald	0.8043	10	0.9999

b) Unrestricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-7.5982	3.3152	5.2529	**0.0219**	
T_GAP	1	1.8893	0.8628	4.7953	**0.0285**	6.615

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39.393	21.314
SC	40.689	23.906
-2 Log L	37.393	17.314
R-Square		0.5246
Max-rescaled R-2		0.6998

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	20.0785	1	<.0001
Score	12.1898	1	0.0005
Wald	4.7953	1	0.0285

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
10.9937	9	0.2761

c) Unrestricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-8.0971	3.8211	4.4905	**0.0341**	
FOLL	1	-4.6675	2.2331	4.3689	**0.0366**	0.009
D_WAIT	1	0.7599	0.3620	4.4066	**0.0358**	2.138
O_GAP	1	1.5208	0.6433	5.5883	**0.0181**	4.576

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39.393	22.631
SC	40.689	27.814
-2 Log L	37.393	14.631
R-Square		0.5696
Max-rescaled R-2		0.7598

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	22.7619	3	<.0001
Score	14.1560	3	0.0027
Wald	5.7675	3	0.1235

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
4.7997	6	0.5697

d) Restricted Model 1

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-10.573	4.7525	4.9493	**0.0261**	
MUP	1	-2.3998	2.4232	0.9808	0.322	0.091
D_WAIT	1	0.2577	0.2848	0.8184	0.3656	1.294
entry	1	0.225	1.5003	0.0225	0.8808	1.252
T_GAP	1	2.4628	1.1287	4.7608	**0.0291**	11.738

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39.393	24.994
SC	40.689	31.473
-2 Log L	37.393	14.994
R-Square		0.5638
Max-rescaled R-2		0.7520

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	22.3991	4	0.0002
Score	12.9886	4	0.0113
Wald	5.2874	4	0.2591

e) Restricted Model 2

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-10.5867	4.7742	4.9172	**0.0266**	
MUP	1	-2.5502	2.1900	1.3560	0.2442	0.078
D_WAIT	1	0.2650	0.2815	0.8864	0.3464	1.303
T_GAP	1	2.5030	1.1029	5.1504	**0.0232**	12.219

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39.393	23.016
SC	40.689	28.200
-2 Log L	37.393	15.016
R-Square		0.5634
Max-rescaled R-2		0.7516

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	22.3765	3	<.0001
Score	12.2733	3	0.0065
Wald	5.2813	3	0.1523

f) Restricted Model 3*

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio Point Estimate
Intercept	1	-8.6936	4.0688	4.5653	**0.0326**	
D_WAIT	1	0.1275	0.2114	0.3635	0.5466	1.136
T_GAP	1	2.0271	0.9607	4.4522	**0.0349**	7.592

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39.393	22.934
SC	40.689	26.822
-2 Log L	37.393	16.934
R-Square		0.5313
Max-rescaled R-2		0.7087

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	20.4584	2	<.0001
Score	12.2417	2	0.0022
Wald	4.4574	2	0.1077

* Model was selected as preferred model in its category