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Baseline Analysis of Driver Performance at Intersections for the Left-Turn Assist and Intersection Movement Assist Applications

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16. Abstract

This study supports development of left turn assist (LTA) and intersection movement assist (IMA) applications that provide warnings to drivers crossing intersections. The goal is to support improved intersection collision warning applications design by enhancing understanding of intersection behavior, identifying metrics and test procedures through analysis of real-world data, and providing information used to reduce false alerts and nuisance alerts. To do this, a literature review was conducted to identify previous research into metrics for driver behavior at intersections, and databases from two naturalistic driving studies were queried to identify scenarios that could be analyzed as examples of normal or baseline turning behavior. Crashes were also identified in a national crash database and analyzed as examples of driving where alerts would have been useful. The analyses focused on estimating the size of accepted gaps -- the time from when the driver started to cross or was first able to cross after the vehicle reached the intersection and any lead vehicles ahead had moved out of the way until the oncoming vehicle reached the point where their trajectories crossed -- and what factors affected the choice to accept a gap of a given size.

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List of Acronyms

ANOVA	analysis of variance
BS	between subject
CDS	Crashworthiness Data System
CI	confidence intervals
EDR	event data recorder
df	degrees of freedom
FHWA	Federal Highway Administration
FT	field test
GES	General Estimates System
HCM	Highway Capacity Manual
HV	host vehicle
IMA	intersection movement assist
IQR	interquartile ranges
ITE	Institute of Transportation Engineers
LTA	left turn assist
LTAP-OD	left turn, across path – opposite direction
LTAP-LD	left turn, across path – lateral direction
LTIP	left turn into path
NASS	National Automotive Sampling System
OV	oncoming vehicle
POV	principal other vehicle
PPET	predicted post-encroachment time
PRT	perception-reaction time
RFS	Richmond Field Station
RTIP	right turn into path
SCP-L	straight crossing paths – left
SCP-R	straight crossing paths – right
SD	standard deviation
SV	subject vehicle
VAD	vehicle awareness device
Volpe Center	Volpe National Transportation Systems Center
V2V	vehicle-to-vehicle
WS	within subject

Executive Summary

Left turn assist (LTA) and intersection movement assist (IMA) applications are designed to help prevent collisions that occur when drivers cross the paths of oncoming traffic at intersections. Together, these applications cover six scenarios (the LTA covers the first and, the IMA covers the rest).

- **Left turn across path – opposite direction (LTAP-OD)** is when a driver makes a left turn in the face of oncoming traffic coming from the opposite direction.
- **Left turn across path – lateral direction (LTAP-LD)** is when a driver makes a left turn across the path of traffic coming from the side (from their left).
- **Left turn into path (LTIP)** is when a driver makes a left turn into the path of traffic coming from the side (from their right).
- **Right turn into path (RTIP)** is when a driver makes a right turn into the path of traffic approaching from the side (from their left).
- **Straight crossing paths – left (SCP-L)** is when a driver crosses the intersection driving straight across the path of oncoming traffic approaching from the left.
- **Straight crossing paths – right (SCP-R)** is when a driver crosses the intersection driving straight across the path of oncoming traffic approaching from the right.

Like other safety applications, the effectiveness of these systems is improved by reducing the number of false alerts and "nuisance alerts." Nuisance alerts are alerts that, although technically true, are not perceived as helpful by the driver. For example, an alert issued when the driver was only inching forward into an intersection for a better view of traffic, and not yet intending to make the turn.

This study is designed to support the LTA and IMA applications for light vehicles by improving our understanding of intersection behavior by providing real-world data and key metrics for characterizing how drivers navigate intersections during normal or baseline driving; i.e., in situations where no alert is needed, both for signalized and unsignalized intersections (the analysis of baseline driving is complemented by crash data, which provides context for comparison). This objective is intended to support the overarching goal of knowing when alerts should and should not be issued.

This information can be used in test procedures, such as setting the turn or crossing speed when testing LTA and IMA applications on a test track, and to assist developers in designing and implementing more effective (reduced nuisance alert) applications.

This study consisted of three parts.

1. A literature review of previous research on intersection behavior and warning systems.
2. An analysis of naturalistic driving data from two field operational tests to characterize normal baseline driving (when alerts should *not* be issued).
3. An analysis of crash database records (when alerts *should* be issued).

Review of Previous Research

A review of the literature was conducted to identify and summarize previous research into driver behavior at intersections. In brief, the main takeaways include:

- Strong evidence that variables such as intersection approach, the size of gaps when drivers turn, and crossing behavior, vary substantially between individual intersections.

- Strong evidence that individual intersection-crossing trajectories vary substantially due to conditions such as a lead vehicle being present and what traffic signal (e.g., red or green light) the driver encounters.
- Age effects have been seen in gap selection behavior, but do not show up in all variables (they were not seen in turning time or stopping location, for example).
- Gender effects appear in some studies but not in others.
- Models of driver behavior need to include an array of variables in order to accurately predict driver behavior.

Analysis of Baseline Scenarios

To characterize normal or baseline driving at intersections, the databases from two different naturalistic driving studies were queried for information. These studies were the Safety Pilot Model Deployment in Ann Arbor, Michigan, and the Driver Adaptation study in Washington, DC. Both databases included information on vehicle speed, yaw, steering wheel rotation, brake and gas pedal status, as well as numerous onboard cameras showing views in all directions from the car as well as the interior of the cabin. A primary metric to characterize intersection-crossing scenarios was the size of the gap; i.e., the time from when the driver started to cross or was first able to cross (after the vehicle reached the intersection and any lead vehicles ahead had moved out of the way) until the oncoming vehicle reached the point where their trajectories crossed.

LTA and IMA events were queried and then confirmed using manual review of the videos, and the relative timings of the vehicle and any oncoming traffic were recorded. Useful events were rare due to low traffic density or, where busy, to intersections often having protected left-turn lights that stopped oncoming traffic when vehicles turned. Nonetheless, together the two databases yielded 772 useful events by 107 drivers. These included 193 events where the driver proceeded into or accepted the gap and 579 where the driver chose instead to wait for the oncoming vehicle to pass or reject the gap. For most analyses, the values were averaged per driver.

As a counterpoint to the analysis of normal or baseline driving, the Crashworthiness Data System (CDS) database was queried to identify similar situations in which a crash resulted. Specifically, events from 2008 to 2014 were used provided the crash was severe enough that one of the two vehicles involved had to be towed from the scene due to damage. Of these, only events where both the turning and the oncoming vehicles were equipped with event data recorders (EDR) were used since they provided data on the vehicle speed, throttle, and brake status for the last 5 seconds before impact—all of which could be used for many cases to estimate the gap size. This query yielded 194 events.

The key results from this analysis include:

- ***Gap lengths:*** *Averaged across scenario for each driver, the average minimum gap size for drivers was 3.6 s, which was just under two standard deviations from the mean (6.0 s, range = 3.6 – 10.9 s,* n *= 71). Over 94 percent of accepted gaps were longer than the average rejected gap (mean = 3.4 s, range = 0.9 – 7.5 s,* n *= 100).*

  Accepted gap length varied between scenarios, with the largest for SCP-L (7.1 s, 5.0 – 11.7 s, n *= 18) and RTIP (6.8 s, 2.5 – 9.4 s,* n *= 21), followed by LTAP-LD (6.4 s, 3.8 – 8.6 s,* n *= 18), SCP-R (6.0 s, 4.5 – 8.0 s,* n *= 7), LTIP (5.9 s, 3.5 – 7.6 s,* n *= 7), and LTAP-OD (5.0 s, 3.6 – 6.6 s,* n *= 36).*

  Accepted gaps were shorter in the crash database than in baseline, with an average overall adjusted length of 2.5 s (range = 0.7 – 4.2 s, n *= 105). LTAP-OD also had the smallest gaps (1.8 s, 0.5 – 3.5 s,* n *= 45) and, excluding LTIP since it was a single event, SCP-L had the largest (3.0 s, 1.4 – 4.1 s,* n *= 19).*

- ***Crossing lanes:*** *For LTAP-OD, the average gap was larger when crossing only one lane (5.1 s, 3.8 – 6.6,* n *= 23) than when crossing two lanes (4.9 s, 3.6 – 6.5,* n *= 17), but this was a small effect.*
- ***Dedicated turning lanes:*** *Although subjects turned into slightly shorter gaps from dedicated turning lanes (4.9 s, 3.6 – 6.6,* n *= 31) than from regular lanes (5.2 s, 3.9 – 6.5,* n *= 7) in LTAP-OD, the effect size was small. The same small effect was seen in the crash database results, with turns from a dedicated lane (1.7 s, 0.5 – 3.5,* n *= 34) than from regular lanes (2.1 s, 1.5 – 2.8,* n *= 11).*
- ***Road profile:*** *For LTAP-OD, there was a medium effect of road profile in the crash database cases, with level roads having smaller gaps (1.6 s, 0.5 – 3.5 s,* n *= 31) than uphill roads (2.0 s, 0.5 – 2.8 s,* n *= 9). No effect was seen for LTAP-LD, SCP-L, or SCP-R.*
- ***Specific intersection:*** *There was substantial variation in average gaps between the eight intersections with the most events, ranging from 4.4 to 7.7 s, although the sample sizes were quite small for most of these intersections.*
- ***Intersection type (number of intersecting roads):*** *For LTAP-OD, average gaps were longer at 4-way intersections (5.1 s, 0.3 – 5.1 s,* n *= 27) than side streets[1] (4.9 s, 3.6 – 6.5 s,* n *= 11) and 3-way intersections (4.6 s, 3.9 – 5.1 s,* n *= 4), but the effect was small. For all scenarios combined, there was no effect between 3- and 4-way intersections.*
- ***Age:*** *There was no effect of age overall in the baseline data, and only a small effect for certain scenarios—but the direction of this effect varied between scenarios. Conclusions were limited by sample size. There was likewise no strong effect of age in the crash data.*
- ***Gender:*** *Men turned into gaps that were on average smaller (5.4 s, range = 3.6 – 7.5 s,* n *= 31) than those into which women turned (6.5 s, 3.9 – 10.9 s,* n *= 23)—a medium effect. The same pattern was true for all scenarios individually. There was no effect of gender in the crash data.*
- ***Light:*** *No effect for day versus night, though this analysis was hampered by a small number of events at night. Results were inconsistent for crashes.*
- ***Weather:*** *No effect for clear versus adverse, though this analysis was also hampered by an almost complete lack of events in adverse weather.*
- ***Road surface:*** *Average accepted gaps in baseline were shorter on dry roads (6.0 s) than on slippery roads (6.5 s) for all scenarios combined, though the opposite was found for LTAP-OD, which had longer dry gaps (5.0 s) than slippery (4.6 s).*

  There were medium and large effects in the crash data, but only for LTAP-LD and SCP-R, and the direction of these effects was different, and there too, sample sizes were small.
- ***Distraction:*** *There was no effect overall. There was a small effect for LTAP-OD, in which drivers tended to drive into* longer *gaps when distracted (mean = 5.2 s, range = 4.0 – 6.2 s,* n *= 7) than when not (4.9 s, 3.6 – 6.6 s,* n *= 32), and a large effect for RTIP, with drivers turning into* shorter *gaps when distracted (6.0 s, 2.5 – 7.9 s,* n *= 5) than when not (7.2 s, 5.0 – 9.4 s,* n *= 19, but the sample sizes were small (for example, the size of the effect for RTIP was largely due to a single gap of 2.5 s accepted by a distracted drivers).*

  The crash database events showed no strong patterns (just a weak effect for shorter gaps while distracted for LTAP-LD).

[1] Side streets included driveways and parking lot entrances.

- ***Speed:*** *Crossings from stopped generally followed the same pattern, accelerating at about the same rate from about 4 – 5 mph at the beginning of the maneuver. The average length of acceleration varied, though: 10 seconds later, the average speed varied from 11.5 mph for SCP-L (*n *= 25 events) to 31.2 mph for RTIP (*n *= 36). Both LTAP-OD turns from stopped and without stopping had converged to about the same speed (15.4 and 13.3 mph, respectively) by that point.*
- ***Acceleration:*** *For the first 2 seconds of acceleration from stopped (starting when vehicle speed exceeded 4 mph), for all scenarios combined, drivers accelerated by a median of 1.8 m/s^2 (mean = 1.8 m/s^2, range = 0.6 – 3.3 m/s^2,* n *= 106). Individual scenario medians ranged from 1.7 m/s^2 for LTAP-OD to 2.3 m/s^2 for LTIP.*
- ***Throttle:*** *Median delay between brake release and throttle application for baseline crossings from a stop was 0.5 s and ranged from 0.2 to 0.6 s for individual scenarios.*
- ***Steering wheel angle:*** *At the beginning of turns, average steering wheel angle varied from 55.0 degrees for LTAP-OD (cross without stop) (*n *= 24) to 112.6 degrees for LTIP (*n *= 11). At the maximum point of turn, it varied from 138.8 degrees for LTAP-OD (cross without stop) to 195.0 degrees for LTAP-OD.*
- ***Turn signal:*** *Turn signal use was at 81 percent for all turning scenarios, and ranged from 50 percent for LTIP to 96 percent for LTAP-OD.*

Discussion

Several of the findings in this study have potential relevance for the design of crossing-path collision warning systems. Foremost is the finding that, in line with previous research, gap size remains a good indicator of driver behavior. The utility of other variables, such as the moderate gender effect observed here, is dependent upon the details of how a developer designs and implements the application to warn and suppress nuisance alerts.

A limitation to the study was a potential confound with gap availability. In the case of each variable explored, comparisons between different subgroups presupposed equal distributions of available gaps. In other words, it is possible that drivers turned into smaller gaps in one condition because traffic there was dense enough that small gaps existed; in another area, traffic density might be low enough that drivers ended up turning into larger gaps only because no smaller gaps existed. Gorjestani et al. [1] found a similar effect and the issue is addressed by Troutbeck in a response published at the end of Cassidy et al. [2]. That said, if the level of traffic reliably correlates with the different conditions, then these factors may still demarcate what affects a driver’s likelihood to drive into a given gap in a given situation.

1 Introduction

Intersections are frequent sites for vehicle collisions. To reduce their frequency and the harm that they cause, applications are being developed to warn drivers of impending collisions at intersections (Figure 1). However, even if the predictions of these applications are highly accurate, because of the rarity of collisions in everyday driving, false alerts will still occur [3]. Additionally, there will be alerts—nuisance alerts—that, although true according to the logic of the warning algorithm, are not perceived as helpful by the driver, possibly due to their frequency, timing, intensity, or modality [4]. This combination of false and nuisance alerts can undercut the effectiveness of the warning application by annoying drivers, eroding trust in the application, and leading them to ignore or even disable the application [5, 6, 7, 8, 9, 10]. Nuisance alerts have been mentioned by participants in warning-system evaluations; e.g., Stearns and Vega [11], Nodine et al. [12], and Nodine et al. [13]. For this reason, it is important to minimize false and nuisance alerts in order to achieve an effective intersection-collision warning application.

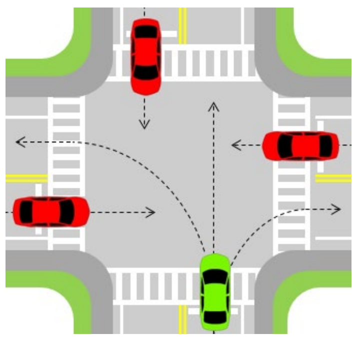

Figure 1. Possible Intersection Maneuvers

Identifying nuisance alerts before they occur is challenging, for two reasons in particular. First, what constitutes a nuisance alert varies from one person to the next. For example, some may find alerts comforting or reassuring even when aware of the threat, whereas others will find nearly every tone from the system an irritation unless the event is a very close call.

The timing of alerts may also affect whether an alert is perceived as a nuisance or not, since alerts issued too early may not be understood and may therefore be ignored [14, 4, 15].

Nuisance alerts may also result from aggressive driving, such as pushing into a gap that is too small and counting on the oncoming vehicle to slow. The driver making the turn might regard the alert to be a nuisance in that case, but since the behavior is risky, it may not be desirable to suppress the alert.

The second reason nuisance alerts are difficult to identify is that driver intentions are difficult to anticipate in the first place. In other words, no sensitivity threshold is acceptable if the driver is not even planning to make the maneuver for which the alert is being issued. This is partly because driving styles vary between individuals: release of the brake pedal may reliably indicate the start of a turn for one driver, whereas for another a rolling stop might continue well into an intersection before the turn is initiated. Future systems may be able to learn a driver's particular style, or enable the driver to customize the sensitivity threshold, but for now we need a generalized understanding of driver behavior at intersections in order to reduce the occurrence of nuisance alerts.

1.1 Study Objective

This brings us to the aim of this study, which is:

> *To improve our understanding of intersection behavior by identifying metrics and providing real-world data that describes how drivers navigate both signalized and unsignalized intersections.*

This objective supports the overarching goal of knowing when alerts should and should not be issued. In other words, it supports designing a better application for warning of intersection collisions.

Another use for the study is to produce estimates of typical driver behavior that can be used to define conditions in test procedures, such as setting the turn speed when testing intersection collision warning systems on a test track, and to assist developers in designing and implementing more effective (reduced nuisance alert) applications.

1.2 Scope of Analysis: LTA and IMA Scenarios

Of the many types of collisions that can occur at an intersection—a driver can be struck from the left, the right, or the front, and may be struck while turning left, right, or going straight—this analysis will focus on the scenarios addressed by the LTA and IMA warning applications. LTA warns against left-turn across-path, opposite direction (LTAP-OD) collisions, in which a driver is struck by an oncoming vehicle while trying to make a left turn (Figure 2, Table 1). IMA warns against five different scenarios involving collisions with cars coming from the side while making turns or driving straight. Najm et al. [16] provides more background information on these scenarios.

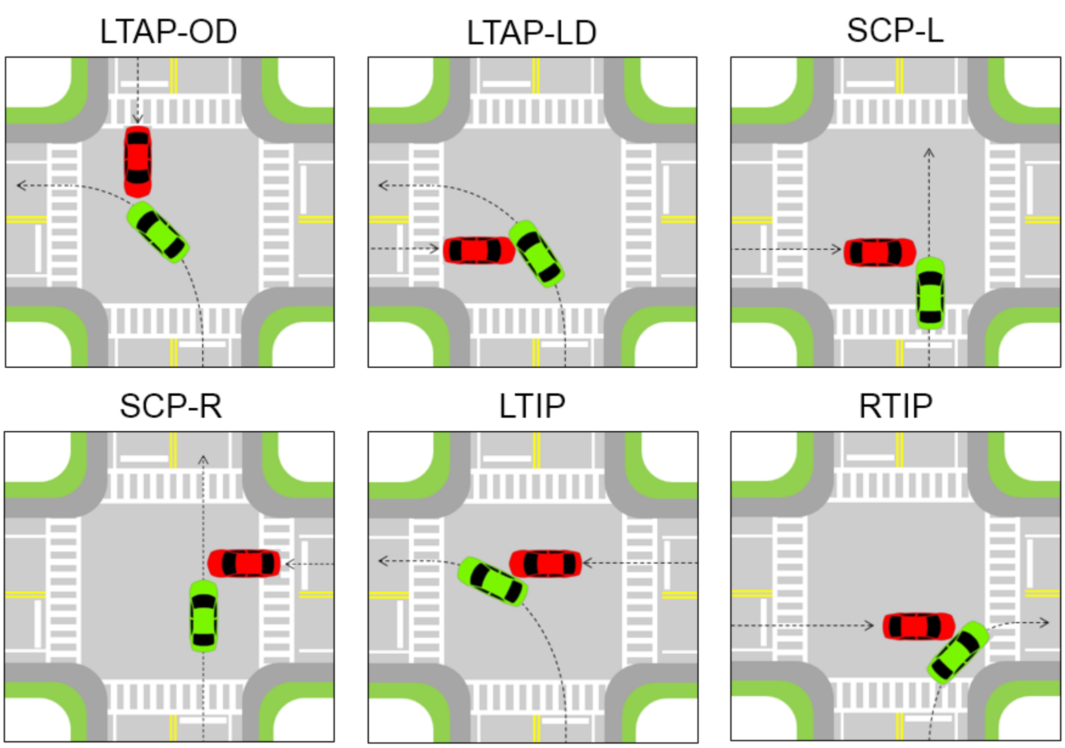

Figure 2. Diagrams of the LTAP-OD and Five IMA Scenario Types

Table 1. Acronyms for the Six Scenario Types

Acronym	Full name	Addressed by
LTAP-OD	Left turn, across path – opposite direction	LTA
LTAP-LD	Left turn, across path – lateral direction	IMA
LTIP	Left turn into path (merge conflict)	
RTIP	Right turn into path (merge conflict)	
SCP-L	Straight crossing paths – left	
SCP-R	Straight crossing paths – right	

1.3 Overview of Analysis and Report

The aim of this analysis—identifying key metrics and providing real-world data that describes how people drive through intersections—is broad and there are numerous variables that could be used, from vehicle speed, acceleration, turn signal use, steering wheel angle, the length of accepted and rejected gaps, the shape and layout of the intersection, the weather, the age or gender of the driver, etc. This task will be broken down as follows in this report.

1. Conduct a literature review of metrics that could and have been used to characterize intersection crossing behavior (**Chapter 2**).
2. Present the results of a new exploration of two existing databases of naturalistic driving field operational tests (**Chapter 3**).
3. Describe an analysis of events found in a crash database (**Chapter 4**).
4. Discuss the results and characterize what questions remain open (**Chapter 5**).

2 Literature Review

This section summarizes key sources in the existing literature of driver behavior at intersections. In addition to surveying the metrics that have been used and summarizing many of their findings, we have sought to identify remaining gaps in the knowledge.

A condensed version of the literature review is given here, with the full review available in Appendix A.

2.1 What Are the Possible Driver Behavior Metrics?

Implicit in every collision warning is an assumption of driver behavior during the time until impact: generally, the logic behind the alert assumes that the driver will continue their current behavior. Driver behavior, however, is notoriously difficult to predict and exhibits wide variability from one person to the next. In some cases, even the driver may not yet know what they are going to do, as noted by Bougler et al. [17]: the decision about when to turn is "fluid and constantly being re-evaluated with an expectation of a change in conditions (e.g., the signal may change from green to amber). Drivers are, in essence, prepared to change their decision and stop at a moment's notice."

Michon [18] characterized the driving task as comprising three levels:

1. **Strategic:** planned routes and goals
2. **Tactical:** route is broken down into short-term objectives and maneuvers
3. **Operational:** the individual control operations of the vehicle needed to perform the maneuvers.

The first two levels must be inferred by the inputs in the third. For the third, the available sources of information are currently limited to instrument configurations (e.g., indicator and pedal statuses, steering wheel angle); vehicle kinematics (e.g., speed, acceleration, heading); location (e.g., intersection, lane, traffic signal); or a combination of those factors. Furthermore, which of these metrics are useful predictors and at what threshold or configuration may vary depending on another set of factors, such as weather, road conditions, traffic density, etc.

A good place to start is to set aside the complexity and first model the typical steps in an intersection crossing. From that understanding, points where errors are likely to occur can be identified and the metrics that best indicate their occurrence can be chosen.

2.1.1 Modeling How Drivers Cross Intersections

The following studies have attempted to produce an algorithmic description of the decision points and relevant factors to performing intersection crossings. Although not all scenarios are included here, in some cases little modification would be needed to adapt them to the missing scenarios.

In a Federal Highway Administration (FHWA) review, Richard, Campbell, and Brown [19] break down the perceptual, cognitive, and psychomotor subtasks involved in the various stages of various intersection-crossing scenarios in greater detail than can be summarized here. However, some of the idealized speed profiles for these breakdowns are shown in Appendix A (Figures 50, 51, 52, 53, and 54). Generally, though, they make the following generalizations across scenarios about the various stages and their associated difficulties (note: not all scenarios will require all of these stages; e.g., lane change or turning):

- **Approach:** Moderately demanding visually in order to check lights, scope out intersection, traffic, etc., all under potential time pressure.

- **Prepare and execute lane change:** More time pressure than regular lane changing due to approaching intersection, requiring monitoring mirrors and over shoulder often while decelerating in conjunction with vehicles in destination lane.
- **Deceleration/stop:** Not high workload; generally a combination of visually monitoring lead vehicle and cognitively assessing its trajectory to maintain a safe following distance.
- **Decision to proceed:** The primary difficulty here is time pressure.
- **Intersection entry:** Time pressure due to quickly checking for hazards (lights, oncoming vehicles) in multiple locations, especially when the vehicle does not come to a full stop before proceeding; some of these tasks may use the same information-processing resources, leading to further bottleneck.
- **Prepare for Turn:** "The primary bottleneck in this segment is a difficult and forced-paced gap-judgment task that is complicated by having to quickly cycle among other tasks involving checking for hazards (e.g., in turn path, following vehicle) that are distributed throughout the visual environment. This is also likely to be a high-stress situation, because the consequences of making an error in the gap judgment task could be a collision with a fast-moving vehicle."
- **Execute Turn:** Initial portion has high workload due to precise maneuvering and hazard assessment under time pressure due to acceleration and potential interactions with other vehicles. Also high stress due to potential collision with fast-moving vehicles.

In-depth algorithmic steps for specific scenarios are outlined in Appendix A.

2.1.2 Identifying Potential Driver Error Points

This section reports on work that identified driver error points, in some cases working directly from the breakdown of driver behavior modeled in the previous section.

Chovan et al. [20] list possible collision-causing errors that could occur at each of the major steps of an LTAP-OD (Table 2).

Table 2. Sources of Driver Error When Making an LTAP, Adapted From Chovan et al. [20]

Driver Task	Possible Errors
Approach the intersection	Driver might be unaware of the intersection ahead and its geometry.
Signal	Driver might not signal to other traffic.
Decelerate	Driver might not decelerate sufficiently to process intersection information properly.
Perceive traffic control device	Driver might be unaware of traffic control device altogether or might be unaware of signal characteristics.
Heed traffic control device	Driver might not perceive correct device characteristics.
Perceive color of traffic light	Driver might be unaware of the status (flashing versus solid) or color (red, amber, green) of a light.
Respond appropriately to color of light	Driver might exhibit incorrect behavior to a particular light characteristic.
Observe other traffic	Driver might be unaware of other traffic (crossing or oncoming).
Judge gap in oncoming traffic	Driver might misjudge the gap in or velocity of oncoming traffic.
Judge gap in cross traffic	Driver might misjudge the distance of the gap in traffic or the velocity of oncoming traffic if he or she is distracted by cross traffic.
Edge out into traffic to confirm clearance when the driver's vision is obstructed	Driver might not realize that vision is obstructed or might edge out into traffic without confirming information.
Check the pathway	Driver might not check the pathway or might misperceive objects (vehicles or pedestrians) in the pathway. Driver might not anticipate other traffic behavior properly.
Adjust velocity to turn	Driver might turn too fast or too slow.
Complete the left turn	Driver might stop before the turn is completed.

Bougler et al. [17] distilled the possible causes stemming from driver error to four:

1. Failure to judge safe time gaps correctly.
2. Failure to judge the speeds of closing vehicles.
3. Failure to see the oncoming vehicle (i.e., "looked but did not see").
4. Obstruction of the driver's view by an opposing vehicle.

2.1.3 Defining Useful Alerts

However, just because a driver commits one of the errors listed in the previous section, it does not follow that they should receive an alert. For example, although running a red light might merit an alert of some kind, if there is no oncoming vehicle, an IMA or LTA alert might be perceived as a nuisance.

Pierowicz et al. [21] suggest issuing alerts when several criteria are satisfied, including the detection of an oncoming vehicle that is on a collision course (Figure 3).

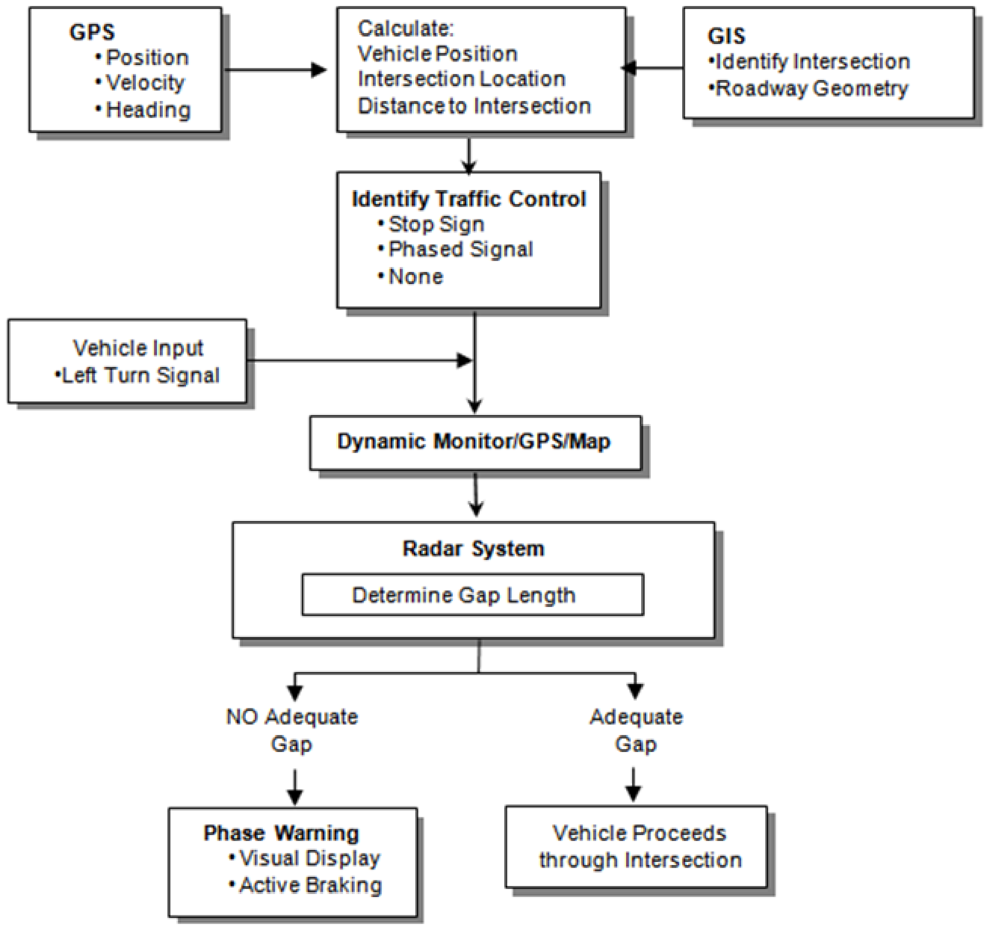

Figure 3. An LTAP Algorithm [21]

2.2 Existing Research Into Metrics of Driver Behavior

This section is broken down by driver-behavior metrics used in previous research, beginning with the predominant metric in the literature: gap length.

2.2.1 Gap Length

Provided they do not have the right of way, a driver's task generally boils down to assessing and choosing an appropriate gap. It is also the primary criteria for most collision warning systems. In this section, following a definition of gaps and the effect of gap distribution and oncoming-vehicle speed, some findings of gap sizes are presented by scenario.

Gap Defined. According to Brilon et al. [22], "The estimation of critical gaps from observed traffic flow patterns is one of the most difficult tasks in empirical traffic engineering science." They note that the "critical gap," i.e., the gap length at which a driver is equally likely to go as not go,[2] has over 20 to 30 different methods of estimation. After reviewing a selection of those, the authors select two models that do well, but conclude that "it is difficult to understand which procedure is reliable and which is not."

[2] The *Highway Capacity Manual 2010* [114] defines the critical gap as "the minimum time interval in the major-street traffic stream that allows intersection entry for one minor-street vehicle." The 2016 [29] edition uses the same definition but relabels it the "critical headway."

Likewise, Gattis and Low [23] noted that "the use of different critical gap modeling techniques produced results for various movement combinations that varied widely." Ashalatha and Chandra [24] found 12 to 38 percent variation between six different models, although they argue that this was partly due to the inability of these models to handle the mixed traffic present at the two intersections they considered in Kerala, India.

Gaps are often defined as the time between two passing vehicles—back bumper of the first to front bumper of the second. This is different from the "lag," which measures from arrival at the intersection or the changing of a light and for which there may not be a first vehicle. Although there may be some differences in driver behavior between preferences for lags and for gaps [23, 25], including potentially greater variance in lag times than in gaps [26], others have combined them [27].

But, as noted by Cassidy et al. [2], individual drivers are not homogenous. The question then is what summary statistic to use for generalizing gap preferences across the population—do you use the minimum gap size used by the most aggressive driver? Earlier editions of the *Highway Capacity Manual* (HCM) advocated using medians, but as pointed out by Kittelson and Vandehey [28], this technique is dependent on the distribution of gap sizes, which often includes very large gaps that can skew the values in a way that represents gap availability rather than driver behavior. Instead, they suggested incorporating the rejected gap data as well by calculating the critical gap. But, as pointed out by Gorjestani et al. [1], "critical gap estimation techniques are used to support highway capacity modeling, and are not intended for safety applications." They go on to say that "the application of critical gap is well suited for *describing* driver behavior in terms of highway capacity, but it is not well suited as a point at which to *modify* driver gap acceptance/rejection behavior." Gorjestani et al. themselves use the 80th percentile rejected gap as another measure for summarizing gap preferences.

In gap-acceptance theory, it is usually assumed that drivers are consistent and homogenous [29]. However, as Cassidy et al. [2] note, individual drivers are not even consistent with themselves over time, let alone the same as everyone else. Instead, acceptable gap sizes will vary according to a number of other factors. A few of those are mentioned here (gap distribution and oncoming vehicle speed), and others, such as environmental or demographic factors, are addressed in the rest of the report, in particular Section 3.

Gap Distribution Matters. There is evidence that driver behavior is influenced not just by the gap opening up in front of them, but by the distribution of gaps that they have been experiencing. For example, the threshold for what constitutes an acceptably large gap decreases the longer the driver has had to wait. This may be due to the number of untaken gaps that have passed [30, 31], the time spent getting to the front of the queue [28], or the total waiting time [32, 33, 31]—although Gorjestani et al. [1] found no effect of total waiting time. Pollatschek et al. [34] hypothesized that acceptable gap size may decrease based on the expected delay until the next gap if the driver passes on the one currently open.

As Cassidy et al. [2] note, "it is worth reiterating that two factors—minor street delay and major street flow—influence gap acceptance in opposite ways…. the gap size with a 50-percent chance of being accepted [the critical gap] increases with major street flow. Conversely, we found that added delay [queueing] leads to a decrease in the estimated value of a critical gap." In other words, critical gap measurements are dependent on traffic, but the direction of the effect is different for major and minor roads.

Gaps are Affected by Oncoming Vehicle Speed. In one study of drivers merging into cross traffic, drivers appeared to show "a bias toward underestimation of high speeds and overestimation of lower ones," which affects the estimation of gap sizes [35]. In a second study, conducted in a driving simulator, the likelihood of turning into a gap of a certain length increased the faster the speed of the approaching vehicle [36]. These results likely apply for oncoming traffic as well—perhaps even more so given the weaker visual cues used to judge the speed of an approaching vehicle.

Another way to set alert thresholds is noted by Ragland et al. [27], who suggest warning against actions that a typical driver would avoid—in other words, to base warnings not on the kinematics of what is technically possible in avoiding collisions, but rather on the movements that are frequently (and presumably safely) performed by people in the real world. Similarly, Chovan et al. [20] argue that warnings should be set to omit situations that are psychologically uncomfortable; i.e., "close calls."

The following gap lengths have been found for the different scenarios:

- **SCP.** Observations of rural intersections across three states by Gorjestani et al. [1] using roadside equipment found little effect of time of day on the distribution of *rejected* gaps (they did not use accepted gaps as their primary measure), and found little variation—either by state or by maneuver type, their data set including some turns as well—in rejected gap lengths, with 80 percent rejecting gaps 6.5 s or less. From this, assuming one second of time to comprehend an alert, they suggested setting warning timing to gaps shorter than 7.5 s.

  The HCM gives base critical gaps of 6.5 s for through traffic on a minor road for crossing both two and four lanes [29]. These are referred to as "base" critical gaps because, as needed, additional delays could be subtracted or removed, e.g., for the percentage of heavy vehicles, the grade, and three- versus four-leg intersection design.

- **LTIP.** Using roadside sensors at 13 stop-controlled intersections in Illinois, Missouri, and Pennsylvania, Harwood et al. [37] used recordings of gaps into which drivers did and did not turn to calculate the critical gap. To do this they used two methods: the Raff method [38], where the intersection between cumulative distributions of accepted and rejected gaps was found; and logistic regression on the same pool of accepted and rejected gap lengths. For LTIP scenarios from a minor road onto a major road, they found a critical gap of 8.0 s by the Raff method and 8.2 s by logistic regression, which they considered to be in good agreement with a study by Lerner et al. [39] that found a gap of 7.0 s and a study by Kyte et al. [40] that found a gap of 7.1 s.

  The Raff method of calculating the critical gap is sensitive to the traffic flow [41, 42]. Guo et al. [43] modeled the dependency, showing that a critical gap of 5.6 s calculated at a traffic flow of 0.05 vehicles per second would decrease to 2.5 s if the traffic increases to 0.45 vehicles per second.

  The HCM gives base critical gaps for left turns from a minor road of 7.1 s for crossing two lanes, 7.5 s for crossing four lanes, and 6.4 s for crossing six lanes [29]. For left turns from a major road, the critical gaps are shorter: 4.1 s for two and four lanes, and 5.3 s for six lanes.

- **RTIP.** Harwood et al. [37] used the same approach for RTIP, finding critical gaps of 6.3 s by the Raff method and 6.5 s by logistic regression. They again considered their findings to be in agreement with a gap of 7.0 s found by Lerner et al. [39] and 6.2 s found by Kyte et al. [40].

  For right turns from a minor road, the HCM gives base critical gaps of 6.2 s for crossing two lanes, 6.9 s for crossing four lanes, and 7.1 for crossing six lanes [29].

- **LTAP-OD.** Ragland et al. [27] conducted a study of driver behavior turning left at five intersections in the San Francisco Bay Area. Using video data, they characterized the distribution of gaps—here defined as the length of time between two oncoming vehicles—available to drivers. Gaps over 12 seconds in length were excluded. The authors also characterized the distribution of gaps for where the driver did and did not make the turn and fitted their data with logistic regression functions. They found that roughly 30 percent of gaps presented to drivers were 2 s long, 18 percent were 3 s long, and 12 percent were 4 s long (Figure 4, n = 833).

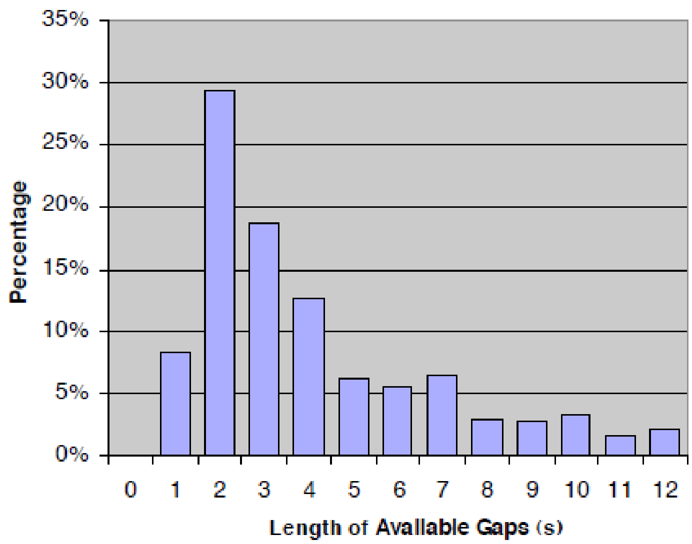

Figure 4. Gap Lengths in Ragland et al. [27]

Drivers never turned when the gap was under 3 s and always turned when it was over 12 s (Figure 5). The percentage of times drivers turned increased step-wise for gap lengths between 3 and 12 s: 15 percent turned when the gap was under 4.1 s, 50 percent when the gap was under 6.0 s, and 85 percent when it was under 8.6 s. Given the variation seen between intersections and between drivers, and since they expect to see variation between different genders and between different weather or lighting conditions, Ragland et al. suggest tailoring warning applications to these parameters: "parameters of the logistic function could be used to characterize differences across intersections, across conditions within the same intersection, and across different categories of drivers."

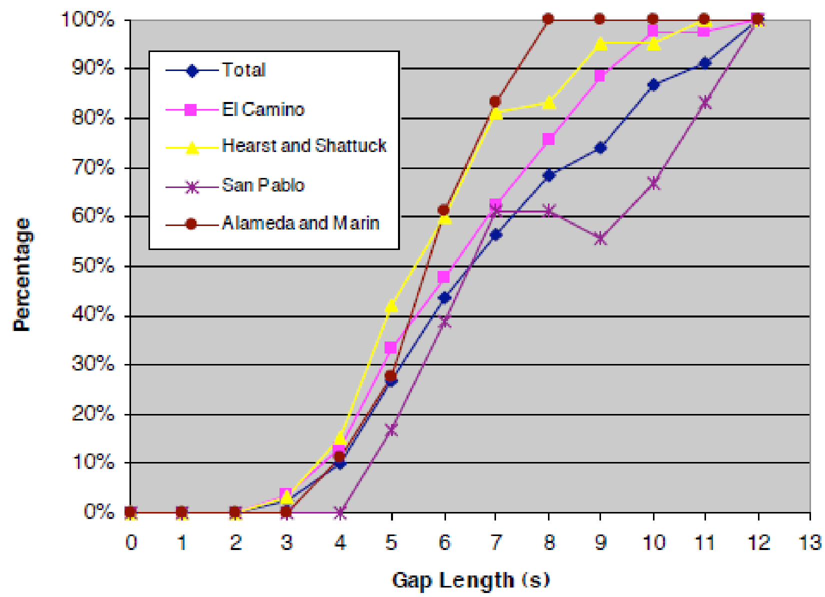

Figure 5. Percentages That Turn by Gap Length [27]

Bougler et al. [17] noted three challenges to predicting potential collisions based on lag/gap length:

1. Further work to determine how best to measure gaps is needed.
2. There was no obvious cut-off point in gap length or criteria for determining where a warning threshold should be set (though they noted that their subjects in the Richmond Field Station (RFS) study tended to agree with the warning application and that its mere presence may have made them more cautious in turning).
3. Intersections varied significantly in terms of turning time, traffic volume, available gaps, and approach speeds. Like Ragland et al. [27], they questioned whether LTAP-OD algorithms need to be fine-tuned to individual intersections.

2.2.2 Speed

Speed profiles by Richard, Campbell, and Brown [19] for vehicles approaching intersections are shown in Appendix A (Figures 50, 51, 52, 53, and 54).

SCP. Since the required distance to stop will increase with vehicle speed, the point at which a driver needs to decide whether or not to cross an intersection should also vary with speed. Ferlis [44] took advantage of this relationship in a conceptual analysis where he developed an algorithm for warning drivers of an impending collision when approaching a signalized intersection. Specifically, his algorithm identified potential red-light violators based on their speed 141 feet (43 m) before the stop line (at that point light vehicles traveling over 35 mph would be incapable of stopping in time without severe braking at over 2.9 m/s^2). Warning one of the two drivers at that point would be sufficient to prevent about 88 percent of those collisions, he argued. Two studies found similar effectiveness using simulator and test-track experiments [45, 46], though others have been more critical of the use of single-point detection algorithms [47].

Noble et al. [48] proposed a different model, aimed at distinguishing red- from yellow-light runners. Their model uses a multivariate adaptive regression splining technique to predict velocity based on distance from the stop line and a number of categorical variables, including vehicle type, time of day, road-surface condition, and weather.

Liu [49] found evidence that drivers encountering SCP scenarios at unsignalized intersections in China, where the authors note gap-forcing behavior is common, will generally yield to the faster driver. They studied an intersection where the speed limit was just under 19 mph (noting that "many exceeded the speed limit"), and found via decision-tree analysis that drivers encountering a vehicle approaching from the *left* made their decisions 0.9 – 1.2 s before reaching the crossing point and that drivers encountering a vehicle approaching from the *right* made their decisions 0.9 – 1.3 s before reaching the crossing point (the difference between left and right was not statistically significant). Distance and raw (not relative) speed were less significant factors.

LTAP-OD. Speed profiles for approaches to intersections (as well as throughout the turn) were collected in an experiment on left-turn behavior conducted by Bougler et al. [17] and also described in Cody et al. [50]. In the study—referred to as the Berkeley Field Test (FT)—23 subjects drove an instrumented vehicle around a 2-by-4-block route 10 times in Berkeley, CA, during off-peak hours, making left turns at each intersection. Three of the intersections had left-turn pockets ("pockets" are dedicated left-turn lanes, as shown with yellow shading in Figure 6) and all had a green light for left turns. The speed profiles they observed showed fairly consistent patterns, both for turns without stopping (Figure 7) and for turns with stopping (Figure 8).

Note that in Figure 7 "no interference" means no influence from other vehicles, pedestrians, or changes in traffic lights. "POV at turn" means there was an oncoming vehicle (a "principal other vehicle"). "Driver error" means a mistake such as running a red light or starting the wrong maneuver at the intersection. "Lead" means the driver was following another vehicle. "Light change" means the light changed from red to green while the driver was in the left-turn lane. In Figure 8, "Trajectory 1" is when the driver turned without stopping and "Trajectory 4" is when they turned after stopping in the intersection but not at the stop bar.

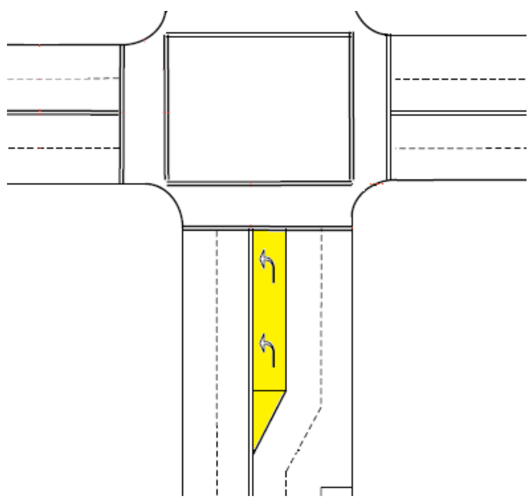

Figure 6. Dedicated Left-Turn Pocket [17]

Bougler et al. [17] observed the following results pertaining to intersection approach:

- Turns without stopping and with no lead vehicle included minimum speeds of 11.2 to 15.6 mph.
- Turns where the vehicle slowed to let an oncoming vehicle pass included minimum speeds from 4.5 to 8.9 mph.
- Vehicles generally entered the left-turn lane at 20.1 to 29.0 mph.

- Drivers constantly reevaluated their decision, prepared to stop if another vehicle appeared or the light changed, with reaction times around 0.4 s.
- In general, driver decisions to turn without stopping or to stop can be distinguished beginning 17 m, or 2 s, from the stop bar (and therefore that the decision point was reached about 0.5 s before that).

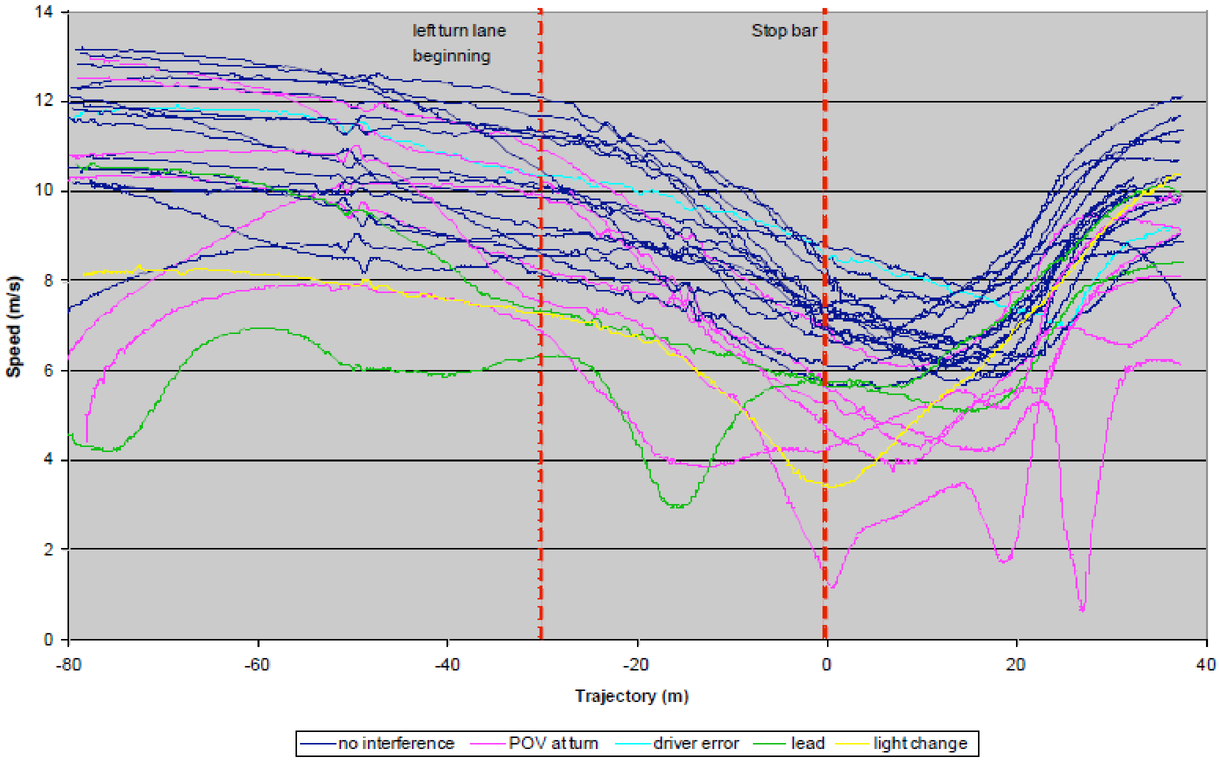

Figure 7. Speeds During Left Turns Without Stopping [17]

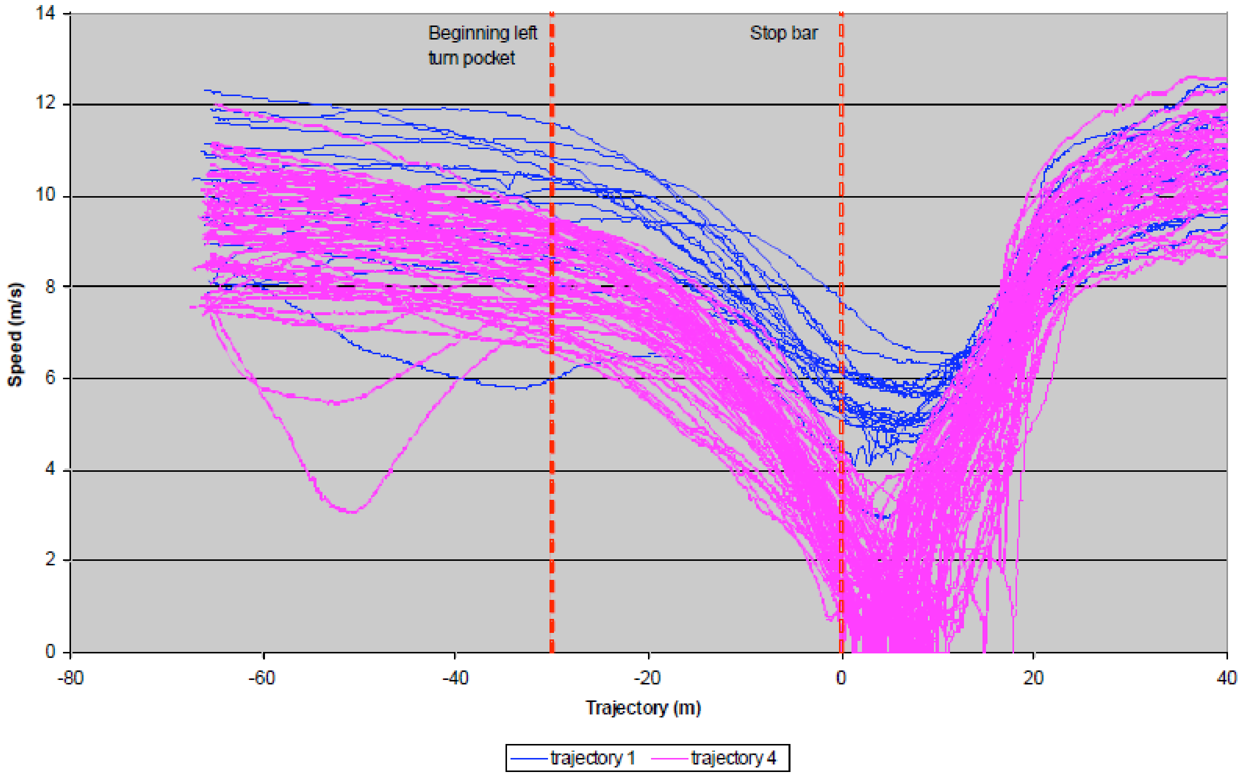

Figure 8. Speeds During Left Turns With Stopping [17]

Bougler et al. [17] also conducted a second experiment (the "RFS Test") that used the same vehicle as the Berkeley FT but at a controlled intersection at the RFS in Richmond, California, where gap lengths could be more accurately controlled and a warning application could be used.

Of particular relevance to our question is the note by the authors that "in both studies it was very difficult to accurately predict from the [driver's] approach speeds whether the driver intended [to] turn or stop to let the POV clear." With regard to the decision point, the RFS Test found little difference in rated timeliness of warnings that came 2, 3, or 4 s from the stop bar, although 3 s appeared to be optimal (additionally, younger drivers were more amenable to a later warning and older drivers to an earlier warning). In terms of brake timing, which is a more objective measure than driver ratings, the 2 s warning came after the typical driver had already initiated braking and the 3 s warning came about a half second before.

Working with the same application as Bougler et al. [17], Misener et al. [51] determined that a last-second warning allowing enough time to stop should be issued around 14 m from the collision point. Unfortunately, the speed profile distributions of drivers intending to stop and those intending to proceed were indistinguishable at that distance, meaning alerts issued that early would produce a large number of nuisance alerts. According to the authors, "the most challenging part of implementing a last-second warning for the LTAP-OD scenario is finding a way to reliably predict the driver's intent to attempt a turn in front of the [oncoming vehicle] or to come to a stop and let the [oncoming vehicle] pass."

Although not specific to LTAP-OD scenarios, a study by Aoude et al. [52] was relevant in showing the effectiveness of two algorithms for identifying potential red-light violators. Although red-light violations are different from LTAP-OD situations, these algorithms could anticipate when a driver moves into the intersection (and needs to be warned) or is coming to a stop. Aoude et al. used data from the United States Department of Transportation Cooperative Intersection Collision Avoidance System for Violations project to evaluate both models. The first model worked best with range to intersection, speed, and longitudinal acceleration as inputs. The second utilized those values as well as estimated time of arrival and the required deceleration parameter.

2.2.3 Turning Time

Turns through intersections are not necessarily clean arcs, so it is important to model the actual turning radii, speeds, and accelerations, as well as any other variables that drivers use in the real world. Good profiles for turn initiation may allow applications to distinguish, for example, between initiating a turn and creeping into an intersection for a better view.

To quantify LTAP-OD behavior, Bougler et al. [17] collected data on driver turns in both their Berkeley FT and the RFS Test. They defined a turn as beginning when the driver releases the brake when in the intersection (front bumper crosses outside line of crosswalk) until they exit the intersection (rear bumper passes the outside line of the crosswalk). They measured turning times between 5.2 and 7.8 s. However, these times are highly dependent upon the intersection. Different trajectories also yielded very different times. For example, a vehicle accelerating from a stop took longer to complete a turn than one that did not stop. The fastest turning speeds were from 11 to 16 mph.

Finally, regarding turning time, an observational study of an intersection in Berkeley, California, recorded the time that LTAP-OD turning maneuvers took using video review [53].

Table 3. Mean Observed Turning Times under Varied Conditions [53]

Type of Turn	Mean Turning Time* (s)	SD	*n*
Pedestrian present in destination sidewalk	4.4	1.5	22
On the fly (without stopping)	2.8	0.5	16
From queue (waited for preceding vehicle)	3.1	0.4	11
During amber or red signal	2.9	0.5	27
All other**	3.1	0.5	41

* Time from first significant turning to clearing oncoming vehicle's lane

** Waiting for gap during green, with no pedestrians present in destination sidewalk

2.2.4 Intersection Geometry

Intersections can vary in size, the number of lanes, whether or not there is a dedicated turn lane, the number of crossing lanes, the geometry of the intersection (straight or curved), and whether there are any visual obstructions such as hills or turns. Even potholes can change how a driver will move through an intersection in terms of speed or course. These differences indicate the need for tailoring data to individual intersection differences.

Shladover et al. [54] set up roadside radar equipment at an intersection in Albany, California, and used it to measure vehicle trajectories at an intersection (Figure 9). The pink trajectories are left turns from a six-lane road with a dedicated left-turn lane into a parking lot, and the blue ones are left turns from the six-lane road onto a smaller, four-lane road, as can be seen in the photo below.

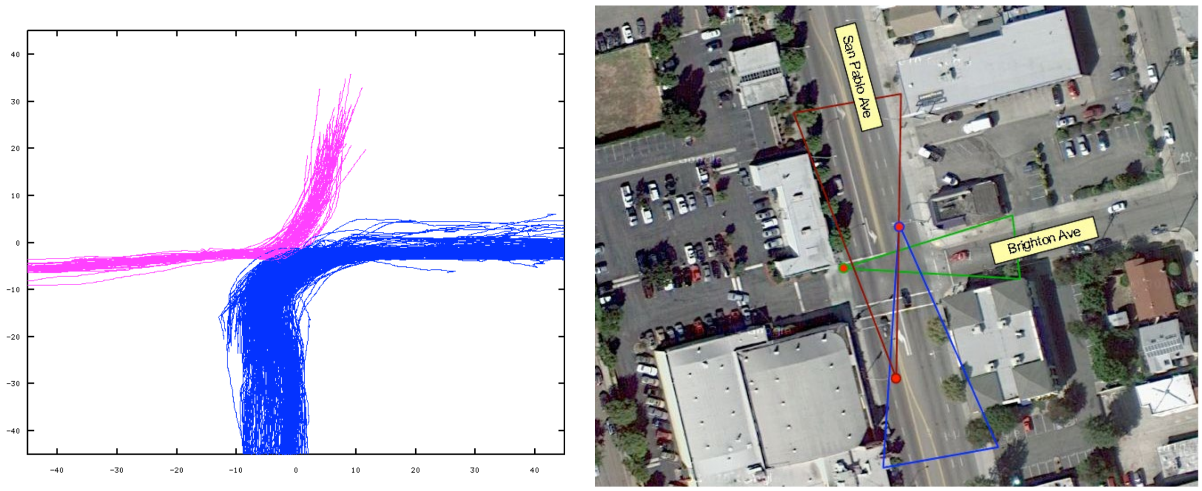

Figure 9. Left-Turn Trajectories at an Intersection [54]

Work on contributory factors in red-light violations summarized by the Institute of Transportation Engineers [55] found that drivers approaching an intersection on a downgrade are less likely to stop than drivers on even or uphill approaches, and that drivers closely following another vehicle through an intersection may be "drawn" into the intersection.

2.2.5 Age and Gender

Driver demographics may also affect how people cross intersections.

Age. One potential factor is age. An FHWA review summarized the evidence as being of high quality and said that "older drivers tend to reject more usable gaps and accept longer wait times than younger drivers; teens display more aggressive gap acceptance than adults" [26].

As reviewed by Oxley et al. [56], older drivers are more likely to be involved in intersection collisions (and more likely to be injured in them) due to the following factors.

- Lower visual acuity makes it harder for them to see other vehicles or traffic signs [57, 58].
- Narrower "useful field of view," or the area of the visual field from which information can be gathered from a quick glance [59].
- Slower reaction times [60].
- With regard to the dilemma zone of whether or not to stop at a yellow light, drivers 65 or older tended to have dilemma zones that lasted longer and were closer to the intersection than for younger drivers [61].
- Underestimation of the speed of oncoming vehicles [62, 63].
- Less agility for initiating evasive maneuvers.
- More prone to poor gap selection.
- Greater difficulty handling tasks of high complexity, including interactions with other road users.
- More susceptibility to distraction from hands-free cellular phones [64].
- Scanning errors [65, 66], particularly to the sides when entering intersections [67].

- A reduced ability to inhibit the primary task of monitoring the vehicle's travel path may result in reduced scanning behavior to check for other vehicles at intersections [68].
- Older drivers are more likely to get into collisions while making left turns [69], leading to the official advice given by some State DOTs to older drivers to make a series of right turns instead.
- According to Chandraratna et al. [70], a driver is 8 percent more likely to crash while making a left turn for every year of age past 65.

That said, older drivers tend to compensate for many of these factors by driving within their abilities [71], avoiding rush hour, reducing driving at night, and some follow the advice of avoiding left turns where possible and waiting for larger gap sizes [72]. Zhou et al. [73] found that elderly drivers (older than 70) were less likely to accept gaps than younger age groups (younger than 35 and 55 to 69).

Romoser and Fisher [74] showed that active simulator training can even compensate for the reduction that older drivers show in looking for threats when making turns. That said, a simulator study by Richard et al. [75] found evidence that older drivers were less likely to accept gaps when they had no view of the traffic and an LTAP-OD assist, preferring instead to rely on their own judgement (they also preferred for the interface to be infrastructure-based, rather than in their vehicles).

However, given these age-related effects, differences do not always show up in the data. Bougler et al. [17] found no effect of age on turning time in the Berkeley FT and concluded that a prediction or warning algorithm need not take age into account. Likewise, no practical differences in stopping location relative to stop bar were seen.

Age effects may also exist at the lower end of the spectrum too, of course, whether shaped by a lack of driving experience or cognitive differences in those whose brains are still maturing. For example, Tupper et al. [31] found that for left- and right-turn maneuvers, teens (under 20 years old) had a critical gap of 5.5 s, which was lower than the 6.5 s they found for adults (age 20 to 64). The authors also note that the difference between teenagers and adults is stronger than that between adults and the elderly.

Gender. Bougler et al. also saw no differences in gender, which is the other demographic factor usually considered in research. Likewise, Sivak et al. [76] found no difference in gender (or age) when evaluating risk-taking behavior in the context of intersection crossing under time pressure in a simulator. On the other hand, two simulator studies did find gender differences, both with women selecting longer gaps [77, 78]. Rakha et al. [61] also found that women were more likely to stop when presented with a yellow light and that their dilemma zone was closer to the intersection than for men. An FHWA review summarized evidence for gender effects on gap acceptance to be mixed and of low quality [26].

Ragland et al. [27] proposed using logistic regression models to optimize acceptable gap lengths for subpopulations. Of course, the same could be done for individual intersections or environmental conditions. Another option is to allow drivers to customize their warning applications by setting the alert sensitivity or even selecting for larger gap sizes.

In a theoretical paper, Dabbour & Easa [79] proposed a solution in more detail. Noting that mistakes in judging gap sizes are more common with certain age groups and people with health conditions, they proposed a warning application that takes into account an individual driver's perception-reaction time (PRT) and their typical acceleration behavior. Specifically, before using the application, a driver would input their age and gender. At an intersection, the warning application would activate when the turn indicator is switched on and the vehicle comes to a full stop. A driver's unique PRT, which includes the time for them to perceive the situation and move their foot from the brake to the throttle, is then used by the application along with their acceleration rate to predict whether the maneuver can be successfully completed during the current gap in traffic. Dabbour and Easa calculated PRTs using a regression modelled in terms of gender and age using 2,160 observations made from a simulator study on 60 subjects, balanced for age and gender, who were asked to cross a variety of unsignalized intersections. The acceleration rate was the maximum provided by the vehicle's performance data multiplied by a correction factor dependent upon the age and gender of the driver and the distance and speed of the approaching vehicle.

2.2.6 Environmental Conditions

Environmental conditions can affect intersection behavior and introduce further complexity into an already complex area. For example, visibility can be affected by light levels, fog, rain, or snow. Road surface conditions, such as rain and ice, can affect acceleration and braking times, potentially changing when a warning should be issued or the level of the response required by the driver to avoid colliding (since many people may underestimate how the conditions affect their vehicle's performance).

SCP. Becic et al. [80] conducted a simulator study set in a recreation of a real rural-highway intersection in Minnesota. Using accepted-gap data from the real-world intersection observed by Gorjestani et al. [1], the simulator safety application was designed to issue alerts when the gap was smaller than those typically accepted in the real world. The results indicated a beneficial effect of the warnings, but only under conditions of limited visibility; i.e., with simulated fog partially obscuring oncoming cross-traffic. According to the authors, "it appears that the drivers' reliance on the [safety application] is reduced when weather and traffic conditions allow them an unrestricted and clear view of the cross-traffic. It is possible that in situations when drivers feel confident in their perceptual judgment and motor abilities, the need to rely on an assistive technology is greatly reduced."

LTAP-OD. As noted by Chovan et al. [20], left-turn maneuvers in general require higher-than-normal cognitive workloads and are often made under stress due to time pressure and perhaps the sense that others are waiting on you. In addition to their effect on vehicle performance, environmental conditions may further increase the driver's stress.

Although there is much research on how environmental conditions affect driving, there appear to be few that look specifically at intersection behavior, particularly LTAP-OD. One example is by Rakha et al. [81], who found that drivers avoided smaller gaps as rain intensity increased.

A study of three signalized intersections in Virginia that logged over 5.5 million crossings and identified over 8,000 instances of potential red-light violations (excluding emergency vehicles and trailers) was conducted by Doerzaph et al. [82]. Exploration of the subset of those events that were SCP or LTAP-OD maneuvers (about 3,000 events) and a selected baseline group for comparison yielded an unexpected effect: violation likelihood was six times higher in cloudy weather than on clear days and 1.8 times higher in low-light conditions than in daylight. The authors speculate that "greater visibility of the signal in cloudy and low-light conditions could lead drivers to be less attentive to the signal. The lower level of attentiveness could increase the driver perception reaction time and, therefore, increase the likelihood of a violation; however, additional research is required."

Zohdy et al. [33] found that critical gaps (calculated using logistic regression) for LTAP-OD events at an intersection in Virginia increased linearly with rain intensity, which they observed ranging from no rain to 9.4 cm/hour. In total, they observed 2,017 events in dry conditions and 713 in rain.

2.2.7 Turn Signal

Chovan et al. [20] list three factors present during the approach that could be used to identify an impending left turn at an intersection.

1. Turn indicator activation.

2. Deceleration with a green light or right of way.
3. Merging into a left-turn lane.

The turn signal can clearly indicate driver intent, and is already used as a prerequisite condition for several warning applications. Indeed, without the turning indicator it can be impossible to know whether to issue a warning about a vehicle approaching from the right since the driver might only be turning right rather than going straight or turning left (and if they are turning left, the gap will be a different length than if they are going straight).

Turn signals may also be used by the oncoming vehicle, so the turn indicator status of other vehicles can be useful too, as noted by Chovan et al. [20]. The primary difficulty with using turn indicator status is unreliability, since not all drivers signal. Furthermore, when they do signal, there is likely wide variation in how long before a turn and at what distance from the intersection they switch it on. Consequently, there is a need to research how drivers use turn indicators, including the timing of when drivers activate their turn indicator.

Although studies of intersection behavior commonly record turn indicator status, we found only one study of turn indicator use, conducted by Ponziani [83], who himself noted that he could find no other formal research into turn indicator use. In this study, a single observer tallied turn signal use and neglect while driving in an unmarked vehicle around Dayton, Ohio. Data was collected in different weather conditions, at different times of day, and on different days of the week. All vehicles were counted except for emergency vehicles, bicycles, and mopeds. Of 10,000 vehicle turns observed over the course of the study, about 75 percent used their turning indicators. The study did not specify the type of turn being performed.

2.2.8 Distraction

Distraction is a contributing factor for a significant percentage of intersection-crossing scenarios. According to the 2004-2008 General Estimates System (GES) national crash database, for LTAP-OD events, distraction of the driver turning left contributed to 21 percent of LTAP-OD collisions at signalized intersections (distraction of the driver of the oncoming vehicle was a contributing factor for only 4 percent of collisions) [84]. For non-signalized intersections, distraction was a contributing factor 29 percent of the time for the driver of the turning vehicle for LTAP-OD (and was again 4 percent for the driver of the oncoming vehicle). For SCP at signalized intersections, distraction was a contributing factor in 13 percent of collisions. Distraction is ideally easily addressed by a warning application.

Although technically a form of inattention rather than distraction [85], failing to look for oncoming traffic due to being engaged with another aspect of the task of driving requires similar research methods to identify (tracking eye glances or head turns) and may be similarly addressable via warning applications. Thus, the lack of scanning behavior shown by older drivers [74, 68, 67] is of relevance here. In particular, their control population data (young, experienced drivers) can be used to characterize normal intersection behavior.

Scanning behavior is particularly difficult to measure in LTAP-OD scenarios due to the angle of oncoming traffic being essentially straight ahead. This makes it harder to evaluate attention to oncoming traffic than cross traffic, which requires turning the head to the side and is what both of the Romoser studies focused on. The only study of eye or glance behavior that specifically addresses LTAP-OD scenarios was by Muttart et al. [86], who compared glance behavior between motorcyclists and car drivers, finding that motorcyclists were less likely to make a last glance in the direction of maximum threat (oncoming traffic) when making a turn. Specifically, for cars the last glance was toward oncoming traffic 48 percent of the time (± 33 percent standard deviation). For motorcycles, it was toward oncoming traffic only 30 percent of the time (± 29 percent).

Cognitive distraction is more difficult to detect since the driver’s eyes may remain on the road. One way to identify cognitive distraction is via eye-tracking technology able to detect a narrowing of eye glances toward straight ahead and decreased checking of the periphery [87, 88] (More information on eye-tracking technology and machine learning to gauge driver intent is outlined in Appendix A).

As noted by Neale et al. [47], the effectiveness of warning applications will be lower for the distracted or inattentive driver since, lacking situational awareness, they will be more likely to be surprised by the warning and its contextual meaning. As a result, they suggest that warning timing should be calibrated to these types of inadvertent violators (in the context of red-light violations) rather than “malicious” violators who are aware of what they are doing and will maintain faster reaction times. That said, reaction times vary depending on degree of distraction and specific aspects of the intersection and situation, making it very difficult, if not impossible, to create generalizable values [89].

2.3 Summary

In conclusion, the studies reviewed above made the following points about driver behavior when crossing intersections in the presence of oncoming traffic.

- There is strong evidence that variables such as intersection approach, the size of gaps when drivers turn, and crossing behavior vary substantially between individual intersections.
- There is strong evidence that individual trajectories vary substantially due to conditions such as a lead vehicle being present and what traffic signal (e.g., red or green light) the driver encounters.
- Age effects have been seen in gap selection behavior, but do not show up in all variables. They were not seen in turning time or stopping location, for example.
- Gender effects appear in some studies but not others.
- Models of driver behavior need to include an array of variables in order to accurately predict driver behavior.

3 Analysis of Baseline Driving

This chapter describes an analysis of normal or "baseline" driver behavior while crossing or making left or right turns at intersections with oncoming traffic. The analysis is designed to support the goal of knowing when alerts should and should not be issued by identifying metrics that describe how drivers navigate through intersections in such scenarios. This information can be used in test procedures and to assist developers in designing and implementing more effective (reduced nuisance alert) applications.

To accomplish these aims, the analysis focuses on two questions.

1. What characterizes a typical intersection crossing?
2. What variables affect/indicate a driver's decision to cross?

The analysis is a post hoc exploration of the data from two recent naturalistic driving studies. After a brief description of these data sources, the methodology of the analysis and the results are presented. Results are discussed in Section 5.

3.1 Data Sources

The two databases used for this analysis are the Safety Pilot Model Deployment [90] and Driver Adaptation [91]. Brief descriptions of the studies can be found by reading the full reports.

3.1.1 Safety Pilot Model Deployment

As part of the U.S. DOT's Intelligent Transportation Systems research program, the Safety Pilot Model Deployment was conducted in 2012 to allow for an independent, real-world evaluation of a safety application system for passenger vehicles. The system, based on vehicle-to-vehicle (V2V) communication technology, issued alerts for potential collisions in a variety of different scenarios. The evaluation focused on application capability, safety impact, and driver acceptance.

The study included 127 participants who were balanced for gender and across three different age groups: 20-30, 40-50, and 60-70 years old. For six months, each participant drove a passenger vehicle that was provided by one of eight different auto manufacturers and was equipped with a fully integrated V2V system. All of the participants lived and worked in Ann Arbor, MI, and in addition to the integrated vehicles, approximately 2,390 other vehicles were equipped with vehicle awareness devices (VADs) capable of transmitting but not receiving V2V signals. These additional vehicles increased the likelihood that participants in the integrated vehicles would encounter V2V-transmitting vehicles on the road.

Each integrated vehicle contained six cameras and captured views in all directions as well as inside the cabin. The camera data was synched with multiple channels of data collected by the V2V system and by onboard sensors. Data, including video, was collected at a rate of 10 Hz whenever the vehicle ignition was turned on. These data channels included the following, excerpted from Nodine et al. [90].

- In-vehicle data, including vehicle inputs (e.g., steering/throttle/controls) and vehicle dynamics (e.g., speed/acceleration).
- V2V data, including information about other equipped vehicles within range (e.g., speed/heading/location).
- External sensors recording the location of surrounding objects and the vehicle's position within the lane (e.g., lane tracking/forward radar).
- Application data, including information about when and why alerts were issued to the participants.

In total, the integrated vehicles produced around 792 million records (at 10 Hz) and 22,000 hours of video. The data was collected and processed by Virginia Tech Transportation Institute and sent to the Volpe Center for further processing and analysis.

Within the Safety Pilot dataset, the driving data is organized by individual trips made by participant vehicles and drivers. A “trip” is created each time a driver started their vehicle from an off state. The 127 drivers made 97,542 unique trips during the research period.

All IMA events and some of the LTA events were found in the Safety Pilot dataset.

3.1.2 Driver Adaptation

The Driver Adaptation project, conducted by Leidos[3] under contract from the Volpe Center, assessed adaptation by drivers to vehicle-based collision warning systems in a naturalistic driving environment. Specifically, 37 volunteers—all Leidos employees under 30 who lived and worked in the Washington, DC, area—drove 24 Cadillac SRXs equipped with factory-standard advanced safety systems, including collision warning systems and automatic braking. Drivers used their vehicles for day-to-day driving for either 3, 9, or 12 months. Typically, their driving consisted of their commute to and from work. Subjects were balanced for gender, with 19 women and 18 men.

Each vehicle contained four cameras showing views to the front, the back, and two inside the cabin. The camera data was synched with multiple channels of data collected from a global positioning system (GPS) sensor, driver input (e.g., turn signal and brake light status), vehicle dynamics (e.g., speed, longitudinal and lateral acceleration), active safety systems (e.g., adaptive cruise control status), vehicle safety (e.g., automatic braking system status and traction control status), and radar. Data was collected whenever the ignition was on and GPS initiated.

The study produced around 374 million records (at 10 Hz) and 10,400 hours of video. This data was collected and processed by Leidos and sent to the Volpe Center.

The Driver Adaptation dataset was only queried for LTA events.

3.2 Methodology

In general, the methodology consisted of finding valid events through a combination of database querying and manual video review of the onboard video cameras, manually coding those videos, and statistically analyzing the resulting data set to identify typical crossing behavior and those parameters that had an effect on crossing behavior as measured in terms of the length of gaps drivers drove into. These steps are described in detail below.

The methodology used to identify intersection-crossing events evolved over the course of the study and a slightly different methodology was used for scenarios addressed by the LTA application and those addressed by the IMA.

3.2.1 LTA Event Selection

For the LTA application, i.e., LTAP-OD events, the general approach involved searching through the two databases for events where a driver made a left turn in the presence of oncoming traffic (without oncoming vehicles, there would be no gap to measure).

The following steps outline the approach used to identify LTAP-OD events that would be useful for this study.

[3] Leidos Holdings, Inc., formerly SAIC.

1. *Identify all instances where vehicles crossed intersections using their GPS coordinate feeds.*
2. *Determine which of those intersections were the busiest.*

   The busiest intersections—those with at least 75 percent participant driver engagement—were identified using the count of vehicle crossings relative to the entire database.

   However, reviewing these intersections using the onboard cameras revealed that most of the major intersections in the studies had left-turn arrow traffic signals (see Figure 10, which shows the intersection of Plymouth Road and South Huron Parkway in Ann Arbor). The presence of these signals meant that whenever a vehicle made a left turn at that intersection, drivers were guided by the light and not by a decision based on perceptions of risk or reflecting individual driving characteristics. Furthermore, when drivers turned at those intersections, another light halted oncoming traffic. This meant that these intersections, which included most of the busy intersections in the city, did not include LTAP-OD events useful for this study.

Figure 10. Left-Turn Arrows at an Intersection (Image Produced Using Google Street View)

As a result, a combination of query parameters and manual video review was used to find busy intersections without left-turn lights. This included looking at places where left-turn signals were less common, such as intersections between main roads and side roads (usually residential). Unfortunately, these roads had less traffic and therefore provided fewer useful events (see Figure 11, which shows the intersection of Green Hills Drive, Earhart Road, and Waldenwood Drive in Ann Arbor).

Google Maps was then used to identify which of those intersections in Ann Arbor and Washington, DC, had high traffic volumes.

Figure 11. A Residential Intersection (Image Produced Using Google Street View)

3. *Identify left-turn events at these intersections.*

   The next step was to identify left-turn events at the intersections found by the previous steps. The GPS system was not precise enough to accurately determine when a vehicle turned at an intersection, so vehicle dynamics were used as well. Specifically, we used steering wheel rotation less than 100 degrees counterclockwise (where zero means no rotation) and yaw less than -8 degrees for Safety Pilot and less than zero degrees for Driver Adaptation (the differences were due to slight differences in how the two datasets were set up).

4. *Confirm event validity, including oncoming traffic.*

   Not all left turns are made in the presence of oncoming traffic. To reduce the sample to those that are, i.e., to only LTAP-OD events, we had originally intended to look at cases where both vehicles were equipped with event data recorders (EDRs) for the Safety Pilot study since that would allow us to easily query instances where both vehicles were at the same intersection at the same time and approaching from the appropriate directions. Unfortunately, these events proved too infrequent to yield adequate LTAP-OD events and it was necessary to look through turn events manually using the onboard video cameras to identify those made in the presence of oncoming traffic.

3.2.2 IMA Event Selection

IMA events were identified via the following steps.

1. *Identify intersections where valid IMA alerts had been issued.*

   The prior analysis of IMA application warnings in the Safety Pilot Model Deployment [90] had involved manually confirming valid instances of IMA alerts. The locations of these events were used to identify intersections where drivers had performed IMA maneuvers.

2. *Subset to unsignalized and uncontrolled intersections.*

   Only intersections without traffic lights were used since signalized intersections tended to stop oncoming traffic and enabled drivers to cross without having to gauge gap sizes.

3. *Select return visits to intersection without issued alerts.*

   Since the analysis is of normal or baseline driving, events where alerts were issued were excluded.

4. *Confirm event validity, including oncoming traffic.*

   As with LTA events, valid events were confirmed via manual video review.

3.2.3 Video Coding

Once the validity of events was confirmed using video review, the videos were also used to glean information about a number of potentially useful aspects of the turn not available from the vehicle-sensor data. This video review was accomplished using a custom-built multi-data analysis tool that displayed all cameras and selected sensor data on a single screen (Figure 12). A complete list of the parameters recorded is given in Appendix B. In general, these parameters included the:

- Times when a driver first had an opportunity to turn, started to turn, reached the collision zone, and cleared the collision zone.
- Times when an oncoming vehicle reached and cleared the collision zone.
- Turn approach ("stop then go from stop line," "stop then go from inside intersection," "rolling speed," "full speed," "stop, start, stop, etc.," and "other").
- Environmental conditions like the lighting, weather, and road conditions.
- Intersection lanes and traffic-control signals present.
- Decision of the driver whether to go or not.

Figure 12. Screen Capture of Tool for Reviewing Onboard Camera Videos

3.2.4 Analysis Metrics

The following metrics were used in this study:

Gaps. For this study, a gap was defined as the amount of time available for a driver to reach and cross the point where its path intersects that of an oncoming vehicle—the “collision zone,” illustrated as red rectangles in Figure 13. A gap, therefore, included what other studies call a “lag” (see Section 2.2.1 for a discussion of the complexities of gap measurement).

Characterizing gap preference across multiple events will be accomplished by plotting raw data, presenting ranges and standard deviations alongside measures of central tendency, like mean and median. Critical gaps will not be calculated since, as articulated by Gorjestani et al. [1], and as summarized in Section 2.2.1, they are suited more to highway capacity and sightline modeling than to safety applications designed to modify driver behavior.

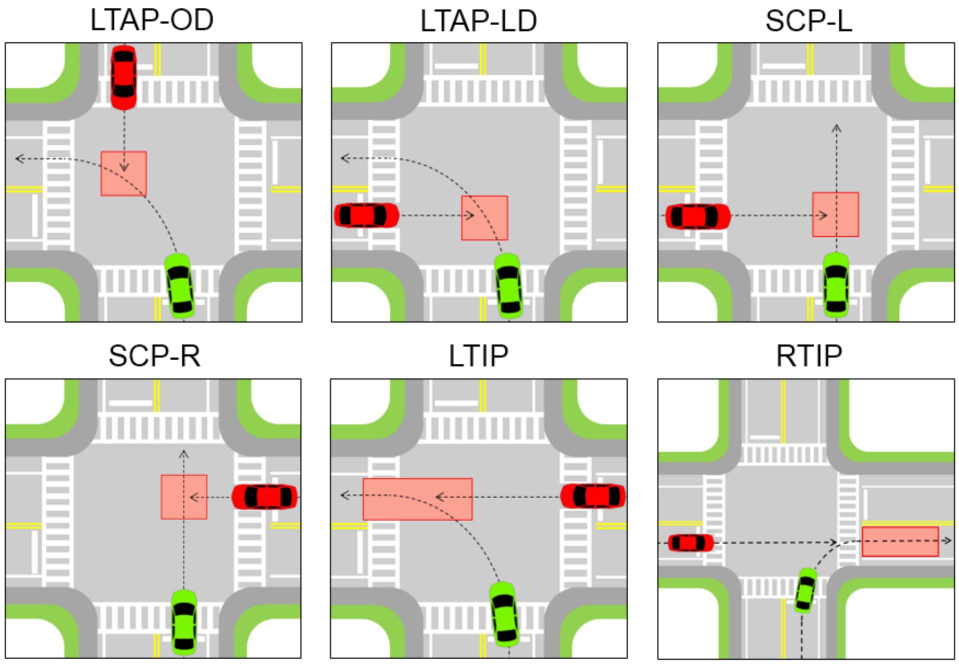

Figure 13. Depiction of the Collision Zones

Gaps could be either "accepted" (the driver proceeds into it) or "rejected" (the driver waits for the vehicle to pass before proceeding). Both had their own criteria for measurement:

- **Accepted Gaps.** When a driver chose to drive into a gap, the length of the gap was measured from when the driver started to cross until the oncoming vehicle reached the collision zone. For a turning event, start time was recorded from when the yaw rate (determined using onboard sensor data), consistently increased beyond 2 degrees per second. For a straight crossing, start time was recorded either as the time stamp when the vehicle started to accelerate or when the driver crossed the white intersection line (if one was present). The end of the gap, when the oncoming vehicle reached the collision zone, was identified using video review. The video was recorded at a rate of 10 frames per second and by using rear- or side-facing cameras and advancing one frame at a time, the position of the oncoming vehicle in the intersection could be measured.

  Estimating the collision zone was particularly difficult for LTIP and RTIP scenarios because they involved accelerating into position ahead of the oncoming vehicle rather than simply crossing paths for a short time. That is the reason the collision zones in Figure 13 are not squares but rather elongated rectangles. Since a longer rectangle would affect how long the oncoming vehicle is in the collision zone but not necessarily when it entered it, we would not expect this to have a significant effect on gap estimates compared to the other scenarios. However, the larger collision zone size combined with the need to use the rear-view cameras to track the oncoming vehicle mean that there could be more variation and less accuracy in the gap estimates for these two scenarios.

- **Rejected Gaps.** When a driver chose to pass on a gap, the length of the gap was measured from when the driver reached the intersection and was first able to cross (after any vehicles ahead in a queue had gone) until the oncoming vehicle reached the collision zone. This first opportunity to turn was noted based on more complicated criteria: of three events—the time when the front wheels reached the solid white intersection line, the time when the vehicle became the first in the queue to go, and the time when oncoming traffic had cleared the collision zone—the time stamp for the last to occur was chosen.

Other metrics. There were a number of potentially useful metrics in the two databases beside gaps.

- Speed
- Acceleration
- Brake and throttle timing
- Steering wheel angle
- Intersection geometry (e.g., dedicated turning lane, number of crossing lanes, traffic control device)
- Gender and age
- Environmental conditions (e.g., day versus night, weather, road surface condition)
- Turn signal usage
- Glare
- Obstruction of the driver's vision
- Distraction status of the driver

We explored these metrics but structured the analysis around gap length, since the question, "Do I have time to cross?," is at the heart of the driver's dilemma in LTA and IMA scenarios. This meant that the analysis was structured around determining typical accepted gap lengths and whether or not these accepted gap lengths were affected by the other variables.

3.2.5 Statistical Analyses

This analysis is comprised of post hoc explorations of a preexisting data set. Since we highlighted interesting and meaningful results from a larger set of results, the probabilities associated with *p*-values and similar significance testing do not apply as they do when testing a preconceived, specific question. The results of exploratory analyses reflect patterns in the particular data set analyzed; additional tests on different data sets are required to establish whether those patterns are real and exist in the world in general.

Effect sizes. Due to the limited use of inferential statistical tests in this analysis, effect sizes with 95 percent confidence intervals (CI) were reported instead of *p*-values. There are multiple ways to measure effect sizes. We used two methods in this analysis: one for comparisons between two groups, and one for comparisons of three or more groups.

- **Cohen's *d*.** The primary measure of effect size used was Cohen's d, which is the difference in the means for two conditions normalized by dividing by the standard deviation. A d of zero means no effect at all and a d of one indicates an effect size of one standard deviation. Although values of d can be outside the range from -3 to 3, at those magnitudes, 100 percent of one group will be below or above the other group's mean. Effect sizes typically are interpreted with values around 0.2 as small, around 0.5 as medium, and over 0.8 as large [92]. Wherever possible, results were also described in real-world terms to aid in clarity.
- **Eta-squared (η^2).** Since Cohen's d can only be used to compare two groups, η^2 was used instead when there were more than two groups. Unlike d, which gives a standardized measure of a difference between means, η^2 is like r^2 in that it measures the proportion of variation in one variable that is explained by the other. A one-way analysis of variance (ANOVA) test is used to calculate η^2, and it is loosely interpreted on a scale from zero to one, with 0.02 as small, 0.13 as medium, and 0.26 as large. A downside is that η^2 is biased toward exaggerating effect sizes with

small sample sizes. However, this bias can be utilized in an exploratory study, since it can be considered an increase in sensitivity—if no effect is detected, the evidence that it does not exist is therefore stronger. Furthermore, η^2 has an advantage over alternatives in that it can be used to compare unequal sample sizes. For η^2 values only, the 90 percent CI was used instead of 95 percent CI since values cannot be less than zero.

Inferential statistics. In spite of the focus on effect sizes, there were a few instances in this analysis where standard inferential statistical tests were used. These instances included comparing data derived from different databases before pooling it. In these cases, parametric tests such as *t*-tests were used once normality was established using the Shapiro-Wilk test, and once equal variance was established using Levene's test. The reason for using inferential statistics in those cases is that they are pre-planned checks needed as part of the experimental design of conducting an exploration. When non-parametric tests like Mann-Whitney comparisons were used instead, medians and interquartile ranges (IQR) were reported instead of means and standard error.

Avoiding pseudoreplication. Multiple events were averaged per driver in order to avoid pseudoreplication, a form of double counting that falsely inflates the sample size, violates the assumption of independence behind any statistical tests used, and overly weighs drivers who have more events than the others [93].

Within- and between-subject comparisons. Comparisons were conducted within-subject (WS) whenever the sample size was large enough ($n \geq 8$). WS tests not only offer greater power for detecting differences, but are especially useful when dealing with small samples with large amounts of variation in behavior from one individual to the next. When there were insufficient subjects for a within-subject comparison, between-subject (BS) comparisons were conducted instead. In this analysis, the BS comparisons usually included a few drivers present in both groups, which should help to reduce the inter-subject "noise" in the data and make the signal more clear.

All statistical tests were conducted using RStudio, version 1.0.136 [94], which ran R version 3.3.2 (2016-10-31).

3.3 Results

Analyses of the data from the Safety Pilot and Driver Adaptation databases are presented below, starting with an overview of the number of events found, a comparison of the two databases, and exploration of individual variables like gap length, age, weather, etc. These results are discussed in Section 5.

3.3.1 Relevant Events and Involved Drivers

With both databases combined, the queries yielded 772 events, including 193 where drivers accepted the gap and 579 where they rejected it. The majority of these events were LTAP-OD events and the fewest were LTIP and SCP-R events (Table 4).

Table 4. Number of Events

Gap	LTAP-OD	LTAP-LD	LTIP	RTIP	SCP-L	SCP-R	Sum
Accepted	83	24	12	36	25	13	193
Rejected	136	37	119	151	80	56	579
Sum	219	61	131	187	105	69	772

These events were spread unevenly across 107 drivers, 71 of which had gap-accept events and 100 of which had gap-reject events (64 had both gap-accept and gap-reject events). Figure 14 shows the distribution of events per driver, broken down by scenario. Each bar in the chart shows the number of gap-accept events (dark blue, stacked below) and gap-reject events (light blue, stacked above) for each driver. The drivers are arranged along the horizontal axis in descending order of the number of gap-accept events they had. These numbers ranged for a given scenario from a minimum of one gap-accept event to a maximum of 18 (Table 5). The median number of crossing events for each scenario type was 1.0. Gap-reject events were more frequent and had medians ranging from 1.0 to 2.0 for individual scenarios.

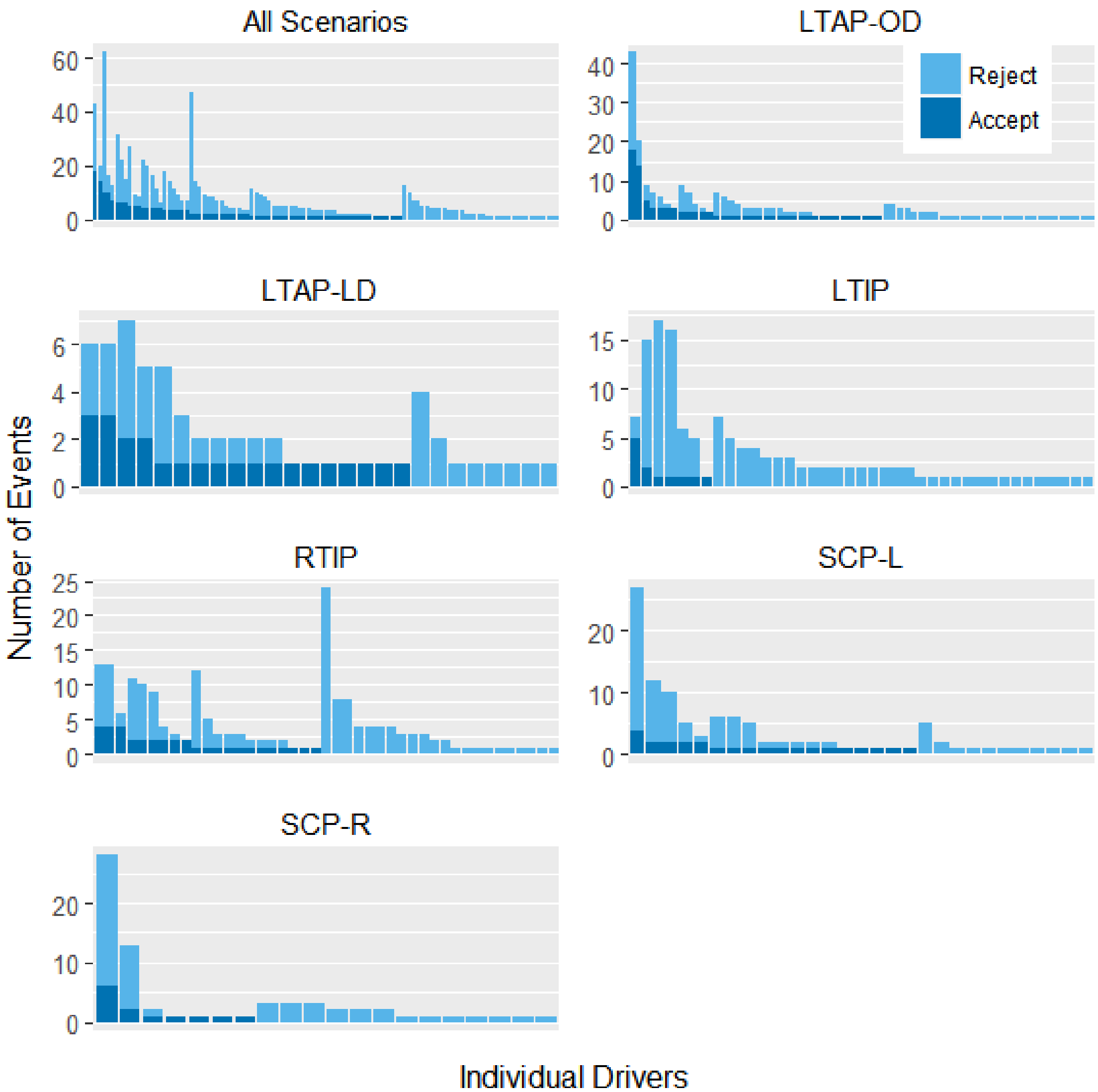

Figure 14. Number of Events per Driver

Table 5. Number of Events per Driver

Scenario	Accepted Gaps per Driver					Rejected Gaps per Driver				
	Median	Mean	SD	Range	*n*	Median	Mean	SD	Range	*n*
LTAP-OD	1.0	2.3	3.5	1 – 18	36	1.0	2.5	3.5	1 – 25	54
LTAP-LD	1.0	1.3	0.7	1 – 3	18	1.0	1.9	1.3	1 – 5	19
LTIP	1.0	1.7	1.5	1 – 5	7	2.0	3.1	3.7	1 – 16	38
RTIP	1.0	1.7	1.1	1 – 4	21	2.0	3.9	4.4	1 – 24	39
SCP-L	1.0	1.4	0.8	1 – 4	18	1.0	3.3	4.9	1 – 23	24
SCP-R	1.0	1.9	1.9	1 – 6	7	1.5	3.5	5.5	1 – 22	16
All Scenarios	2.0	2.7	3.1	1 – 18	71	3.0	5.8	8.0	1 – 52	100

More details on intersection types will be discussed below, but as an overview, the 193 gap-accept events in our sample took place at 33 different locations. These locations were primarily intersections, but also included side streets and parking lot entrances. Figure 15 shows the location of the events that took place in Ann Arbor, Michigan. Figure 16 shows overhead views of a sample of intersections where events took place in both Ann Arbor and Washington, DC.

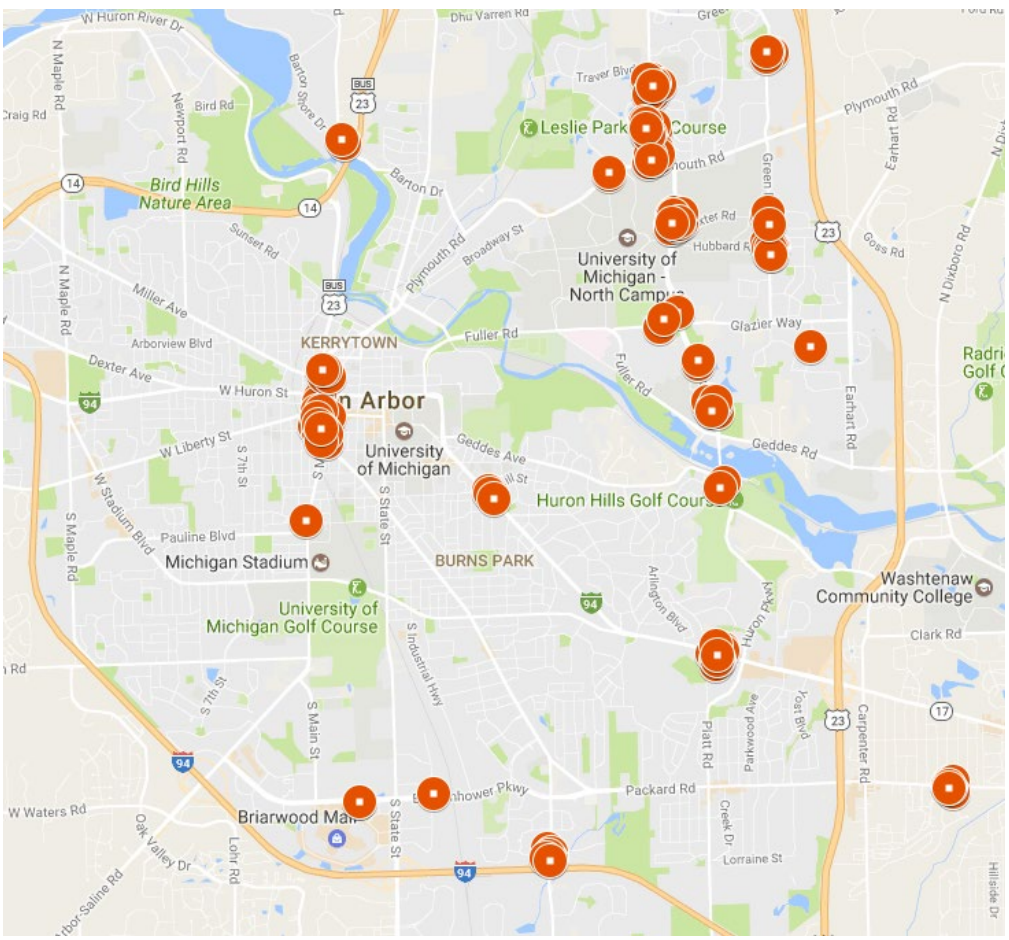

Figure 15. Location of Events in Ann Arbor (Image Produced Using Google Maps)

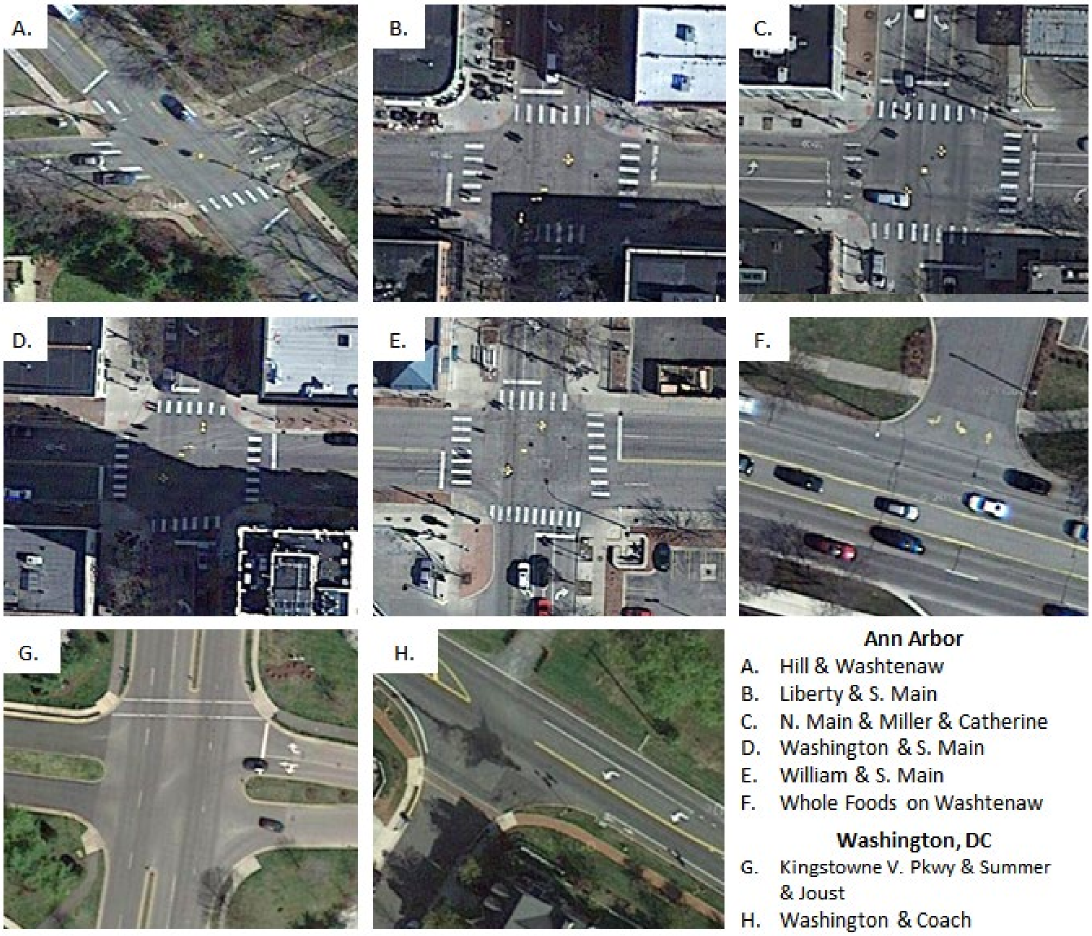

Figure 16. Sample Intersections Where Events Took Place (Images from Google Maps)

3.3.2 Pooling the Two Databases

Unlike the IMA events, which were all from the Safety Pilot dataset, LTA events (i.e., LTAP-OD events) were found in both Safety Pilot and Driver Adaptation (Table 6; note that since most drivers appear in both the gap-accepted and gap-rejected rows, the totals are not the sum of the number of accepts and rejects).

Table 6. LTAP-OD Counts by Database

Gap	Safety Pilot		Driver Adaptation		Total	
	Events	Drivers	Events	Drivers	Events	Drivers
Accepted	47	31	36	5	83	36
Rejected	90	46	46	8	136	54
Total	137	56	82	10	219	66

Average gap lengths varied slightly between databases: compared to Safety Pilot, the average accepted gap in Driver Adaptation was 0.2 s shorter and the average rejected gap was 0.6 s longer (Table 7). The difference between accepted gaps was not statistically significant (independent *t*-test, $t = -0.37$, df = 34, $p = 0.72$, two tailed). Figure 17 shows the distribution for each database, with the rectangles encompassing the bootstrapped 95 percent confidence intervals and the vertical line inside showing the mean. Since there was no clear evidence of a difference between the two databases, the data was pooled for all subsequent analyses of LTAP/OD events.

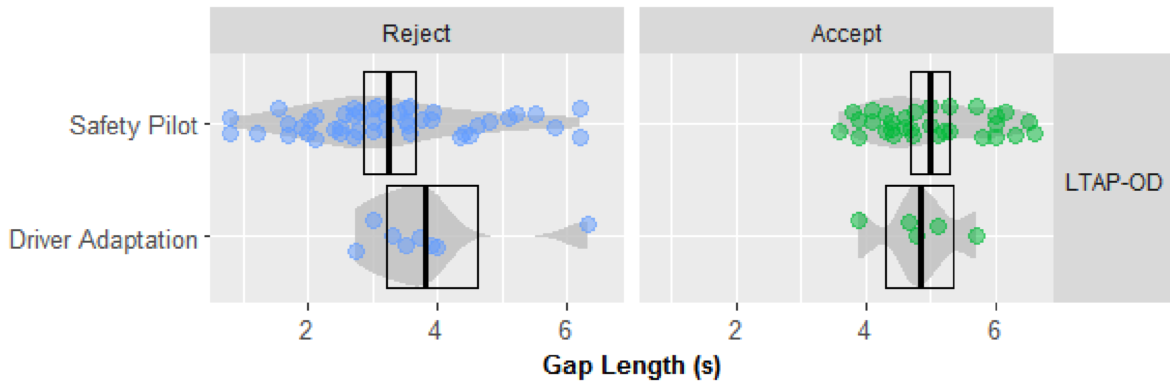

Figure 17. LTAP-OD Gap Lengths by Database

Table 7. LTAP-OD Gap Lengths by Database

Scenario	Gap	Database	Mean (s)	SD (s)	Range (s)	*n*
LTAP-OD	Accepted	Driver Adaptation	4.8	0.7	3.9 – 5.7	5
		Safety Pilot	5.0	0.9	3.6 – 6.6	31
	Rejected	Driver Adaptation	3.8	1.1	2.8 – 6.3	8
		Safety Pilot	3.2	1.3	0.8 – 6.2	46

3.3.3 Gap Lengths

Unless otherwise noted, all values are driver averages (with each point in a plot representing an individual driver). The effects other variables may have had on gap lengths will be discussed below in their own subsections.

As expected, for all types of scenarios, the average accepted gap was longer than the average rejected gap (Table 8) and effect sizes were large.[4] Figure 18 shows the individual driver values in a scatter plot and Figure 19 shows the same data as probability density functions (with blue for rejected gaps and green for accepted).

[4] Note: Only the subset of drivers with both accepted- and rejected-gap events could be used in the WS comparisons. Since not all drivers had both types of events, the WS sample sizes (*n*) are smaller than the BS sample sizes.

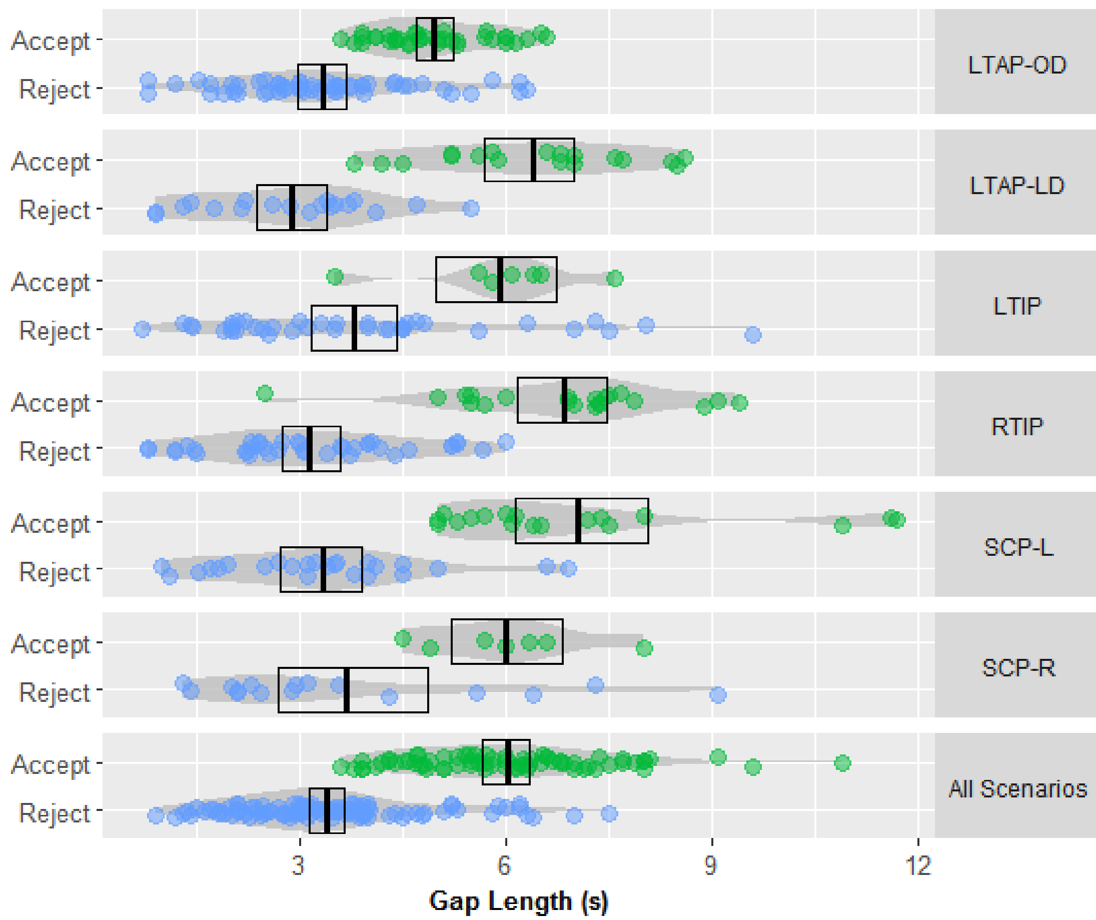

Figure 18. Gap Lengths by Scenario (Scatter Plot)

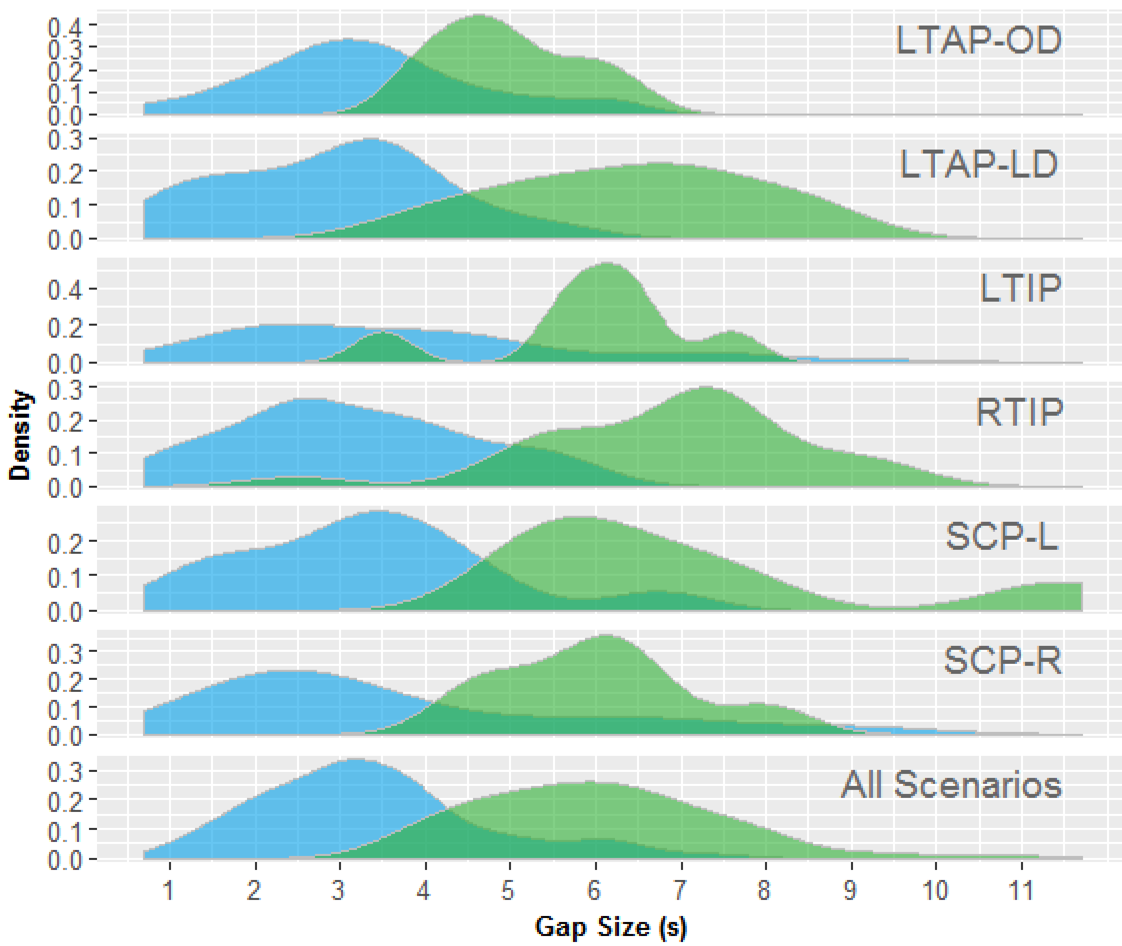

Figure 19. Gap Lengths by Scenario (Probability Density Function)

Table 8. Gap Lengths by Scenario

Scenario	Gap	Mean (s)	SD (s)	Range (s)	*n*	Effect Size (*d*, 95% CI)
LTAP-OD	Accepted	5.0	0.8	3.6 – 6.6	36	Large (WS, *n* = 24)
	Rejected	3.3	1.3	0.8 – 6.3	54	1.2 (0.6 – 1.9)
LTAP-LD	Accepted	6.4	1.5	3.8 – 8.6	18	Large (WS, *n* = 11)
	Rejected	2.9	1.3	0.9 – 5.5	19	3.0 (1.6 – 4.4)
LTIP	Accepted	5.9	1.3	3.5 – 7.6	7	Large (BS)
	Rejected	3.8	2.1	0.7 – 9.6	38	1.1 (0.2 – 2.0)
RTIP	Accepted	6.8	1.6	2.5 – 9.4	21	Large (WS, *n* = 18)
	Rejected	3.2	1.4	0.8 – 6.0	39	2.8 (1.8 – 3.9)
SCP-L	Accepted	7.1	2.2	5.0 – 11.7	18	Large (WS, *n* = 13)
	Rejected	3.4	1.5	1.0 – 6.9	24	1.4 (0.4 – 2.3)
SCP-R	Accepted	6.0	1.2	4.5 – 8.0	7	Large (BS)
	Rejected	3.7	2.3	1.3 – 9.1	16	1.2 (0.1 – 2.2)
All Scenarios	Accepted	6.0	1.4	3.6 – 10.9	71	Large (WS, *n* = 64)
	Rejected	3.4	1.3	0.9 – 7.5	100	1.5 (1.1 – 1.9)

There was a large effect of scenario for accepted gaps ($\eta^2 = 0.27$, 90 percent CI = 0.1 – 0.4). Much of this effect seems to be due to the LTAP-OD gaps being smaller, since all pairwise comparisons with LTAP-OD events yielded a large effect (Cohen's $d > 1.1$). Pairwise comparisons between the other scenarios varied from negligible ($d \leq 0.02$) to medium ($d \leq 0.6$).

The lower end of the range may be one of the more useful measures provided since the mean is so dependent on the upper end of the range. Since the minimums are averages of driver averages, it is possible that more extreme event minimums are hidden by the averaging. However, the minimums by event were generally the same as by driver since many drivers have only one event to average: The only scenarios with events shorter than the minimum by-driver averages were LTAP-OD, which had a gap of 3.0 s (by-driver minimum = 3.6 s) and SCP-L, which had a gap of 4.9 s (by-driver minimum = 5.0 s).

Another way to show the relationship between gap length and turning is with a cumulative density distribution showing the percent of drivers who have accepted a gap by the time it reaches a certain length (Figure 20). The figure also shows the percent of gaps that have been rejected as a function of length. For all scenarios combined, 80 percent of accepted gaps were 7.1 s or less. For the individual scenarios, the 80th percentile gap size was smallest for LTAP-OD and longest for SCP-L (Table 9).

Table 9. 80th Percentile Gap Lengths

Scenario	80th Percentile Accepted Gap (s)
LTAP-OD	5.8
LTAP-LD	7.7
LTIP	6.5
RTIP	7.7
SCP-L	7.8
SCP-R	6.5
All Scenarios	7.1

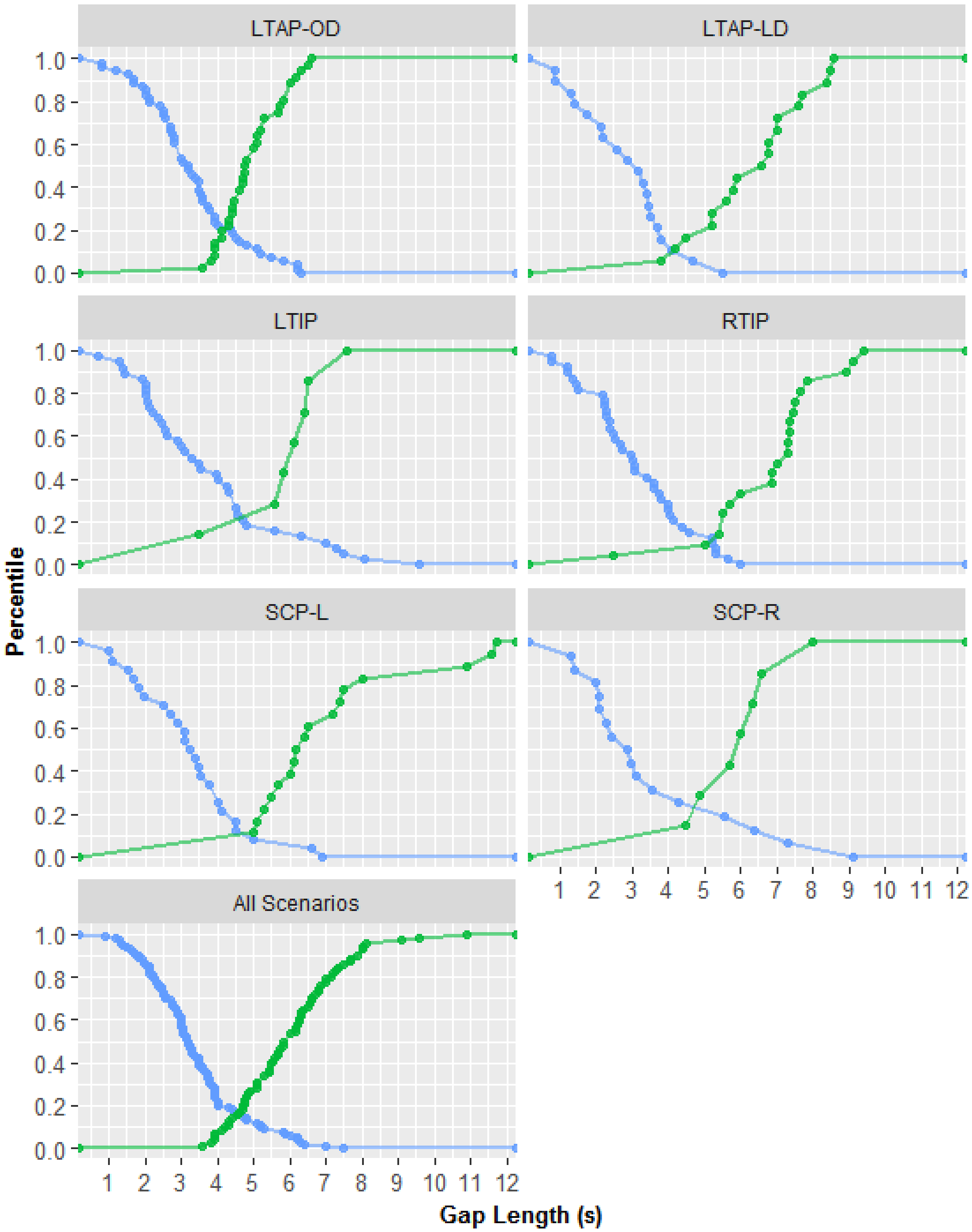

Figure 20. Cumulative Density Percentiles by Gap Length

3.3.4 Speed

GPS data was too imprecise to align vehicle crossing speeds based on their location in the intersection, so crossings were synchronized based on maneuver start time, which was identified during video review and set as time zero. The crossing speeds are plotted in Figure 21. For this and other plots of turn speeds, individual events were not averaged by driver and each line represents a single event. This means that some drivers are overrepresented; in total, there were 190 events for 71 drivers. The black lines indicate the average speed profiles for the events in that plot.

IMA crossings generally started from stop (or nearly stopped), but LTA events also included turns made without stopping. For clarity, LTA events without stopping were put into a separate bin if the turning vehicle's speed never dropped below 4 mph. Based on this criterion, 49 vehicles came to a stop and 34 drove through without stopping. The average speed values at the start of the crossing and after 10 seconds are shown in Table 10.

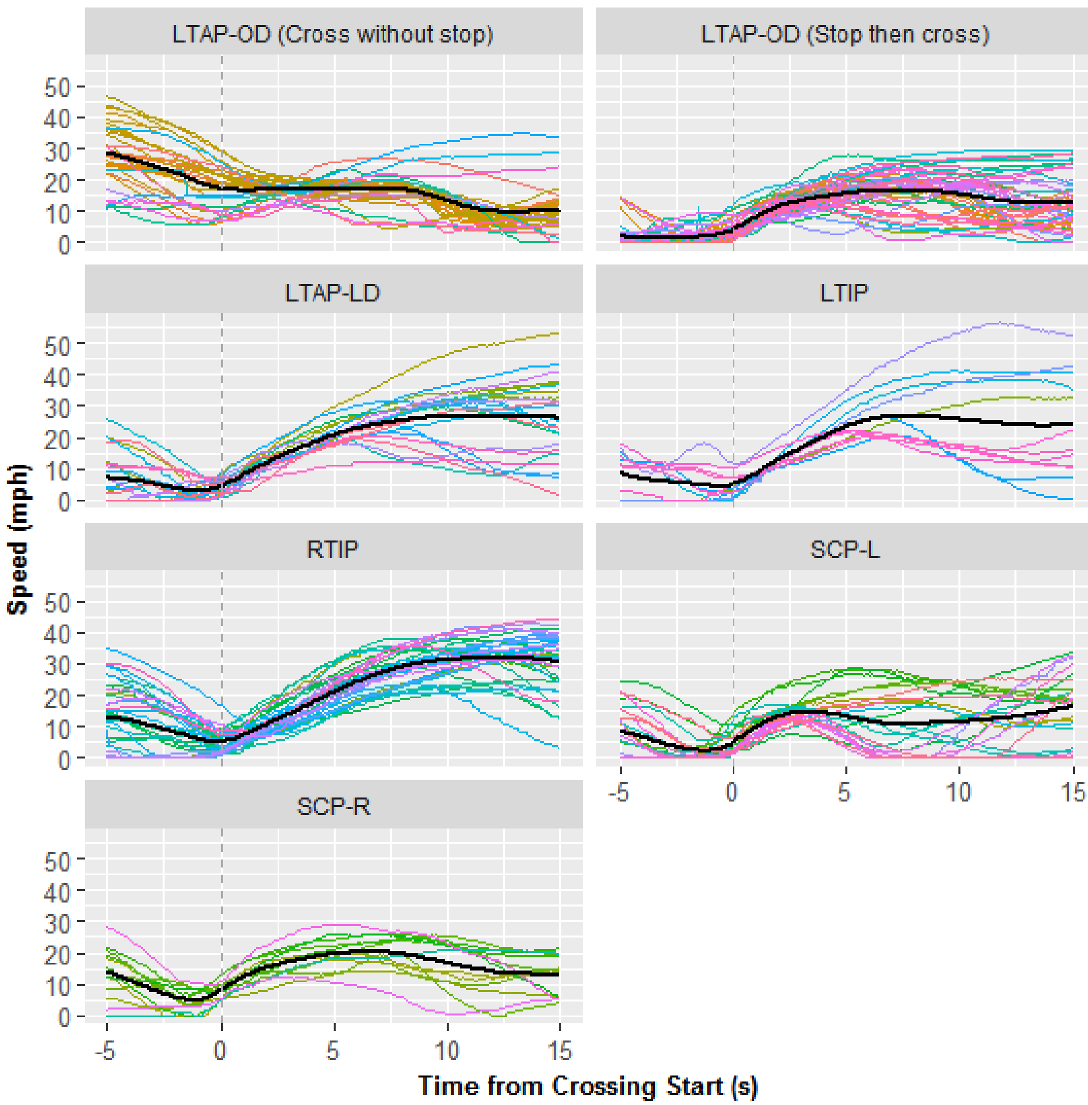

Figure 21. Speed While Crossing

Table 10. Average Speeds at Start and 10 Seconds Later

Scenario	Average speed at start (mph)	Average speed 10 s later (mph)	*n*[5]
LTAP-OD (Cross without stop)	17.3	13.3	34
LTAP-OD (Stop then cross)	4.3	15.4	49
LTAP-LD	4.5	26.6	23
LTIP	5.2	25.7	12
RTIP	5.3	31.2	36
SCP-L	5.2	11.5	25
SCP-R	8.3	16.7	13

3.3.5 Acceleration

Speeds for the first 2 seconds of acceleration are shown on the left in Figure 22 (turns made without stopping are omitted). Since some vehicles crawled for a while before accelerating into the curve, the two-second windows were started only when the vehicle had achieved a speed of 4 mph. Only windows overlapping the point of maximum turn were used. For each line, the solid part of the line indicates the selected window and the dotted line the unselected part. The heavy black lines indicate the average speeds for the lines in that plot where there were at least six events to average.

The frequencies of the speed changes for each event over the window are plotted on the right side of Figure 22, with the vertical red lines indicating the median changes in speed (Table 11).

Table 11. Acceleration Over the First 2 s

Scenario	Mean (m/s^2)	Median (m/s^2)	Range (m/s^2)	*n*
LTAP-OD (from stopped)	1.7	1.7	0.6 – 3.2	41
LTAP-LD	1.9	1.9	1.1 – 3.0	19
LTIP	2.2	2.3	1.4 – 3.3	8
RTIP	1.7	1.8	0.7 – 2.6	19
SCP-L	2.1	2.0	1.3 – 3.2	12
SCP-R	1.9	2.1	0.6 – 3.2	7
All scenarios (from stopped)	1.8	1.8	0.6 – 3.3	106

[5] These scenario totals sum to 192, rather than 190. The reason for this is that for two events where a subject was making a left turn, oncoming vehicles were approaching from both the left (LTAP-LD) and right (LTIP), meaning the same turn shows up in both of those plots for those two people.

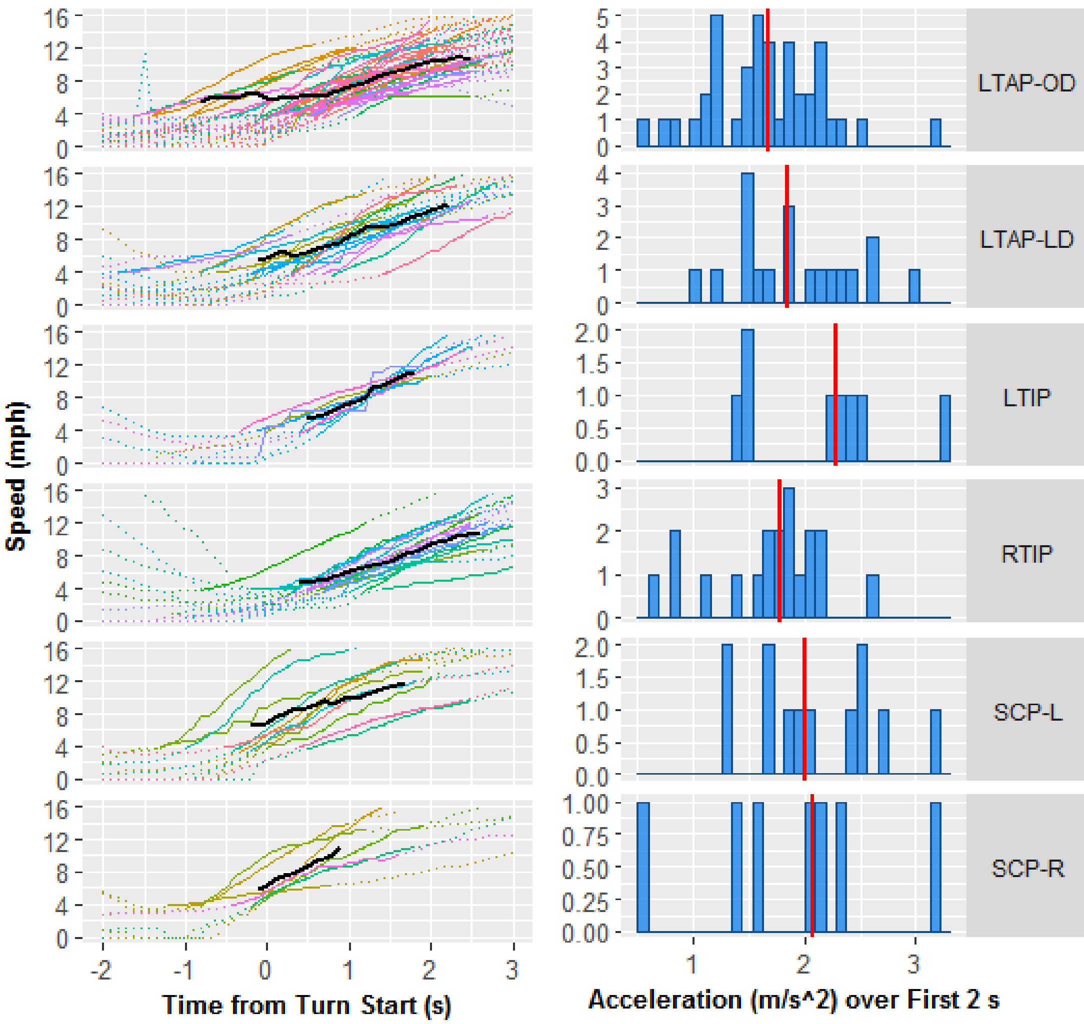

Figure 22. Speeds for the First 2 Seconds and the Frequency of the Changes in Speed

Although we might expect the acceleration to be stronger for smaller gaps, there was no clear or consistent relationship between those variables across different scenarios (see Figure 62 in Appendix D).

3.3.6 Brake and Throttle Timing

To visualize driver input on the vehicle controls, in particular the relationship between brake and throttle use, data was plotted for each intersection crossing event. Figure 23 below shows the LTAP-OD events and Figures 55 – 59 in Appendix C show the other scenarios. Red rectangles indicate brake activation and the thickness of the horizontal blue lines indicates percentage of throttle depression. Black brackets indicate the gap into which the driver turned, starting with their first opportunity to turn (judged during video review and used to synchronize the different events) and ending when the oncoming vehicle reached the collision zone. The angle brackets (“<” and “>”) indicate when the vehicle was in the collision zone. Not all vehicles in Safety Pilot reported throttle data and events with no throttle were dropped.

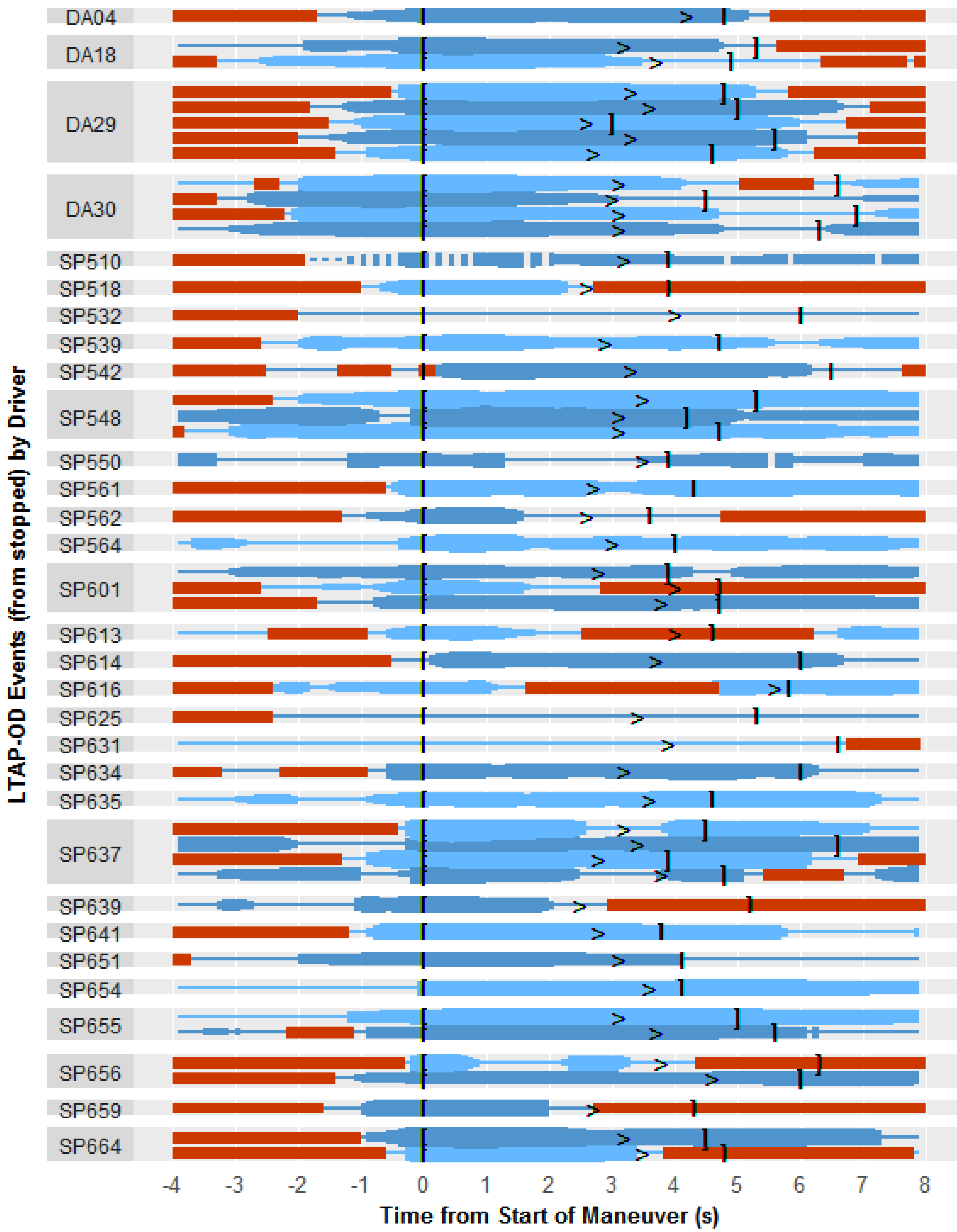

Figure 23. Brake and Throttle for Individual LTAP-OD Events

Brake-to-throttle delay. The mean delay between brake release (the last time the brakes were on before the start of the maneuver) until the first application of throttle (to over 4.5 percent) was 0.5 s for all scenarios combined, and ranged from 0.1 s for LTAP-LD to 0.8 s for RTIP (See Table 32 and Figure 60 in Appendix C for more details).

As can be seen above in Figure 23 (and in Figures 55 – 59 in Appendix C), in some cases the first throttle application was not the main one powering the vehicle through the turn.

Throttle-to-gap delay. Nearly all drivers increased their throttles before the start of the gaps (itself usually measured by vehicle yaw). This delay, from throttle application (to past 4.5 percent) to gap start had a median value of 0.8 s for all scenarios combined, and ranged 0.1 s for RTIP to 1.1 s for SCP-R (see Table 32 and Figure 61 in Appendix C).

3.3.7 Steering Wheel Angle

Steering wheel angles were plotted over the course of turns in Figure 21. The horizontal axis shows time from the start of the turn (denoted as time zero), and the vertical axis shows the steering wheel angle, with zero denoting no turn and positive values denoting right turns. The black lines show the average steering wheel angle for that scenario.

Unfortunately, the data recorders for Safety Pilot appeared to max out at 189 degrees (positive and negative), resulting in a plateau that obscured the true peaks of the wheel rotations. Since this artifact did not exist for Driver Adaptation events, a second average line (the dashed line) was plotted for the LTAP-OD scenario (the only scenario for which Driver Adaptation data was available) for Driver Adaptation cases.

The division of LTAP-OD into two bins based on whether or not the vehicle stopped first is the same as was used for the speed curves above.

Like for turn speed, individual events were not averaged by drivers for this plot and each line represents a single event. This means that some drivers are overrepresented; there were 151 events for 61 drivers.[6]

The average steering wheel angle at the start of the turn and at the maximum point of the turn is shown by scenario in Table 12.

Table 12. Average Steering Wheel Angle at Turn Start and at Maximum

Scenario	Average steering-wheel angle at start (degrees)	Average maximum steering wheel angle (degrees)	*n*
LTAP-OD (Cross without stop)	49.6 (DA* = 55.0)	146.6 (DA = 138.8)	34 (DA = 24)
LTAP-OD (Stop then cross)	83.3 (DA = 55.7)	195.0 (DA = 250.2)	49 (DA = 12)
LTAP-LD	72.6	183.1	23
LTIP	112.6	188.7	11
RTIP	106.7	165.5	34

** DA = Driver Adaptation events only*

[6] There were 151 events in the steering wheel data even though there were 155 gap-accept turning events because of dropping the two events mentioned in Footnote 5 and due to missing data.

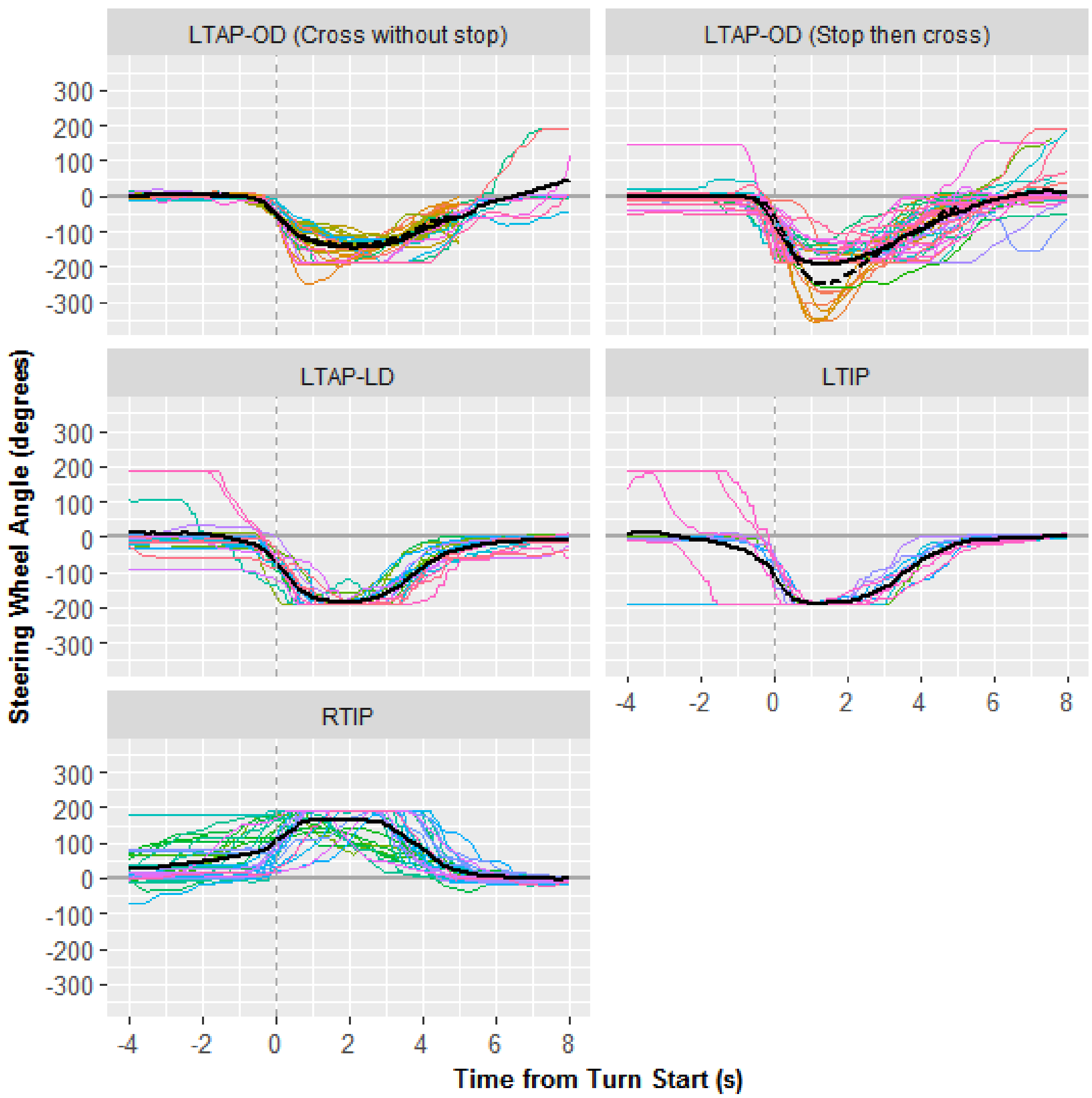

Figure 24. Steering Wheel Angle While Crossing

3.3.8 Intersection Geometry

Intersection geometry was evaluated in terms of the number of lanes the driver had to cross (crossing lanes), whether or not there was a dedicated turning lane, what kind of traffic control device was present, the specific intersection, or the type of intersection in terms of the number of intersecting streets.

Crossing Lanes. One factor likely to play a role in the decision of how long a gap needs to be in order to turn or cross is the number of lanes that turn or crossing straight has to cross. For this variable, data was available only for LTAP-OD events.

Of 83 gap-accept events, 41 involved crossing one lane and 42 crossing two lanes. Surprisingly, the average gap into which drivers turned was longer when there was only one lane to cross (5.1 s) than when there were two lanes (4.9 s) (Figure 25, Table 13). However, the difference was small (BS comparison, $d = 0.3$; insufficient cases for a WS comparison, $n = 4$), with 61 percent of gaps being longer with one lane than the average gap length for two lanes.

For rejected gaps, the effect occurred in the opposite direction. The difference in means was larger, but so was the variation, so the effect was small.

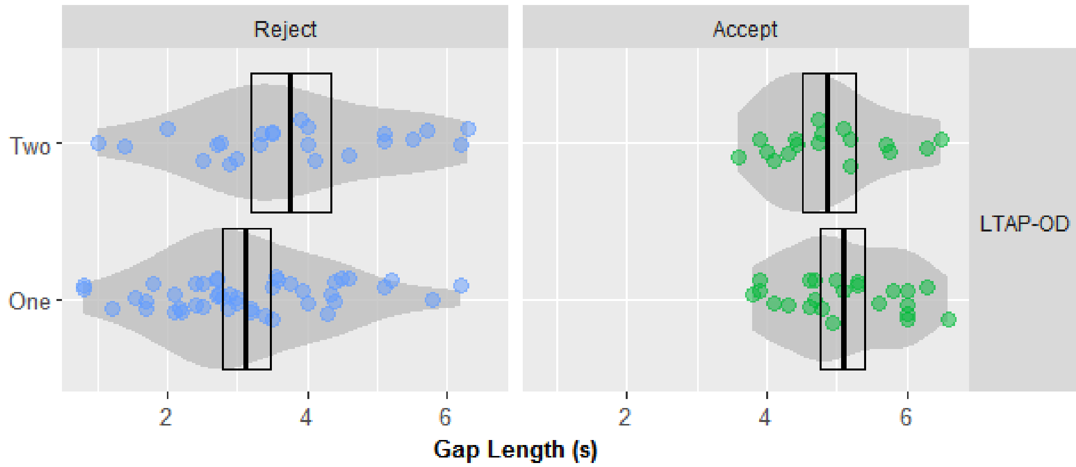

Figure 25. Gap Lengths Compared by Crossing Lanes

Table 13. Gap Lengths Compared by Crossing Lanes

Gap	Scenario	Crossing Lanes	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
Accepted	LTAP-OD	One	5.1	0.8	3.8 – 6.6	23	Small (BS) 0.3 (0 – 0.95)
		Two	4.9	0.8	3.6 – 6.5	17	
Rejected	LTAP-OD	One	3.1	1.2	0.8 – 6.2	44	Small (WS, *n* = 13) 0.3 (0 – 1.2)
		Two	3.8	1.4	1.0 – 6.3	23	

Dedicated Turning Lanes. Information on whether the turning vehicle was located in a dedicated turning lane was also available only for LTAP-OD. Of 83 gap-accept events, 58 events (70 percent) were made from dedicated turning lanes. However, although subjects turned into slightly shorter gaps from dedicated turning lanes (4.9 s) than from regular lanes (5.2 s), the effect size was small (Table 14). There were again insufficient cases for a WS comparison ($n = 2$).

Likewise the average length of rejected gaps was shorter when there was a dedicated turning lane (3.0 s) than when there was none (3.8 s). The effect was stronger: 70 percent of rejected gaps were longer when there was no dedicated turning lane.

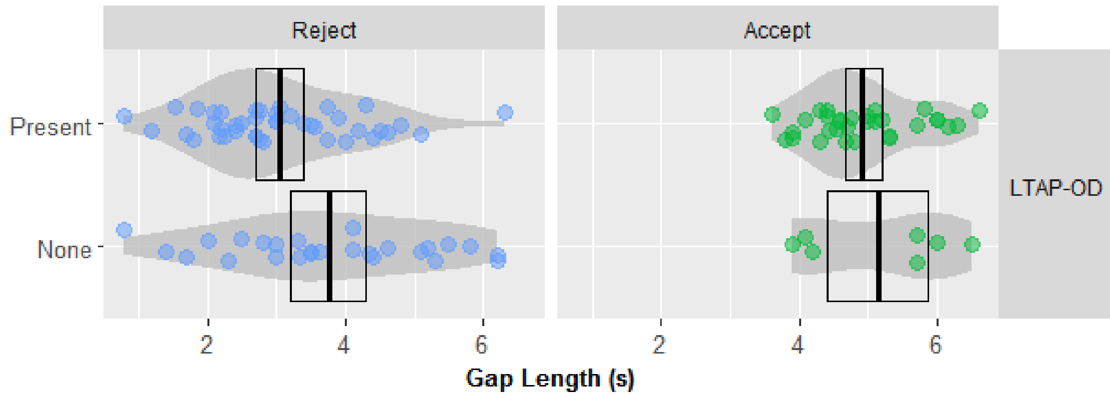

Figure 26. Gap Lengths Compared by Dedicated Turning Lane

Table 14. Length of Gaps With and Without Dedicated Turning Lanes

Gap	Scenario	Dedicated Turn Lane	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
Accepted	LTAP-OD	None	5.2	1.1	3.9 – 6.5	7	Small (BS) 0.3 (0 – 1.2)
		Present	4.9	0.8	3.6 – 6.6	31	
Rejected	LTAP-OD	None	3.8	1.5	0.8 – 6.2	26	Medium (WS, *n* = 14) 0.5 (0 – 1.3)
		Present	3.0	1.1	0.8 – 6.3	42	

Traffic Control Device. There were three types of traffic control devices in our data set: stop signs, traffic lights, and uncontrolled intersections.[7] These included 111, 37, and 44 gap-accept events in the data set, respectively (data was also missing for one event). All of the events with lights were LTAP-OD events. The other scenarios all only had gap-accept events at stop signs.

There were no drivers with events at all three types of devices so a within-subjects comparison was impossible. Between-subject comparisons were also not possible, since the number of events at stop signs (n = 2) was too small to be reliable. See Table 33 and Figure 63 in Appendix E for details.

Intersection ID. Cassidy et al. [2] advised against pooling across different intersections due to variability in gaps. To investigate this variability in our data set, all intersections with at least two gap-accept events per scenario were plotted by intersection ID in Figure 27. This yielded 22 intersections in total, including 8 for LTAP-OD, 5 for LTAP-LD, 2 for LTIP, 4 for RTIP, 3 for SCP-L, and 2 for SCP-R (some intersections were the site of multiple kinds of scenarios and so may be counted multiple times, which is why these numbers sum to 24 rather than 22).

The length of the average accepted gap at the 8 busiest intersections in the data set (the intersections with the most events) varied from 4.4 to 7.7 s (see Table 15, in which the intersections are ordered by mean gap size). The amount of variation explained by this intersection breakdown for all scenarios combined was large. By scenario, the effect was also large for SCP-R, although this was only a comparison of two intersections. The effect was medium for SCP-L, LTAP-OD, LTIP, and RTIP, and small for LTAP-LD. Rejected gap sizes varied as well, particularly for LTAP-LD and LTAP-OD (see Table 34 in Appendix E for details).

[7] A description of intersection types can be found at www.ite.org/uiig/types.asp.

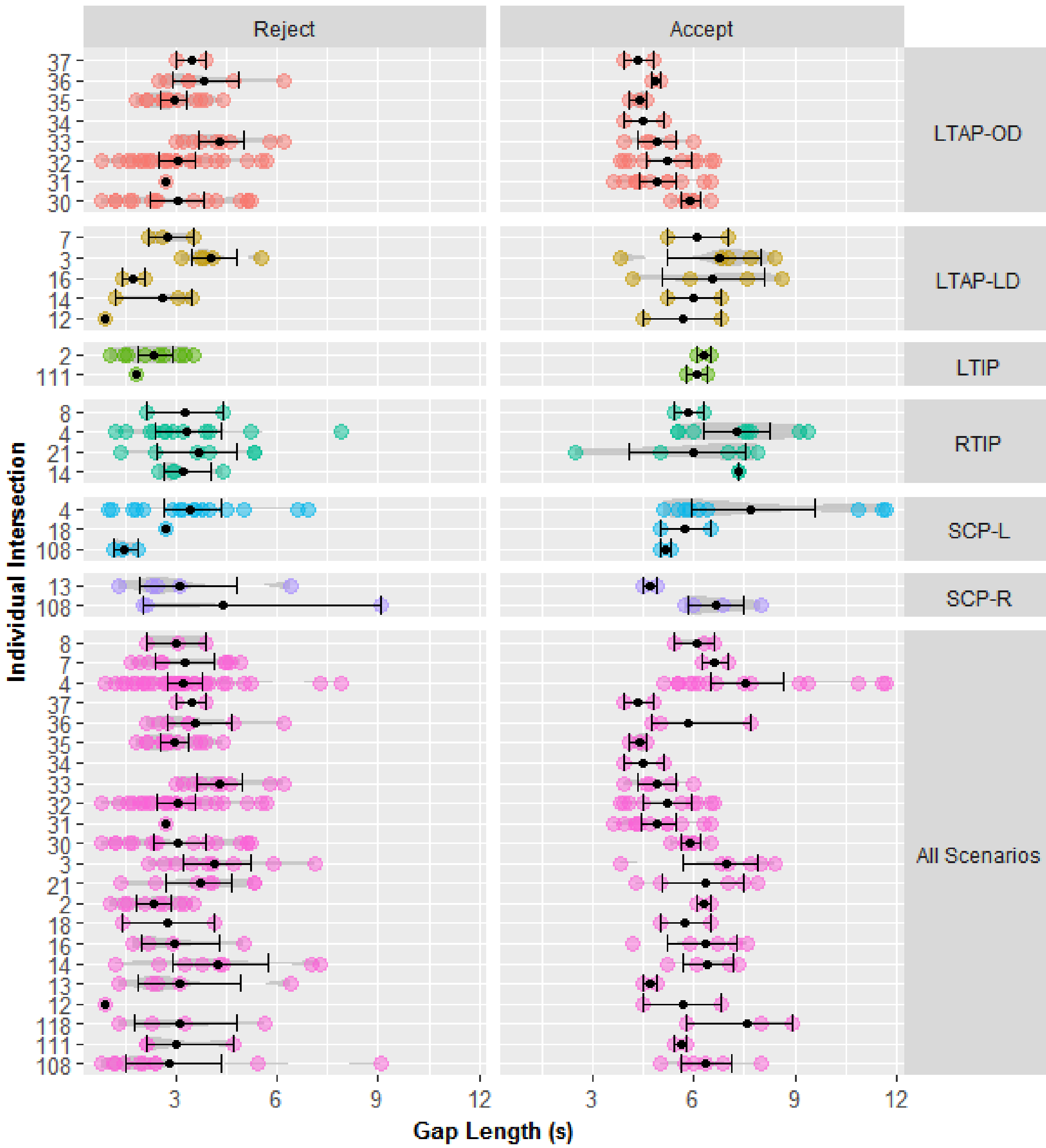

Figure 27. Gap Lengths for Individual Intersections

Table 15. Accepted Gap Lengths for Individual Intersections

	Intersection	Mean (s)	SD (s)	Range (s)	*n*	Effect Size
LTAP-OD	35	4.4	0.3	4.1 – 4.6	3	Medium (BS) η^2 = 0.2 (90% CI: 0 – 0.3)
	37	4.4	0.6	3.9 – 4.8	2	
	34	4.5	0.8	3.9 – 5.1	2	
	31	4.9	0.9	3.6 – 6.5	11	
	33	4.9	0.8	3.9 – 6.0	5	
	36	4.9	0.2	4.7 – 5.0	2	
	32	5.2	1.2	3.8 – 6.6	9	
	30	5.9	0.4	5.3 – 6.5	6	
LTAP-LD	12	5.6	1.6	4.5 – 6.8	2	Small (BS) η^2 = 0.07 (90% CI: 0 – 0.04)
	14	6.0	1.1	5.2 – 6.8	2	
	7	6.1	1.3	5.2 – 7.0	2	
	16	6.6	1.9	4.2 – 8.6	4	
	3	6.7	1.8	3.8 – 8.4	5	
LTIP	111	6.1	0.4	5.8 – 6.4	2	Medium (BS) η^2 = 0.13 (90% CI: 0 – 0.5)
	2	6.3	0.3	6.1 – 6.5	2	
RTIP	8	5.9	0.6	5.4 – 6.3	2	Medium (BS) η^2 = 0.17 (90% CI: 0 – 0.3)
	21	6.0	2.2	2.5 – 7.9	5	
	4	7.3	1.5	5.5 – 9.4	8	
	14	7.3	0.0	7.3 – 7.3	2	
SCP-L	108	5.1	0.2	5.0 – 5.3	2	Medium (BS) η^2 = 0.17 (90% CI: 0 – 0.4)
	18	5.8	1.1	5.0 – 6.5	2	
	4	7.7	2.8	5.1 – 11.7	9	
SCP-R	13	4.7	0.3	4.5 – 4.9	2	Large (BS) η^2 = 0.61 (90% CI: 0 – 0.8)
	108	6.6	1.0	5.7 – 8.0	4	
All Scenarios	35	4.4	0.3	4.1 – 4.6	3	Large (BS) η^2 = 0.39 (90% CI: 0.1 – 0.4)
	37	4.4	0.6	3.9 – 4.8	2	
	34	4.5	0.8	3.9 – 5.1	2	
	13	4.7	0.3	4.5 – 4.9	2	
	31	4.9	0.9	3.6 – 6.5	11	
	33	4.9	0.8	3.9 – 6.0	5	
	32	5.2	1.2	3.8 – 6.6	9	
	12	5.6	1.6	4.5 – 6.8	2	
	111	5.6	0.3	5.4 – 5.8	2	
	18	5.8	1.1	5.0 – 6.5	2	
	36	5.8	1.6	4.7 – 7.7	3	
	30	5.9	0.4	5.3 – 6.5	6	
	8	6.1	0.6	5.4 – 6.6	3	
	2	6.3	0.3	6.1 – 6.5	2	
	16	6.3	1.3	4.2 – 7.6	5	
	21	6.3	1.6	4.3 – 7.9	5	
	108	6.3	1.0	5.0 – 8.0	6	
	14	6.4	1.0	5.2 – 7.3	4	
	7	6.6	0.5	6.2 – 7.0	2	
	3	7.0	1.7	3.8 – 8.4	6	
	4	7.5	2.3	5.1 – 11.7	16	
	118	7.6	1.6	5.8 – 8.9	3	

Intersection Type. One of the central questions in this analysis is what specifically is it about each intersection that explains the variation seen between individual intersections above? One possibility is the number of intersecting streets. Events in the data set included three types of intersections: There were 37 gap-accept events at 3-way intersections, 142 at 4-way intersections, and 13 at the intersection with side streets, including a grocery store parking lot (data was missing for one event). All side-street events were LTAP-ODs (a result of our querying procedure).

However, there was only a small effect of intersection type on accepted gap length for LTAP-OD (BS comparison, $\eta^2 = 0.04$, 90 percent CI: 0 – 0.1) and LTAP-LD events (BS comparison, $d = 0.5$, 95 percent 0 – 1.6; see Figure 64 and Table 35 in Appendix E for details), but these were in opposite directions, and there was no effect for all scenarios combined. For rejected gaps a medium effect existed for LTAP-LD, with longer gaps in 3-way intersections (mean = 3.3 s) than at 4-way intersections (mean = 2.5 s; BS comparison, $d = 0.6$, 95 percent CI: 0.0 – 1.7, $n_{3\text{-way}} = 9$, $n_{4\text{-way}} = 10$).

Omitting side streets and focusing on comparing only 3- to 4-way intersections, the effect for all scenarios combined remained negligible. By scenario, all effects for rejected gaps were negligible except for a medium effect in LTAP-OD (BS comparison, $d = 0.6$, 95 percent CI: 0.0 – 1.8, $n_{3\text{-way}} = 4$, $n_{4\text{-way}} = 27$; insufficient drivers for a WS comparison, $n = 1$) and a small effect for LTAP-LD ($d = 0.49$; no drivers for a WS comparison, $n = 0$).

3.3.9 Gender and Age

Although both the Safety Pilot and Driver Adaptation field operational tests were balanced for gender and age, this balance was not present in the subset of drivers with events in our analysis (Table 16). The unbalanced variables have the potential to confound the effect of the other, e.g., it could be unclear whether a difference in how men choose gaps in LTAP-OD scenarios compared to women is due to gender or to the fact that male drivers were disproportionately older than female drivers.

Table 16. Gender and Age Balance Across Groups

Scenario	Gender	Age Group		
		Younger (20 – 30)	Mid. Aged (40 – 50)	Older (60 – 70)
LTAP-OD	Female	14	17	11
	Male	18	13	17
LTAP-LD	Female	3	11	8
	Male	4	6	5
LTIP	Female	5	11	10
	Male	6	5	8
RTIP	Female	9	14	13
	Male	6	11	7
SCP-L	Female	8	6	11
	Male	9	3	5
SCP-R	Female	7	3	3
	Male	5	2	3
All Scenarios	Female	28	33	29
	Male	31	22	28

Unweighted Means. One way to handle confounds is to present "unweighted" means alongside the more traditional "weighted" means. With weighted means, the total sum is divided by the total *n*, an approach that gives more influence to groups with more data points, e.g., if you have twice as many women in a group, their influence on the overall average will be twice as large. With unweighted means, averages are found within each subgroup and then those averages are themselves averaged. This approach prevents more numerous groups from having extra influence. To reduce the effect of age imbalances when examining gender, the average gap length was found for each age group and then those were averaged for each gender.

Gender. On average, men drove into shorter gaps than women for every type of scenario (Table 17). Figure 28 shows these values by gender, but it also breaks the data points into three rows—one for each age group—to show how age groups varied within the gender groups (to reveal any confounding effects).

For all scenarios combined, the mean accepted gap was 6.5 s for women and 5.4 s for men. The unweighted means were the same in that case. This was a medium effect size and meant that 79 percent of men drove into gaps that were shorter than the average gap into which women drove. The size of the effect for individual scenarios ranged from small, for LTAP-LD, to large, for SCP-R. The large effect in SCP-R was likely due to the group of three outliers with long gap sizes, but the effect was consistent across all scenario types and was small only for LTAP-LD.

All effects were small or negligible for rejected gaps.

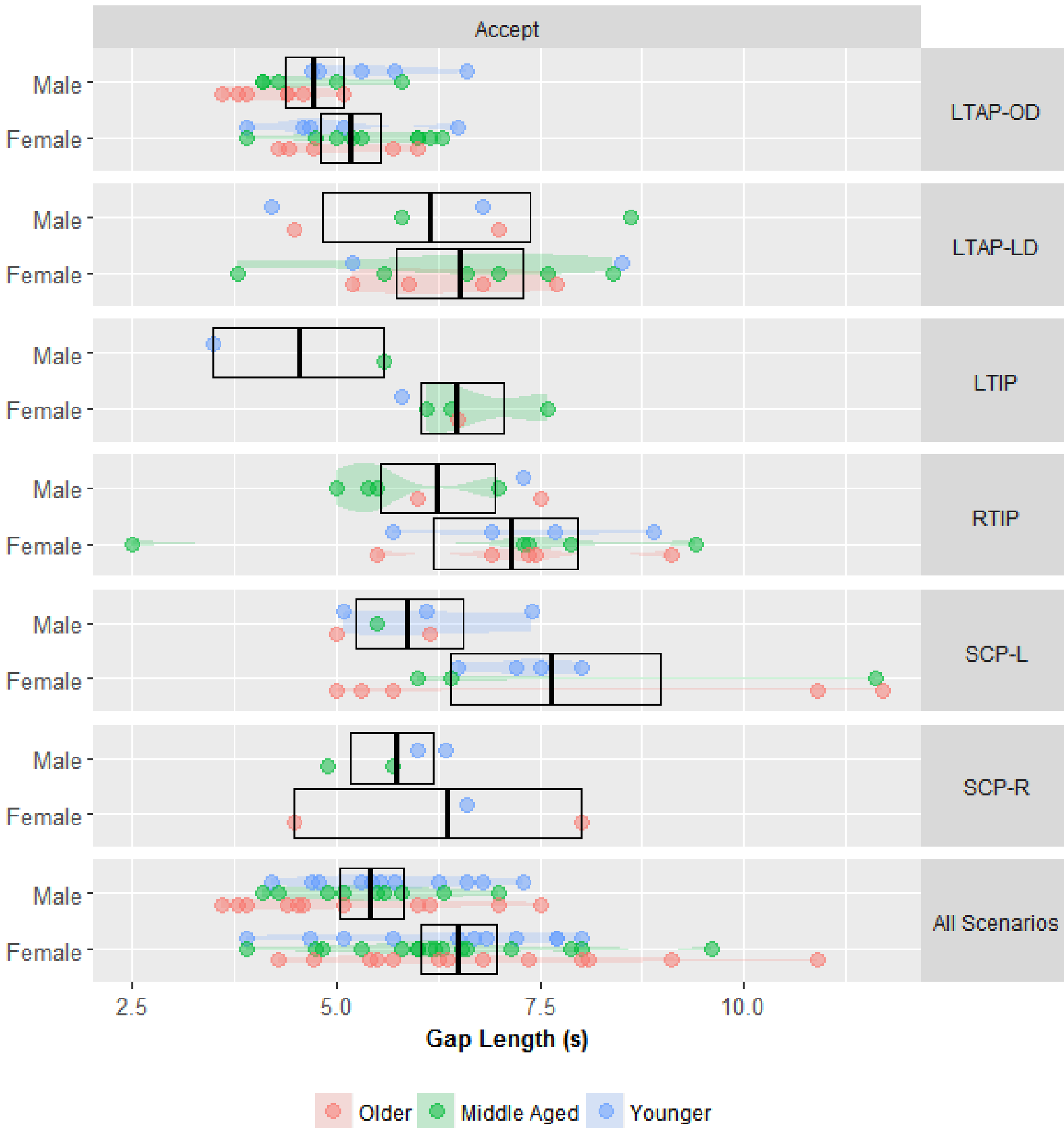

Figure 28. Accepted Gap Lengths Compared by Gender

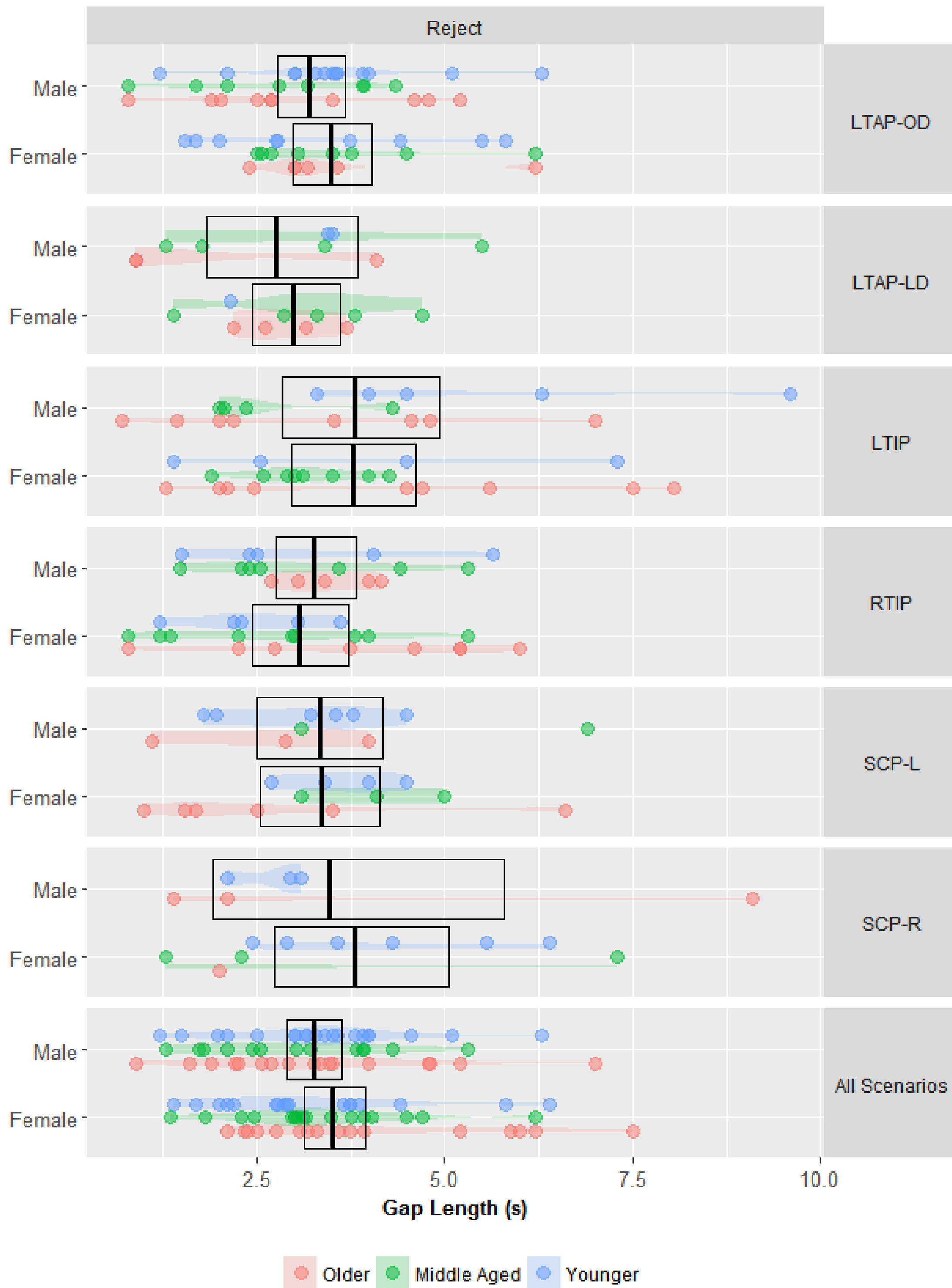

Figure 29. Rejected Gap Lengths Compared by Gender

Table 17. Gap Lengths Compared by Gender

Gap	Scenario	Gender	Mean (s)		SD (s)	Range (s)	*n*	Effect Size (*d*, 95% CI)
			Weighted	Unweighted				
Accepted	LTAP-OD	Female	5.2	5.1	0.8	3.9 – 6.5	19	Medium (BS) 0.6 (0 – 1.3)
		Male	4.7	4.8	0.8	3.6 – 6.6	17	
	LTAP-LD	Female	6.5	6.6	1.4	3.8 – 8.5	12	Small (BS) 0.3 (0 – 1.4)
		Male	6.1	6.1	1.7	4.2 – 8.6	6	
	LTIP	Female	6.5	6.3	0.7	5.8 – 7.6	5	Insufficient *n*
		Male	4.5	4.5	1.5	3.5 – 5.6	2	
	RTIP	Female	7.1	7.1	1.7	2.5 – 9.4	14	Medium (BS) 0.6 (0 – 1.6)
		Male	6.2	6.6	1.0	5.0 – 7.5	7	
	SCP-L	Female	7.7	7.7	2.4	5.0 – 11.7	12	Large (BS) 0.9 (0 – 2.0)
		Male	5.9	5.8	0.9	5.0 – 7.4	6	
	SCP-R	Female	6.4	6.4	1.8	4.5 – 8.0	3	Medium (BS) 0.5 (0 – 2.9)
		Male	5.7	5.7	0.6	4.9 – 6.4	4	
	All Scenarios	Female	6.5	6.5	1.5	3.9 – 10.9	40	Medium (BS) 0.8 (0.3 – 1.3)
		Male	5.4	5.4	1.1	3.6 – 7.5	31	
Rejected	LTAP-OD	Female	3.5	3.5	1.4	1.5 – 6.2	23	Small (BS) 0.2 (0 – 0.8)
		Male	3.2	3.1	1.3	0.8 – 6.3	31	
	LTAP-LD	Female	3.0	2.8	1.0	1.4 – 4.7	10	No effect
		Male	2.8	2.8	1.6	0.9 – 5.5	9	
	LTIP	Female	3.8	3.8	2.0	1.3 – 8.1	21	No effect
		Male	3.8	3.8	2.3	0.7 – 9.6	17	
	RTIP	Female	3.2	3.1	1.5	0.8 – 6.0	22	No effect
		Male	3.3	3.3	1.2	1.5 – 5.6	17	
	SCP-L	Female	3.4	3.5	1.5	1.0 – 6.6	13	No effect
		Male	3.3	3.6	1.6	1.1 – 6.9	11	
	SCP-R	Female	3.8	3.3	2.0	1.3 – 7.3	10	No effect
		Male	3.5	3.5	2.8	1.4 – 9.1	6	
	All Scenarios	Female	3.5	3.5	1.4	1.3 – 7.5	50	Small (BS) 0.2 (0 – 0.6)
		Male	3.3	3.3	1.3	0.9 – 7.0	50	

Age. In terms of age, the drivers in Safety Pilot were divided into three groups: Younger (20 to 31 years old), Middle Aged (40 to 50), and Older (60 to 70). In Driver Adaptation, all drivers were in their mid- to late-twenties and thus were added to the Younger group.

Figure 65 shows gap lengths broken down by age group, but it also shows how the genders varied within each age group to reveal any confounding effects. There was no effect of age for all scenarios combined for accepted gaps (see Table 36 in Appendix F for details on the effect sizes). Gap sizes were the same for all three age groups (means = 6.0 s), and varied only slightly with the unweighted means (6.0 s for Younger and 5.9 s for both Middle Aged and Older). Small effects were observed for LTAP-OD, LTAP-LD, and RTIP, but without consistency between them. For LTAP-OD, the strongest of those three, younger drivers were driving into larger gaps. In general, the statistical power was greatly limited by small sample sizes.

There were small effects for rejected gaps for all scenarios except for LTAP-OD, but little consistency between them in which age groups had longer or shorter gaps.

3.3.10 Environmental Conditions

The environmental conditions described here include night versus day ("lighting"), clear versus adverse weather, and slippery versus dry roads.

Lighting. There were 171 gap-accept events during the day and 21 at night. For all scenarios combined, no difference was found in the average accepted gap between day (6.1 s) and night (5.8 s), yielding a negligible effect size (see Figure 69 and Table 39 in Appendix G for plots and details on effect sizes). A lack of events at night made it impossible to test for most scenarios, but for the two for which comparisons were possible, there was either no effect (LTAP-OD) or a small effect (SCP). A similar set of results was seen for rejected gaps.

Weather. The vast majority of gap-accept events took place during clear weather: There were 179 such events compared to 13 with precipitation or fog. The small number of events under adverse conditions meant that any effects were difficult to identify and, where the sample size was sufficient to run comparisons, no effect was observed for any accepted gaps (see Figure 70 and Table 40 in Appendix G for plots and details on effect sizes). The same is true for rejected gaps with the exception of LTAP-LD, where a medium-sized effect was observed: gaps where drivers chose to wait were on average 2.3 s long under adverse conditions compared to 3.4 s in clear weather. However, given the small sample size ($n = 3$ for adverse weather), and the fact that all those points are within the range of clear weather events, this may be a random sampling effect.

Road Surface Condition. Out of 192 gap-accept events,[8] 25 took place on slippery roads (roads were deemed slippery if it was raining or if the road surface was significantly more reflective). Small effects were observed for all but LTIP and SCP-R, for which there were insufficient cases to analyze (Figure 30, Table 18). For all measurable effects except LTAP-OD, the average gap sizes were longer in slippery conditions. For rejected gaps, there was a medium effect for LTIP, with drivers on average waiting longer in slippery conditions (4.7 s) than in dry conditions (3.6 s).

[8] There were 192 rather than 193 because of because of missing data.

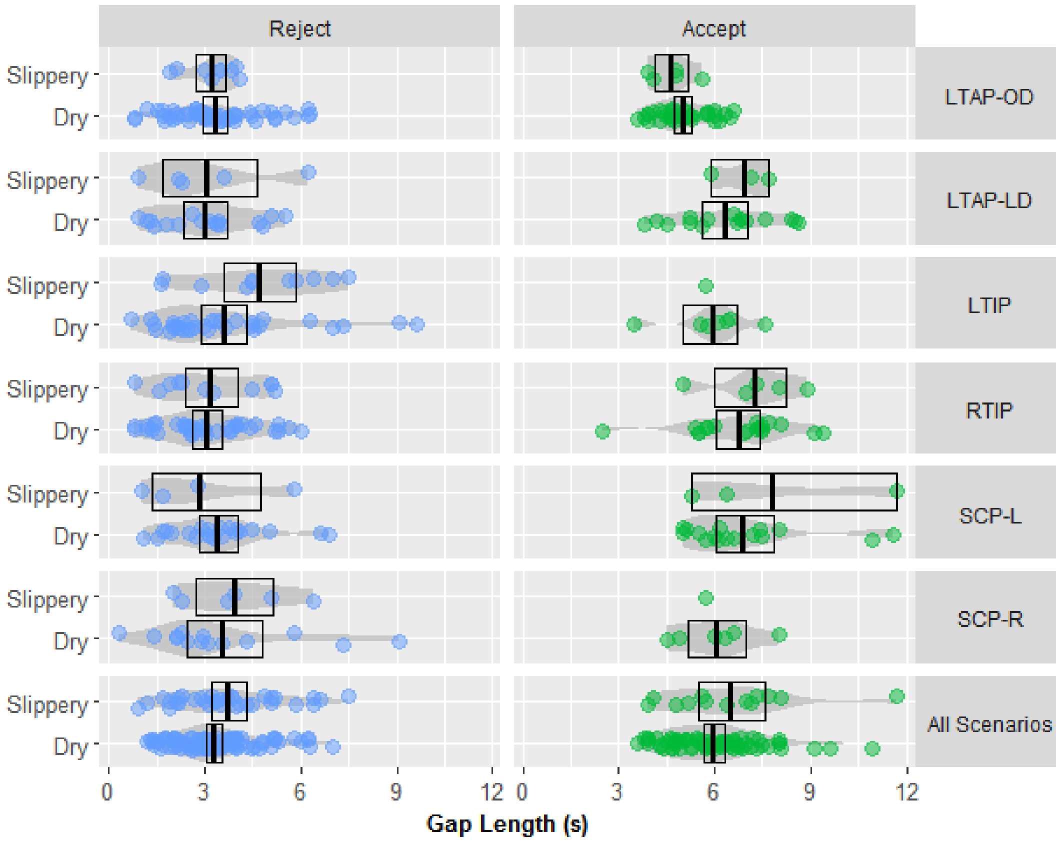

Figure 30. Gap Lengths Compared by Road Surface Condition

Table 18. Gap Lengths Compared by Road Surface Condition

Gap	Scenario	Surface Condition	Mean (s)	SD (s)	Range (s)	*n*	Effect Size (*d*, 95% CI)
Accepted	LTAP-OD	Dry	5.0	0.8	3.6 – 6.6	35	Small (BS) 0.44 (0 – 1.4)
		Slippery	4.6	0.7	3.9 – 5.6	5	
	LTAP-LD	Dry	6.3	1.5	3.8 – 8.6	16	Small (BS) 0.40 (0 – 1.8)
		Slippery	6.9	0.9	5.9 – 7.7	3	
	LTIP	Dry	5.9	1.3	3.5 – 7.6	7	Insufficient *n*
		Slippery	5.7	-	5.7 – 5.7	1	
	RTIP	Dry	6.8	1.6	2.5 – 9.4	19	Small (BS) 0.30 (0 – 1.4)
		Slippery	7.2	1.5	5.0 – 8.9	5	
	SCP-L	Dry	6.9	1.9	5.0 – 11.6	16	Small (BS) 0.42 (0 – 1.8)
		Slippery	7.8	3.4	5.3 – 11.7	3	
	SCP-R	Dry	6.1	1.3	4.5 – 8.0	6	Insufficient *n*
		Slippery	5.7	-	5.7 – 5.7	1	
	All Scenarios	Dry	6.0	1.4	3.6 – 10.9	70	Small (WS, *n* = 12) 0.42 (0 – 1.3)
		Slippery	6.5	2.1	3.9 – 11.7	13	
Rejected	LTAP-OD	Dry	3.3	1.4	0.8 – 6.3	52	No effect
		Slippery	3.2	0.8	1.9 – 4.1	9	
	LTAP-LD	Dry	3.0	1.4	0.9 – 5.5	17	No effect
		Slippery	3.0	2.0	0.9 – 6.2	5	
	LTIP	Dry	3.6	2.2	0.7 – 9.6	33	Medium (BS) 0.53 (0 – 1.3)
		Slippery	4.7	2.0	1.6 – 7.5	11	
	RTIP	Dry	3.1	1.4	0.8 – 6.0	37	No effect
		Slippery	3.2	1.6	0.8 – 5.2	11	
	SCP-L	Dry	3.4	1.5	1.1 – 6.9	22	Small (BS) 0.36 (0 – 1.5)
		Slippery	2.8	2.1	1.0 – 5.8	4	
	SCP-R	Dry	3.5	2.4	0.3 – 9.1	14	No effect
		Slippery	3.9	1.7	2.0 – 6.4	6	
	All Scenarios	Dry	3.3	1.3	1.2 – 7.0	94	Small (WS, *n* =28) 0.42 (0 – 1.0)
		Slippery	3.7	1.6	0.9 – 7.5	34	

3.3.11 Turn Signal Usage

Using the turn signal is the only time when drivers explicitly state their intent to turn. However, this only indicates that drivers intend to turn soon, and is not a precise measure of when they actually will turn. In addition to the fact that drivers vary in how early they indicate a turn, factors outside of their control can add to that time, such as changing lights or other vehicles in the queue ahead of them. As a result, there is little to be gained from looking at turning time without having much more control over the factors involved. Rates of turn signal usage are shown in Table 19 for the accepted-gap events.

Table 19. Turn Signal Usage Rates

Scenario	Yes	No	Percentage
LTAP-OD	80	3	96%
LTAP-LD	18	6	75%
LTIP	6	6	50%
RTIP	21	15	58%
All turning scenarios	125	30	81%

3.3.12 Glare

There were insufficient events (n = 9) for an analysis of the effect of glare.

3.3.13 Obstruction

There were also insufficient events to analyze events where the driver's view was obstructed by objects such as another vehicle or trees (n = 2).

3.3.14 Distraction

Distraction was defined as driving in a state other than fully attentive, e.g., while talking on the phone, texting, adjusting the radio, eating, drinking, or falling asleep. For this analysis, conversing with another passenger was not considered a distraction if the driver's eyes remained focused on the road.

There were 23 gap-accept events (out of 193) in the databases where drivers were classified as distracted. Although there was no effect of distraction by this measure in all scenarios combined, effects were seen for LTAP-OD (a small effect where distracted drivers drove into shorter gaps) and RTIP (a large effect where distracted drivers drove into *larger* gaps, largely caused by a single accepted gap of 2.5 s by a distracted driver) (Figure 31, Table 20). A similar pattern was seen for rejected gaps.

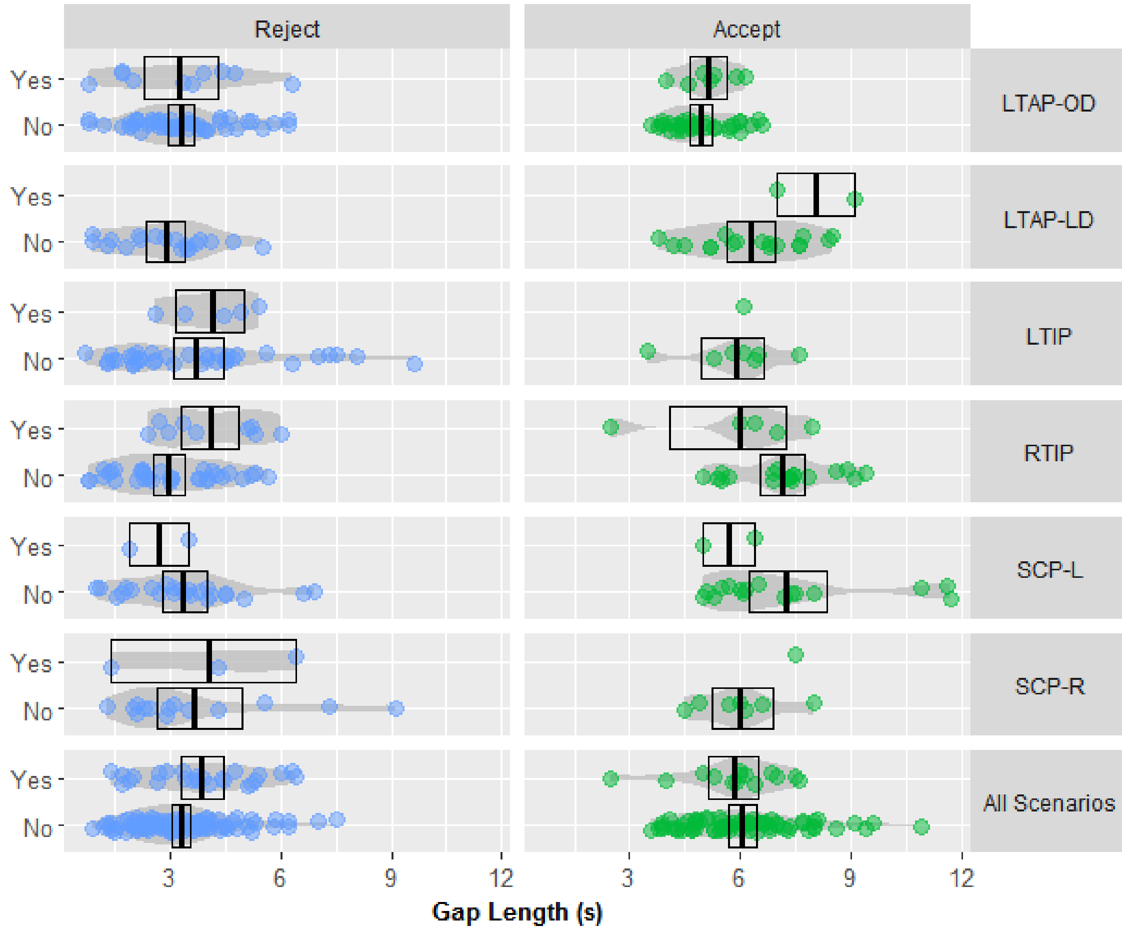

Figure 31. Gap Lengths Compared by Distraction

Table 20. Gap Lengths Compared by Distraction

Gap	Scenario	Distracted?	Mean (s)	SD (s)	Range (s)	*n*	Effect Size (*d*, 95% CI)
Accepted	LTAP-OD	No	4.9	0.9	3.6 – 6.6	32	Small (BS) 0.30 (0 – 1.2)
		Yes	5.2	0.7	4.0 – 6.2	7	
	LTAP-LD	No	6.3	1.4	3.8 – 8.5	17	Insufficient *n*
		Yes	8.0	1.5	7.0 – 9.1	2	
	LTIP	No	5.9	1.3	3.5 – 7.6	7	Insufficient *n*
		Yes	6.1	-	6.1 – 6.1	1	
	RTIP	No	7.2	1.3	5.0 – 9.4	19	Large (BS) 0.81 (0 – 1.9)
		Yes	6.0	2.1	2.5 – 7.9	5	
	SCP-L	No	7.2	2.3	5.0 – 11.7	16	Insufficient *n*
		Yes	5.7	1.0	5.0 – 6.4	2	
	SCP-R	No	6.0	1.1	4.5 – 8.0	7	Insufficient *n*
		Yes	7.5	-	7.5 – 7.5	1	
	All Scenarios	No	6.1	1.5	3.6 – 10.9	68	No effect
		Yes	5.9	1.4	2.5 – 7.6	14	
Rejected	LTAP-OD	No	3.3	1.3	0.8 – 6.2	50	No effect
		Yes	3.2	1.7	0.8 – 6.3	10	
	LTAP-LD	No	2.9	1.3	0.9 – 5.5	19	Insufficient *n*
		Yes	-	-	-	-	
	LTIP	No	3.7	2.1	0.7 – 9.6	38	Small (BS) 0.22 (0 – 0.1)
		Yes	4.1	1.1	2.6 – 5.4	5	
	RTIP	No	2.9	1.4	0.8 – 5.6	35	Large (BS) 0.83 (0 – 1.6)
		Yes	4.1	1.3	2.4 – 6.0	9	
	SCP-L	No	3.4	1.5	1.0 – 6.9	24	Insufficient *n*
		Yes	2.7	1.1	1.9 – 3.5	2	
	SCP-R	No	3.6	2.2	1.3 – 9.1	14	No effect
		Yes	4.0	2.5	1.4 – 6.4	3	
	All Scenarios	No	3.3	1.3	0.9 – 7.5	95	Small (WS, *n* = 20) 0.45 (0 – 1.1)
		Yes	3.8	1.5	1.4 – 6.4	25	

4 Analysis of Collisions

The above analysis of naturalistic driving behavior (Section 3) was aimed at providing information on baseline driving; i.e., regular intersection crossings in the presence of oncoming vehicles that did not result in crashes. The aim was to characterize normal driving that should *not* elicit alerts or automatic control intervention from a collision warning or avoidance system. This section is intended as a counterpoint to that analysis; it should provide information on instances where a warning system *should* have issued a warning or a collision avoidance system should have automatically intervened. These instances were actual LTA- and IMA-applicable crashes identified in a national crash database.

The results of this analysis, which focused on crashes that involved at least one vehicle being towed away due to damage, are described below. In general, the analysis of the crash database records was designed to mirror the methodology used in the analysis of the baseline driving data (Section 3). First, a description of the crash data source is provided below.

4.1 Data Source

All cases in this analysis were drawn from the National Automotive Sampling System (NASS) Crashworthiness Data System (CDS) database, which is maintained by the National Highway Traffic Safety Administration (NHTSA) for the purpose of evaluating motor vehicle safety countermeasures. We used all available data, which was from 2008 to 2014.

CDS case reports include over 600 variables about the crash, including a description and diagram of the crash, photographs of the site and the vehicles involved, and interviews and medical records for the people involved (Figure 32). In some cases, the vehicles were equipped with EDR devices. These devices record the last 5 seconds of activity from certain sensors, including vehicle speed, throttle, brake application, and engine rpm. In the event of a crash, the data is saved.

Figure 32. Sample Scene Diagram and Photo From an LTAP-OD Case From the CDS Database

CDS cases consist of a sampling of 4,000 to 5,000 police-reported crashes a year. To be included, at least one passenger car, SUV, pickup truck, minivan, or van (gross vehicle weight rating under 10,000 pounds) must have been towed from the crash scene due to damage. The database is designed to be nationally representative, following a stratified, multiphase, unequal selection probability design.

More information on the CDS database can be found in Radja [95] and Bean [96].

4.2 Methodology

This methodology was intended to mirror that of the baseline analysis methodology (Section 3.2) as closely as possible. In addition to some descriptive statistics for the cases, the size of the gaps was roughly estimated using the timing of the throttle, brakes, speed, and engine rpm in relation to the time of collision (more details on this estimation process are given below).

4.2.1 Split-Sample Comparison (2008 – 2011 Versus 2012 – 2014)

When this analysis was first conducted, only cases up through 2011 were available. Cases up through 2014 were released shortly thereafter, suggesting the possibility of a split-sample analysis. In other words, by running the tests we conducted on the first sample of data separately on the second set of data, we can see which positive results for the first set were more than random: patterns that show in both samples are more likely to be real. This method was applied for the estimated gap lengths and for age distribution.

Following this split-sample comparison, the data was merged for increased sample size and, unless otherwise noted, the results below are from this combined data set including all cases from 2008 to 2014.

4.2.2 Event Selection

The only selection criterion for inclusion in this analysis was that both vehicles involved be equipped with EDR devices (so that kinematic information on the vehicles would be available). All cases in the CDS meeting that condition were used.

4.2.3 Analysis Metrics

For the most part, the analysis metrics were the same as for the baseline analysis, with the major difference being gaps.

Gaps. Although the definition of a gap is the same as in the baseline analysis, the method of estimating it is by necessity different since the available information is different: for baseline driving we had video of the oncoming vehicle and for the crash database we have only the information recorded by the two vehicles, including speed, engine rpm, throttle application, and brake status. However, one key piece of information we *do* have is the precise time of the collision. If the moment when the vehicle initiated its maneuver can be approximated (and only cases where the moment of initiating the turn seemed clear were included), this enables an estimate of the gap size to be inferred. These estimates are very approximate, though, and should be taken only as an initial exploration of this sort of data.

In general, to estimate gaps, we sought evidence of when the driver had initiated the turn or the crossing action. A sudden, strong throttle increase was taken as the primary indicator of this. The exception was if the vehicle speed had increased substantially (by at least 4 mph to at least 10 mph) without throttle increase, possibly as a result of sudden brake release. Since the vehicles collided in all of these cases, the end of the gap was known with precision since it was recorded as time zero in the EDR.

Since the EDR only recorded data once every second, it was, as elsewhere in this analysis of crash database events, not possible to achieve much precision. Since reactions such as sudden increase in the throttle occurred between two times, the time of the reaction was approximated as the average of those two times. This lack of precision and the fact that all events took place within only a couple seconds of the collision means that possible gaps were limited to only a few possibilities and resemble categorical data more than numerical. Consequently, the amount of information that can be gleaned from statistical analysis of them is limited.

The fact that gap times were here generally estimated using the start of throttle application is different than how they were found in the baseline analysis, where the start of a gap was recorded based on vehicle speed. To enable comparison between the results of these two different methodologies, gap estimates from the EDR data were converted to those of the baseline study by subtracting the median delay observed in the baseline study from throttle application to gap start (median was used instead of mean because of a skew in the distribution). Without this adjustment, the difference in methodology would make gaps in collisions seem longer than they actually were. The sizes of these median delays are given in Table 22 below as well as in Table 32 in Appendix C.

4.2.4 Statistical Analyses

Like the above baseline analysis, this is a *post hoc* explorations of a pre-existing data set and the same approach is taken statistically in both analyses. The exception is for the comparison between the first and second batches of data, which were made for the estimated gap lengths and for driver ages. As above, non-parametric tests were used when the underlying assumptions for parametric tests were not met.

As before, all analyses were conducted using R in RStudio.

4.3 Results

There were 194 events found in the crash database. LTAP-OD events were the most common and RTIP and LTIP the least (Table 21). As a reminder, the reason for the columns 2008 – 2011 and 2012 – 2014 is given in Section 4.2.1.

Table 21. Number of Available CDS Cases With EDR Data

Scenario	2008 – 2011	2012 – 2014	Total
LTAP-OD	29	44	73
LTAP-LD	12	26	38
LTIP	0	5	5
RTIP	1	2	3
SCP-L	17	21	38
SCP-R	18	19	37
Sum	77	117	194

Each event included both a crossing vehicle and the oncoming vehicle that collided with it. The cases are further broken down and analyzed in terms of various other factors below.

4.3.1 Gap Lengths

Out of the 194 CDS cases with EDR data, gaps were estimated for 105. The sizes of those gaps ranged from 1.8 to 3.8 s, with adjustment (Table 22). These gap sizes were shorter than accepted gaps in the baseline for all scenarios, sometimes with little overlap in their distributions (Figure 33). There is no reason to expect a difference between gap sizes for crashes and for rejected gaps in the baseline. Note for Table 22 and Figure 33, “all scenarios” have been adjusted using the “all scenarios” median delay rather than by individual scenario types.

Table 22. Length of Gaps for CDS Cases With and Without Throttle-To-Gap-Start Delay Adjustment

Scenario	Unadjusted gap lengths (s)				Median delay in baseline	Adjusted gap lengths (s)			
	Mean	SD	Range	n		Mean	SD	Range	n
LTAP-OD	2.8	0.9	1.5 – 4.5	45	1.0	1.8	0.9	0.5 – 3.5	45
LTAP-LD	3.5	1.1	1.5 – 4.8	23	1.0	2.5	1.1	0.5 – 3.8	23
LTIP	4.5	-	4.5 – 4.5	1	0.7	3.8	-	3.8 – 3.8	1
RTIP	2.6	1.2	1.8 – 3.5	2	0.1	2.5	1.2	1.6 – 3.4	2
SCP-L	3.8	0.8	2.2 – 5.0	19	0.9	3.0	0.8	1.4 – 4.1	19
SCP-R	3.9	0.6	2.5 – 4.8	15	1.1	2.8	0.6	1.4 – 3.7	15
All Scenarios	3.3	1.0	1.5 – 5.0	105	0.8	2.5	1.0	0.7 – 4.2	105

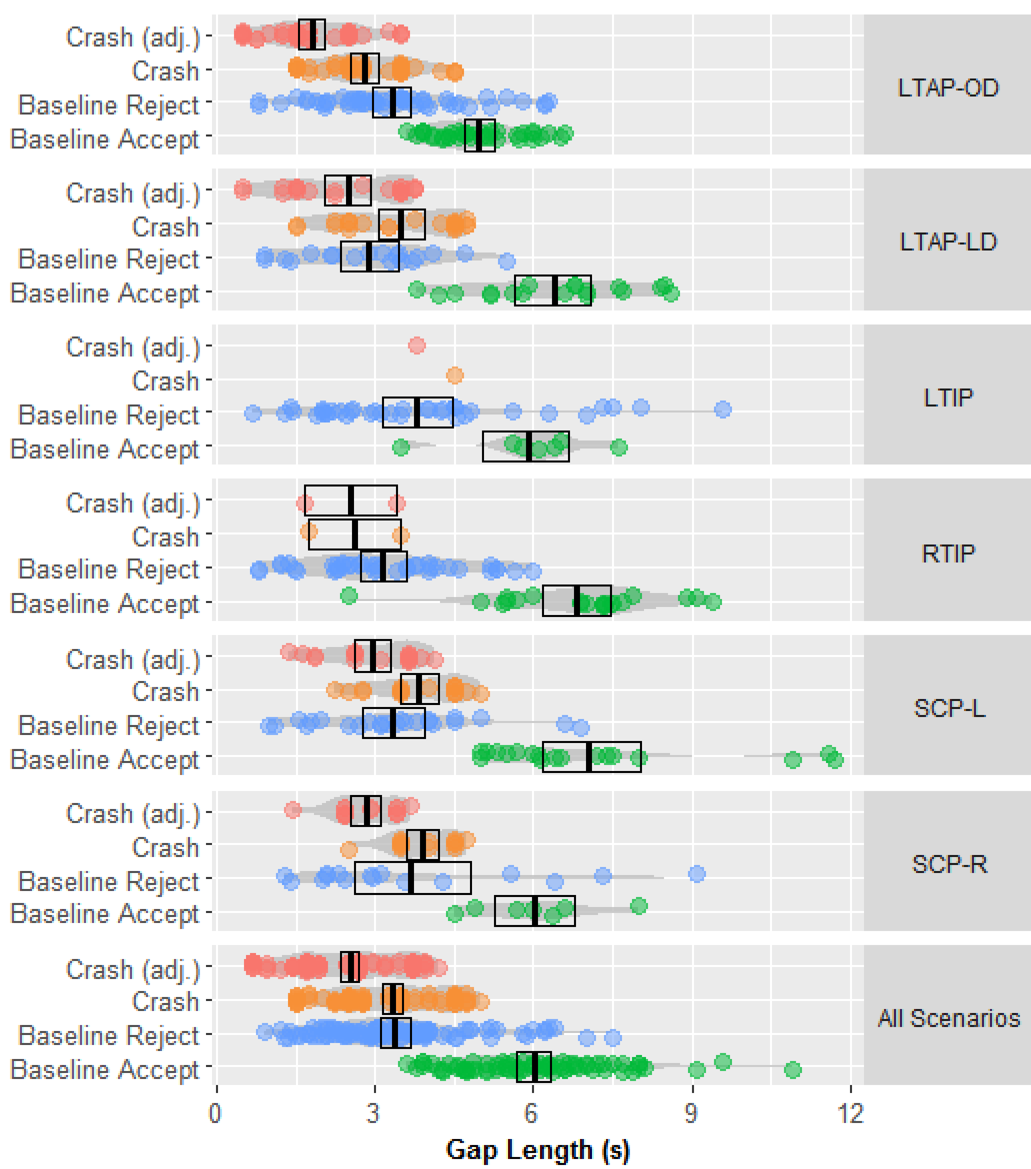

Figure 33. Gap Lengths for CDS Cases Compared to Baseline Events

There was no statistical difference between the estimated gap lengths (with adjustment) for the first batch of data (median = 2.5 s, IQR = 1.2 s, $n = 36$) and the second (median = 2.4 s, IQR = 2.0 s, $n = 69$; Mann-Whitney test, $W = 1137$, $p = 0.48$; a nonparametric test was used instead of a t-test because a Shapiro-Wilk test showed that the gap lengths were not normally distributed).

4.3.2 Speed

As with the baseline data (Figure 21 in Section 3.3.4), speeds during CDS crashes were broken down into approach bins. Specifically, crashes with a minimum speed less than 4 mph were binned as "stop then cross" and the rest were binned as "cross without stop" (Figure 34).

For this plot, to enable comparison, the baseline LTAP-OD events were reclassified into the same bins based on the same criteria using only the values included in the 5-second span. This was done to match the classification of the CDS cases, which only had speed data for those 5 seconds preceding collision.

Note that in this case the horizontal axis is time until gap closing, rather than time from crossing start. For the CDS data, the end of the gap is, of course, the collision. In the baseline case, the end of the gap is when the oncoming vehicle reached the collision zone, though by this point the vehicle had cleared the zone since the turn was safely completed.

The heavy black lines show the average speeds for the events in the plot. For the CDS cases for all scenarios except for LTAP-OD (cross without stop), the average lines skip data on the half second since those include only the subset of cases with data recorded every half second, causing the lines to zig zag, obscuring the general trend.

The average speeds 5 and one second before collision (or, for baseline, when the oncoming vehicle reached the collision zone) are shown in Table 23 for both the CDS data and the window of baseline data shown in Figure 34.

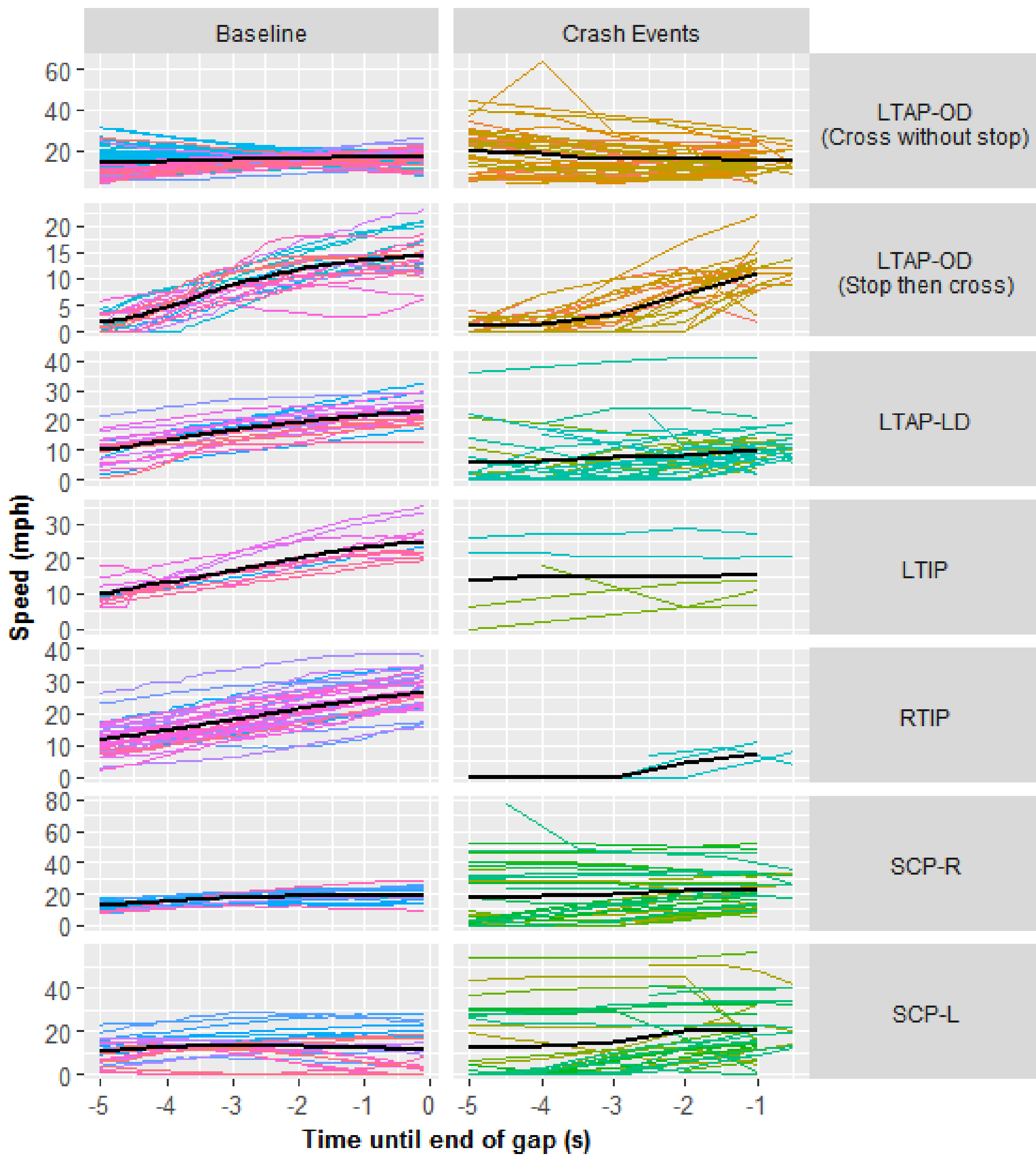

Figure 34. Speed for CDS and Baseline Crossings

Table 23. Average Speeds at -5 and -1 s Before Crash

Scenario	Baseline Events			Crashes		
	Average speeds (mph)		*n*	Average speeds (mph)		*n*
	Start (-5 s)	Near end (-1 s)		Start (-5 s)	Near end (-1 s)	
LTAP-OD (Cross without stop)	13.7	16.6	58	20.6	15.0	45
LTAP-OD (Stop then cross)	1.7	13.5	25	1.0	11.1	27
LTAP-LD	10.0	21.5	23	6.1	10.2	38
LTIP	9.9	23.2	12	13.5	16.0	5
RTIP	11.6	24.2	36	0.0	7.7	3
SCP-L	10.3	12.1	25	12.5	19.9	38
SCP-R	12.6	19.2	13	17.6	23.3	37

4.3.3 Intersection Geometry

Event Counts. The vehicle entered the intersection from a straight street 180 out of 194 times (93 percent) (see “approach geometry” in Figure 35).

Junction type (intersection versus parking lot versus driveway) was only available for LTAP-OD events, and 67 out of those 73 events (92 percent) were at intersections.

Most intersections had traffic lights (108 out of 194 events, or 56 percent), although stop signs (42 events) and uncontrolled intersections (43 events) were both present in around 22 percent of events.

Dedicated turning lane presence was also only available in LTAP-OD cases, where they were noted in 54 out of 73 cases (74 percent). These included turning lanes shared by both directions of traffic.

The number of lanes of oncoming traffic the turning vehicle had to cross varied from one to four. Again, only LTAP-OD events had this information and the majority of drivers—60 percent (44 out of 73)—needed to cross two. Nearly 20 percent (14 events) had only one lane to cross and 16 percent (12 events) had three. In these cases, a turning lane for the oncoming direction was not counted as a lane to cross, except in one case where the turning vehicle crossed the oncoming traffic’s turning lane midway between intersections in order to turn into a driveway. That lane was counted since in that case the driver’s path could intersect any vehicles in that lane.

Finally, in terms of elevation, the majority of events—150 out of 194, or 77 percent—occurred on level roads. The next most frequent events were turns made by drivers going uphill (13%). Ten percent (20 events) were uphill and 12 percent (23 events) were downhill (Figure 36). One event took place at the crest of a hill. In this case, a hill was defined as a gradient over 2 percent.

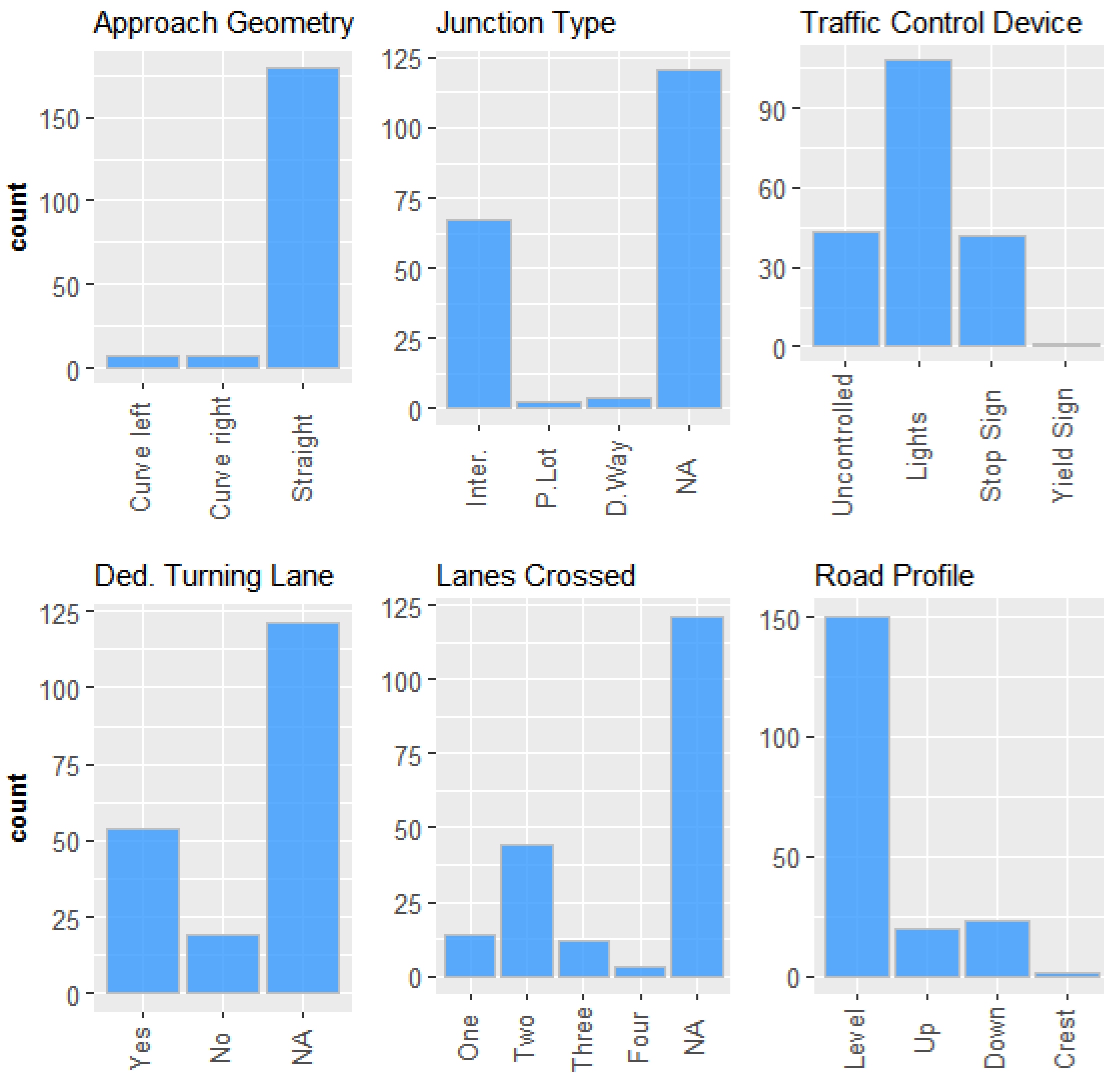

Figure 35. Frequency of Various Intersection Geometry Variables

Figure 36. CDS Examples of Roads With Uphill (left) and Downhill (right) Grades

As with baseline, the effect that different variables had on the selected gap size was explored for the CDS cases. Only two variables showed effects in the same direction for both batches (2008 – 2011 and 2012 – 2014), making them less likely to be random variation: the effect of a dedicated turning lane and the effect of road profile.

Gaps: Dedicated turning lane. Dedicated turning-lane data was only available for LTAP-OD events. Gap estimates were produced for 45 of the 73 cases, and out of those 45 cases, 34 were at dedicated turning lanes. For both batches of data, average gaps were shorter when there was a dedicated turning lane than when there was not (Figure 37, Table 24). However, the effect of turning-lane presence was negligible for the 2008 – 2011 data, and for both combined there was only a small effect, with 65 percent of gaps from dedicated turning lanes being shorter than the average turn from a non-dedicated lane. This was the same pattern seen in the baseline data (Figure 26 in Section 3.3.8).

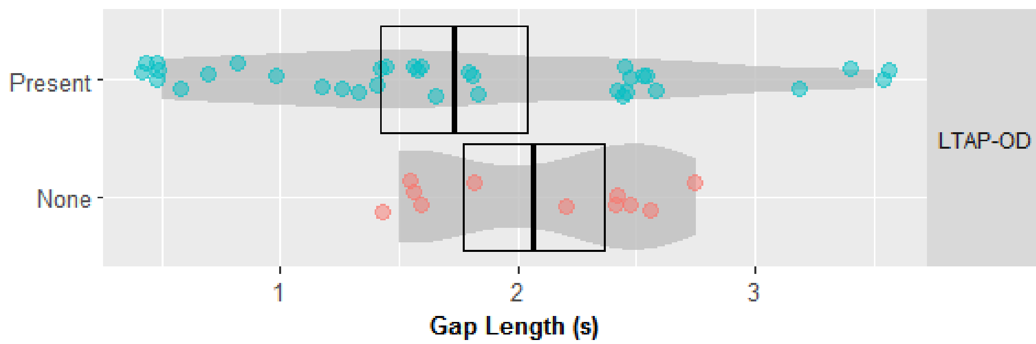

Figure 37. Adjusted CDS Accepted Gap Lengths Compared By Dedicated Turning Lane

Table 24. Adjusted CDS Accepted Gap Lengths Compared by Dedicated Turning Lane

Scenario	Events	Dedicated Turn Lane	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
LTAP-OD	All Data	None	2.1	0.5	1.5 – 2.8	11	Small (BS) 0.39 (0 – 1.1)
		Present	1.7	0.9	0.5 – 3.5	34	
	2008 – 2011	None	1.9	0.5	1.5 – 2.5	5	No effect
		Present	1.7	0.9	0.5 – 2.5	13	
	2012 – 2014	None	2.2	0.5	1.5 – 2.8	6	Medium (BS) 0.53 (0 – 1.5)
		Present	1.7	1.0	0.5 – 3.5	21	

Gaps: Road profile. Road profile data was recorded for all scenarios, but LTIP and RTIP had events only on one type of profile, and LTAP-LD, SCP-L, and SCP-R showed no pattern. Only LTAP-OD showed a pattern across the 45 events that had estimated gap sizes. The sample sizes for non-level roads were unfortunately limited, but looked at separately, both batches showed the smallest gaps for level roads, followed by uphill roads, followed by downhill (Figure 38, Table 25). The effect size was medium in the first batch data, large for the second, and medium for the combined data.

When just events on level roads were compared to events on uphill roads (both of which had larger sample sizes than the downhill roads), the effect was medium for the first batch (BS comparison, d = 0.71, 95 percent CI: 0 – 2.0), small for the second (d = 0.34, 95 percent CI: 0 – 1.5), and medium for both batches combined (d = 0.52, 95 percent CI: 0 – 1.3).

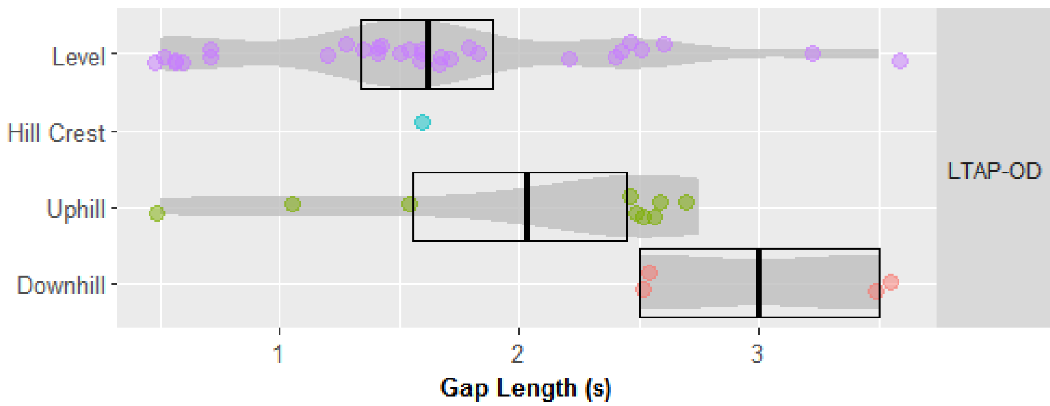

Figure 38. Adjusted CDS Accepted Gap Lengths for Different Road Profiles

Table 25. Adjusted CDS Accepted Gap Lengths for Different Road Profiles

Scenario	Events	Road Profile	Mean	SD	Range	*n*	Effect Size
LTAP-OD	All Data	Downhill	3.0	0.6	2.5 - 3.5	4	Medium (BS) η^2 = 0.23 (90% CI: 0.03 – 0.4)
		Uphill	2.0	0.8	0.5 - 2.8	9	
		Hill Crest	1.5	-	1.5 - 1.5	1	
		Level	1.6	0.8	0.5 - 3.5	31	
	2008 – 2011	Downhill	2.5	0.0	2.5 - 2.5	2	Medium (BS) η^2 = 0.21 (90% CI: 0 – 0.4)
		Uphill	2.1	0.9	0.5 - 2.5	5	
		Hill Crest	1.5	-	1.5 - 1.5	1	
		Level	1.5	0.8	0.5 - 2.5	10	
	2012 – 2014	Downhill	3.5	0.0	3.5 - 3.5	2	Large (BS) η^2 = 0.30 (90% CI: 0.04 – 0.5)
		Uphill	1.9	0.8	1 - 2.8	4	
		Hill Crest	-	-	-	-	
		Level	1.7	0.8	0.5 - 3.5	21	

4.3.4 Gender and Age

Event Counts: Gender. There were 101 women and 74 men in the CDS cases. For 19 cases, the gender was not recorded. Most scenarios were fairly evenly balanced except for LTAP-OD, which had nearly twice as many women as men (Table 26).

Table 26. Gender Balance in CDS Cases

Scenario	Female	Male	Sum
LTAP-OD	43	24	67
LTAP-LD	19	12	31
LTIP	3	1	4
RTIP	1	2	3
SCP-L	17	17	34
SCP-R	18	18	36
Sum	101	74	175

Gaps: Gender. As was done for the baseline gap analysis, unweighted averages were calculated to try to reduce the confound created by the lack of balance across gender. Since SCP-L and SCP-R were already balanced and LTIP and RTIP have very small samples, unweighted averages were only found for LTAP-OD, LTAP-LD, and for all scenarios combined (Table 25 in Appendix F, which shows the results for all scenario types for "all data," but omits scenario results under 2008–2011 and 2012–2014 when there was insufficient data to calculate effect sizes in either batch. Plots of the data are shown in Figure 67, also in Appendix F). In this case, the unweighted averages did not generally differ by more than a tenth of a second.

Overall, in the CDS data, men drove into gaps that were on average slightly longer than women, but this was a negligible effect. By scenario the only effect was for SCP-R, for which there was a medium effect with men driving into longer gaps, but the direction of the effect was in opposite directions for each of the two batches, suggesting that this was random variation in the small sample size.

In short, unlike the baseline data, there was no evidence of a gender effect in the CDS data.

Event Counts: Age. The driver ages in the CDS cases ranged from 16 to 92, with a median of 37 (IQR = 12) and a mean of 42.4 (SD = 20.2) (Figure 39). Ages were divided into bins similar to what was done for the baseline analysis, but instead of 20–31, 40–50, and 60–70, ages were split as below 35, over 55, or between. In terms of these bins as well as looking at the raw ages, the samples were heavily biased towards younger drivers (Table 27). To counteract this imbalance, unweighted averages were calculated for scenarios with adequate sample size and Figure 68 shows the values clustered by gender.

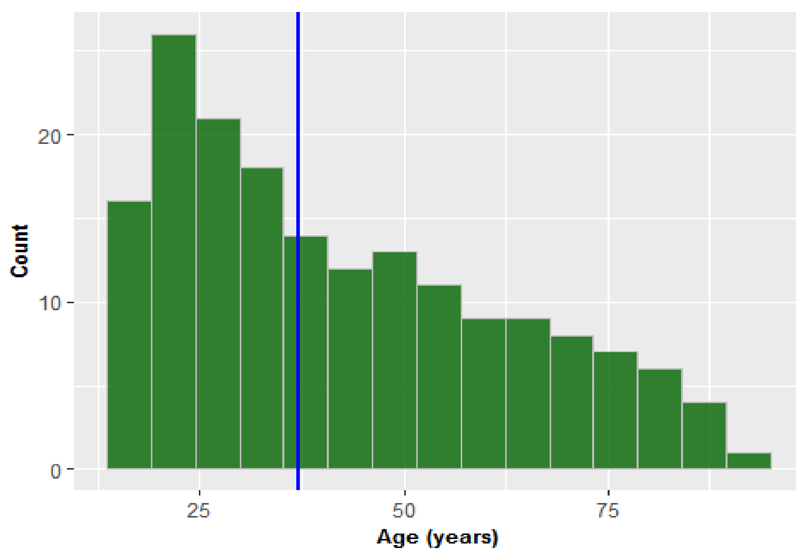

Figure 39. Age Distribution in CDS Cases

Table 27. Age Balance in CDS Cases

Scenario	Younger	Middle Aged	Older	Sum
LTAP-OD	34	18	15	67
LTAP-LD	13	5	13	31
LTIP	2	2	0	4
RTIP	2	1	0	3
SCP-L	18	9	7	34
SCP-R	12	10	14	36
Sum	81	45	49	175

Gaps: Age. The analysis of an effect of age on gap size was conducted in two ways, first by looking at age as a categorical factor (following the same analysis as for gender), and second by correlating the numerical raw ages with gap size.

Looking at age as a categorical factor, there was a tendency for middle-aged drivers to have slightly longer gaps in the CDS cases than either younger or older drivers, particularly for LTAP-LD, which showed a medium effect, but also for LTAP-OD and SCP-R, both of which showed small effects (see Figure 68 and Table 38 in Appendix F for plots and tables). There were insufficient cases to look at LTIP and RTIP, and SCP-L had smaller gaps for middle-aged drivers. However, given the low sample sizes, the inability to conduct the split-sample analysis of LTAP-LD (looking at the two batches separately), and the fact that the effect in LTAP-OD is not consistent for both batches, these results do not suggest a strong effect of age in the crash data.

Looking at gap size as a function of raw age, there was little overall pattern except for a faint suggestion of a parabolic shape with few short gap sizes in the middle of the age range (Figure 40).

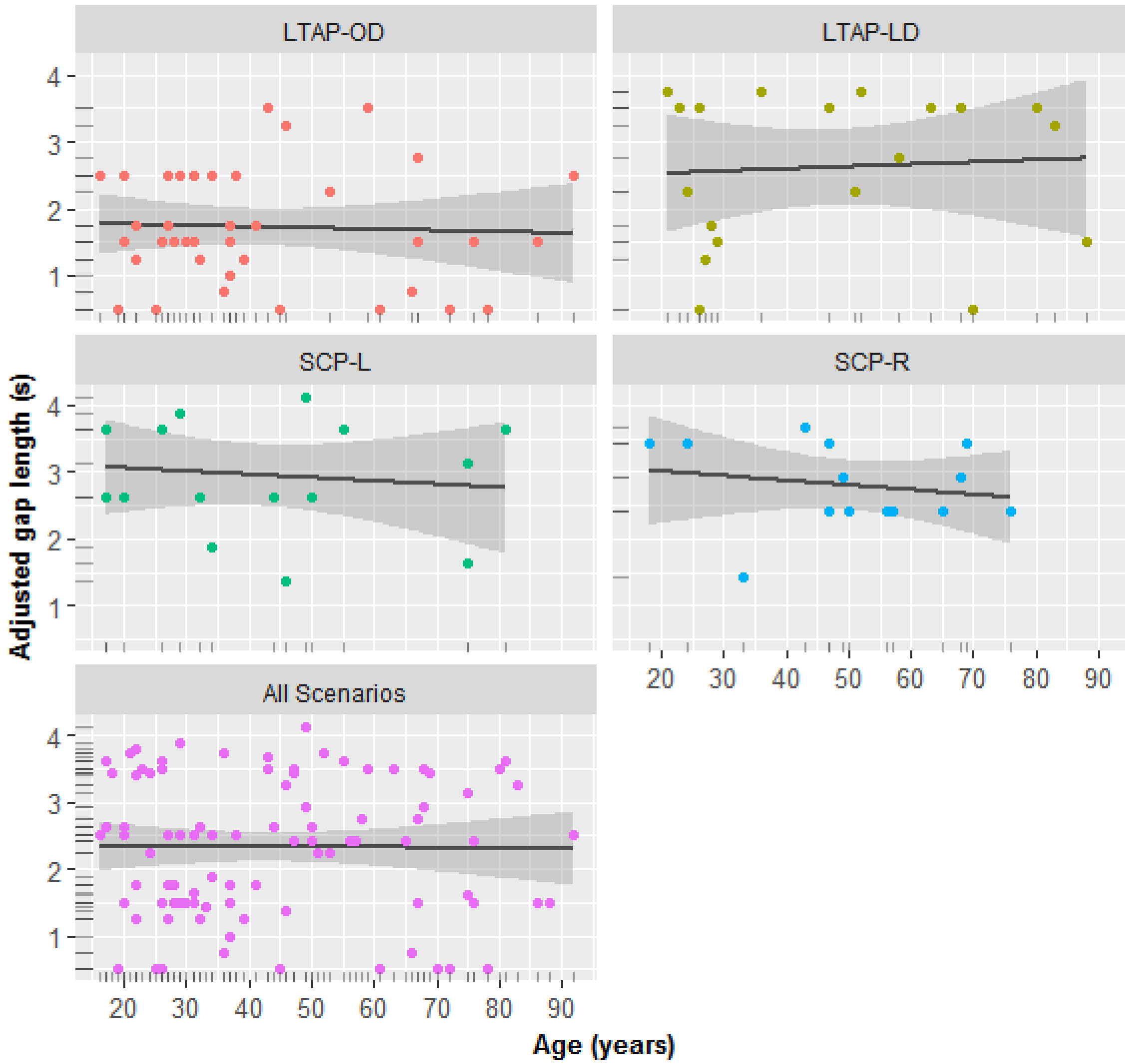

Figure 40. Adjusted CDS Accepted Gap Size by Age

There was no statistical difference between the ages of drivers in the first (median = 38, IQR = 33, $n = 69$) and second (median = 37, IQR = 32.5, $n = 106$) batches of data (Mann-Whitney test, $W = 3673.5$, $p = 0.96$). A nonparametric test was used instead of a *t*-test because a Shapiro-Wilk test showed that ages were not normally distributed ($p < 0.01$).

4.3.5 Environmental Conditions

Event Counts. Three environmental conditions were explored. The first, lighting (day versus night), had 47 out of 193 events taking place at night (Figure 41).

The second, weather (clear versus adverse [rain or snow]), had 26 out of 193 events taking place in adverse weather.

The third and final, road surface condition (slippery versus dry), had 34 out of 193 taking place with slippery roads (recorded as having ice, slush, snow, or being wet).

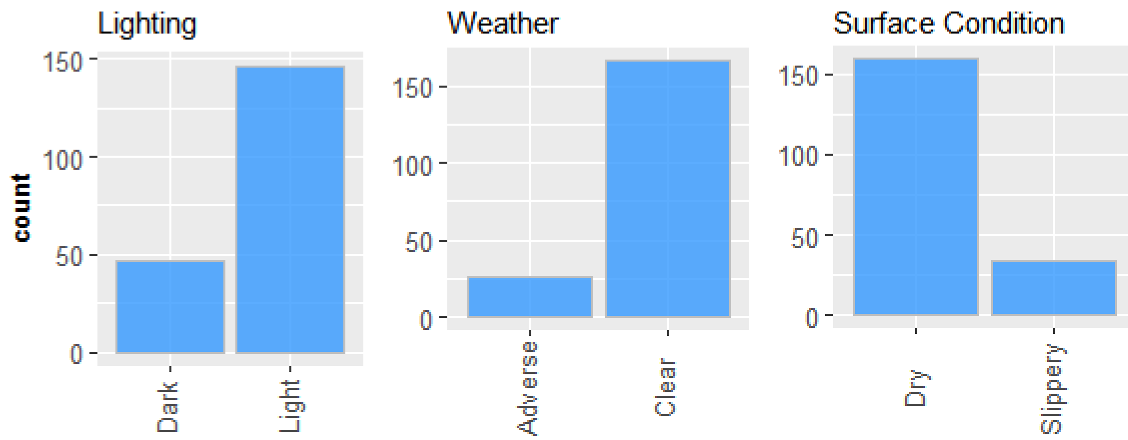

Figure 41. Frequency of Various Environmental Condition Variables

Only two variables showed effects that were consistent for both batches: the effect of lighting and the effect of road surface condition.

Gaps: Lighting. Of 105 cases with measurable gaps, 21 took place at night. Around half of those were LTAP-OD cases. For LTAP-OD, collision gaps were shorter at night; for SCP scenarios, the opposite was true (Figure 42). However, the samples and effect sizes were small with the exception of a medium effect for SCP-R, but there were insufficient cases to look at a split-sample comparison within the batches for that scenario (they are nonetheless included to avoid giving the impression that the trend for all scenarios was like that seen in the LTAP scenarios) (Table 28).

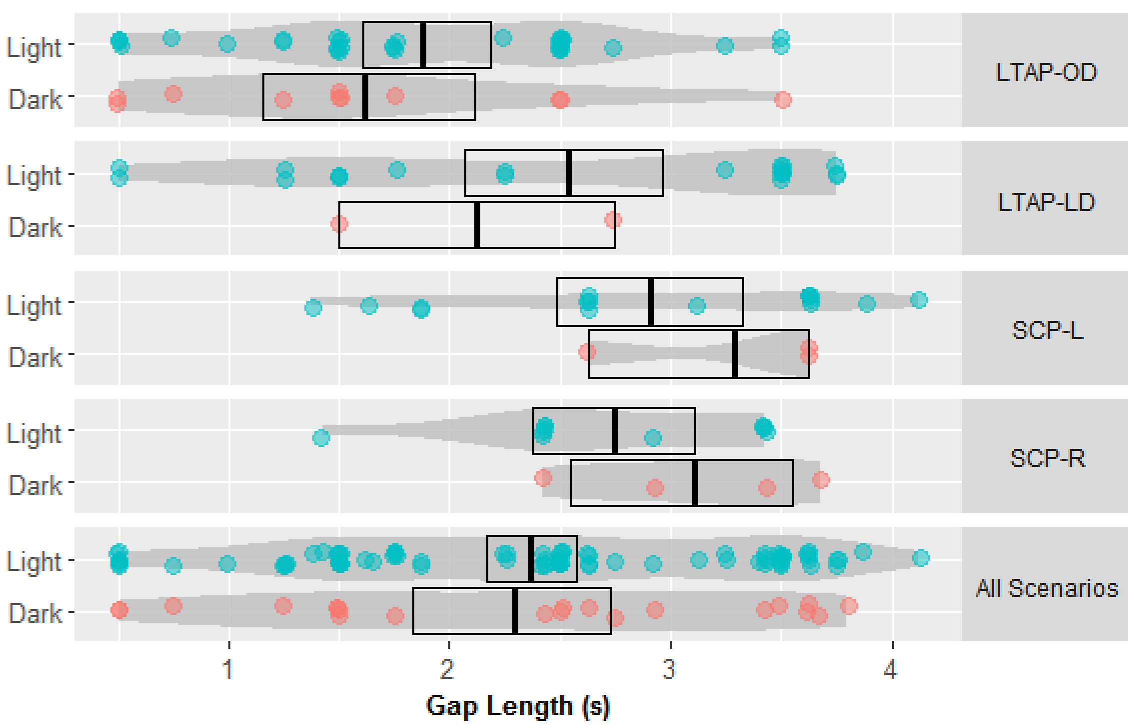

Figure 42. Adjusted Accepted CDS Gap Lengths by Lighting

Table 28. Adjusted Accepted CDS Gap Lengths by Lighting

Events	Scenario	Lighting	Mean (s)	SD (s)	Range (s)	*n*	Effect Size (*d*, 95% CI)
All Data	LTAP-OD	Dark	1.6	0.9	0.5 – 3.5	11	Small (BS) 0.31 (0 – 1.0)
		Light	1.9	0.8	0.5 – 3.5	34	
	SCP-L	Dark	3.3	0.6	2.6 – 3.6	3	Small (BS) 0.46 (0 – 1.9)
		Light	2.9	0.9	1.4 – 4.1	16	
	SCP-R	Dark	3.1	0.6	2.4 – 3.7	4	Medium (BS) 0.59 (0 – 2.0)
		Light	2.7	0.6	1.4 – 3.4	11	
2008 – 2011	LTAP-OD	Dark	1.5	1.0	0.5 – 2.5	5	Small (BS) 0.46 (0 – 1.7)
		Light	1.9	0.8	0.5 – 2.5	13	
2012 – 2014	LTAP-OD	Dark	1.7	0.9	0.8 – 3.5	6	No effect
		Light	1.9	0.9	0.5 – 3.5	21	

Road Surface Condition. For road surface condition, there were two noteworthy effects: a medium effect for gaps during dry road conditions to be shorter in LTAP-LD, and a large effect for them to be longer in SCP-R (Table 29). Although the direction of the effects was the same for the first batch (events from 2008 – 2011), there were insufficient numbers to measure the effect size.

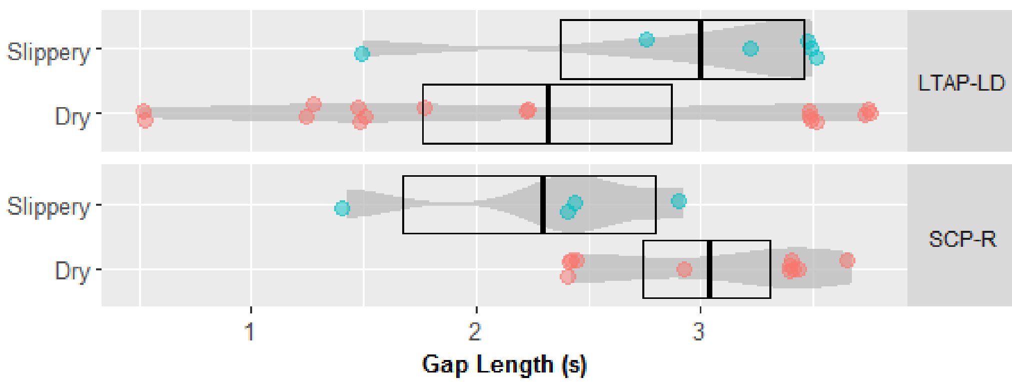

Figure 43. Adjusted CDS Accepted Gap Lengths by Road Surface Condition

Table 29. Adjusted CDS Accepted Gap Lengths by Road Surface Condition

Events	Scenario	Surface Condition	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
All Data	LTAP-LD	Dry	2.3	1.2	0.5 – 3.8	17	Medium (BS) 0.61 (0 – 1.7)
		Slippery	3.0	0.8	1.5 – 3.5	6	
	SCP-R	Dry	3.0	0.5	2.4 – 3.7	11	Large (BS) 1.36 (0 – 2.8)
		Slippery	2.3	0.6	1.4 – 2.9	4	
2008 – 2011	LTAP-LD	Dry	1.2	-	1.2 – 1.2	1	Insufficient *n*
		Slippery	2.8	1.2	1.5 – 3.5	3	
	SCP-R	Dry	2.8	0.5	2.4 – 3.4	6	Insufficient *n*
		Slippery	2.4	-	2.4 – 2.4	1	
2012 – 2014	LTAP-LD	Dry	2.4	1.2	0.5 – 3.8	16	Medium (BS) 0.68 (0 – 2.1)
		Slippery	3.2	0.4	2.8 – 3.5	3	
	SCP-R	Dry	3.3	0.5	2.4 – 3.7	5	Large (BS) 1.71 (0 – 4.2)
		Slippery	2.3	0.8	1.4 – 2.9	3	

4.3.6 Distraction

Event Counts: Distraction. The attention status of the driver was recorded in 42 cases. Only 6 were distracted and 16 "looked but did not see."

Gaps: Distraction. The sample sizes were too small to get reliable results here. The only suggestive pattern that was consistent for both batches was a tendency for gaps to be shorter for crashes that occurred when drivers were distracted (Figure 44). However, it should be noted that there was a lot of noise in the other scenarios and this pattern differed among them. Furthermore, there were insufficient cases to check for the effect size for LTAP-LD in the first batch (2008–2011) and the effect size in the second batch and overall were both only small (Table 30). It is therefore very difficult to tell how much this result is merely random noise.

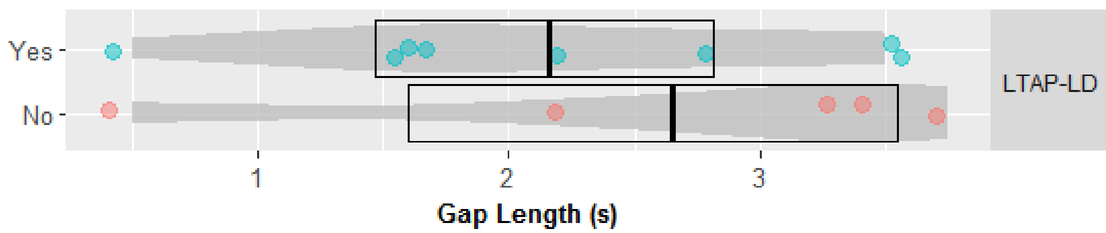

Figure 44. Adjusted CDS Gap Lengths by Distraction

Table 30. Adjusted CDS Gap Lengths by Distraction

Events	Scenario	Surface Condition	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
All Data	LTAP-LD	No	2.6	1.3	0.5 - 3.8	5	Small (BS) 0.43 (0 – 1.8)
		Yes	2.2	1.1	0.5 - 3.5	8	
2008 to 2011	LTAP-LD	No	3.5	-	3.5 - 3.5	1	Insufficient *n*
		Yes	2.5	1.4	1.5 - 3.5	2	
2012 to 2014	LTAP-LD	No	2.4	1.4	0.5 - 3.8	4	Small (BS) 0.33 (0 – 2.0)
		Yes	2.0	1.0	0.5 - 3.5	6	

4.3.7 Turn Signal Usage

No information on the use of turn signals is recorded in this crash database.

5 Discussion

The aim of the study was to improve our understanding of driver crossing of intersections during scenarios covered by the LTA and IMA safety applications and to shed light on when alerts should and should not be issued. Additionally, the results provide estimates of vehicle metrics like vehicle speed and acceleration levels for crossing and turning that could be used in test procedures of crash warning and avoidance systems on test tracks, and in general to assist developers in designing and implementing more effective (reduced nuisance alert) applications.

5.1 Baseline Driving and Collision Results

Overall, this study identified a number of valid intersection crossing scenarios, though fewer than expected due to a combination of low traffic density and the presence of traffic lights (especially protected left-turn signals) that stopped oncoming traffic and meant there were no gaps to observe for the LTAP-OD scenario.

Nonetheless, enough events were identified to characterize intersection crossings and to enable an investigation into what variables played a role in gap selection. The following bullets present the key results from this analysis.

- ***Gap lengths:*** *Averaged across scenario for each driver, the average minimum gap size for drivers was 3.6 s, which was just under two standard deviations from the mean (6.0 s, range = 3.6 – 10.9 s,* n *= 71). Over 94 percent of accepted gaps were longer than the average rejected gap (mean = 3.4 s, range = 0.9 – 7.5 s,* n *= 100).*

  Accepted gap length varied between scenarios, with the largest for SCP-L (7.1 s, 5.0 – 11.7 s, n *= 18) and RTIP (6.8 s, 2.5 – 9.4 s,* n *= 21), followed by LTAP-LD (6.4 s, 3.8 – 8.6 s,* n *= 18), SCP-R (6.0 s, 4.5 – 8.0 s,* n *= 7), LTIP (5.9 s, 3.5 – 7.6 s,* n *= 7), and LTAP-OD (5.0 s, 3.6 – 6.6 s,* n *= 36).*

  Accepted gaps were shorter in the crash cases than in baseline, with an average overall adjusted length of 2.5 s (range = 0.7 – 4.2 s, n *= 105). LTAP-OD also had the smallest gaps (1.8 s, 0.5 – 3.5 s,* n *= 45) and, excluding LTIP since it was a single event, SCP-L had the largest (3.0 s, 1.4 – 4.1 s,* n *= 19).*

As expected, average accepted gaps were longer than average rejected gaps for all scenarios. This is important because any inferences based on differences between gap lengths would be invalid if we could not demonstrate a relationship between gap length and whether or not a driver proceeded. Likewise, whether or not the throttle-to-gap-start delay is subtracted from the crash-database estimates, their values seem reasonable in that they were all shorter than the safely performed intersection crossings in the baseline study. Instead, the drivers who crashed drove into gaps of lengths where baseline drivers chose instead to wait. This consistency increases the likely validity of the gap estimates from the baseline study (and it does so whether the delay is subtracted or not—even without the delay, the estimated gaps were mostly shorter than for successful crossings).

It should be noted, however, that the methodologies for measuring accepted and rejected gaps were slightly different: gap start was measured from the beginning of the crossing maneuver for accepted gaps and from the first *opportunity* to cross for the latter. This lessens the precision of the difference between the two measurements somewhat, but the observed differences were large enough that this likely had a small effect.

A weakness in using means to characterize typical gaps is that they are dependent upon the upper limit of what constitutes a gap. As Kittelson and Vandehey [28] argue, gaps above 11 s contain no meaningful information about how drivers will respond to gaps 5 or 6 s in length and serve only to skew the results of gap analyses. Others have followed this convention of a 12-s ceiling [27, 97, 28, 23], though Gorjestani et al. [1] went up to 15 s. This study was limited by the resolution of the video cameras in our ability to see vehicles beyond a certain distance away. This limitation had the effect of setting a ceiling around 12 seconds, aligning our results with the studies that set the same ceiling for themselves. In any case, the lower end of the distribution appears to be more useful and minimums may be more reliable than averages provided they were still safe maneuvers.

These results mostly agree with previous studies. Ragland et al. [27], for example, found a minimum gap length of 3 s for LTAP-OD. Furthermore, 15 percent of the subjects in the Ragland et al. study turned when the gap was 4.1 s long, which is exactly the same result found here. Their results diverge at higher lengths, however, due to their inclusion of longer gaps—up to 12 s, their cut off—which is higher than we were able to go due to the camera resolution for turning scenarios. So where 85 percent of their drivers turned by the time gaps were 8.6 s long, in this study 85 percent had turned by the time the gaps were only 6 s long. Although they will affect reported mean gap lengths, these differences are likely not very important since the most important factor is the minimum gaps accepted rather than the maximum (as reflected in the fact that an arbitrary cut off has to be applied to the latter).

Critical gap values in the literature varied compared to the averages found here, which is not surprising given the different methodologies. Our mean LTIP gap of 5.9 s, for example, was shorter than the critical gaps of 7.0 s [39], 7.1 s [40], and 8.0 and 8.2 s [37]. It is, however, closer to the critical gap given in the HCM of 4.1 s for turning from a major road into a minor one [29], although the critical gaps for turning from a minor into a major road are probably more relevant, and those were 7.1 s for crossing two lanes. For RTIP, our mean of 6.8 s was more in line with critical gaps in the literature, including 7.0 s for Lerner et al., 6.2 s for Kyte et al., 6.3 and 6.5 s for Harwood et al., and 6.2 and 6.9 s in the HCM for crossing two and four lanes, respectively. Finally, for SCP, our means of 6.0 s (for SCP-R) and 7.1 s (SCP-L) are not far from the HCM values of 6.5 s.

If the scenarios are ranked by decreasing size of the 80th percentile gap, the order is essentially the same as for means: SCP-L, RTIP/LTAP-LD, SCP-R/LTIP, and LTAP-OD. It is interesting that gaps for crashes also followed that pattern, at as far as having the longest gaps for SCP-L and the shortest for LTAP-OD. This probably reflects the fact that it takes little time to cross the collision zone in an LTAP-OD, so those crashes almost always involved smaller gaps. Richard et al. [26] describe gap acceptance as being longer for straight crossing (7.9 s) than for turns (6.7 s).

Like Ragland et al. [27], there was, unfortunately, no sudden increase in the cumulative density function that could be used as an easy threshold for alert timing.

How gap size varied with other factors is described in the bullets below. In all of these cases, comparisons between different subgroups presuppose equal distributions of available gaps. In other words, it is possible that drivers drove into smaller gaps in one condition because traffic there was dense enough that small gaps existed; in another area traffic density might be low enough that drivers ended up driving into larger gaps only because no smaller gaps existed. Gorjestani et al. [1] found a similar effect and the issue is addressed by Troutbeck in a response published at the end of Cassidy et al. [2]. That said, if the level of traffic reliably correlates with the different conditions, then these factors may still usefully demarcate what affects a driver's likelihood to drive into a given gap.

- ***Crossing lanes:*** *For LTAP-OD, the average gap was larger when crossing only one lane (5.1 s, 3.8 – 6.6,* n *= 23) than when crossing two lanes (4.9 s, 3.6 – 6.5,* n *= 17), but this was a small effect.*

The lack of a real effect of the number of lanes a driver had to cross on the gap size may reflect a lack of resolution in the data collection, namely the fact that the lane in which the oncoming vehicle was travelling in was not recorded. Although we might expect drivers to wait for a longer gap for oncoming traffic in lanes further away since they will need time to first travel to that intersection point, there should be no difference in gap time for oncoming traffic in the closest lane regardless of how many lanes there are beyond that. That this lack of an effect is due to methodological limitations is suggested by the presence of such an effect in a study of LTAP-ODs by Hamed and Easa [98].

- ***Dedicated turning lanes:*** *Although subjects turned into slightly shorter gaps from dedicated turning lanes (4.9 s, 3.6 – 6.6,* n = 31*) than from regular lanes (5.2 s, 3.9 – 6.5,* n = 7*) in LTAP-OD, the effect size was small. The same small effect was seen in the crash database results, with turns from a dedicated lane (1.7 s, 0.5 – 3.5,* n = 34*) than from regular lanes (2.1 s, 1.5 – 2.8,* n = *11).*

It is perhaps not surprising that dedicated turning lanes had no real effect on gap selection given that the only real difference is the fact that drivers behind you will also be turning left rather than possibly going straight. Since it is already unclear whether having another vehicle waiting behind affects a driver's choice of gap length, it is unknown whether it would matter if the following vehicle is waiting to turn or proceed straight. Furthermore, the fact that the same pattern of shorter gaps with a dedicated turning lane was present for rejected gaps as well as for the crash-database events suggests that the pattern for accepted gaps may just be an artifact of the basal level of available gaps; e.g., shorter gaps were available at those intersections because they are installed in higher traffic-density areas.

- ***Road profile:*** *For LTAP-OD, there was a medium effect of road profile in the crash database cases, with level roads having smaller gaps (1.6 s, 0.5 – 3.5 s,* n = 31*) than uphill roads (2.0 s, 0.5 – 2.8 s,* n = 9*). No effect was seen for LTAP-LD, SCP-L, or SCP-R.*

It is interesting that collisions that took place on uphill inclines tended to have longer estimated gaps than level roads. Given the small sample size, this may just be random fluctuations in the data, but the same pattern was seen in both the 2008–2011 and the 2012–2014 data. If the pattern is real, more data would be needed to understand why this would be true. If all of these cases are examples of drivers incorrectly choosing gap lengths, why would less-egregious underestimates have been made on the slanted roads? It is possible that a confounding factor lies behind the pattern (again, if it is real), such as speed, which may vary with these types of roads. In short, this result highlights something to look out for in future studies but is not on its own evidence of a pattern.

- ***Specific intersection:*** *There was substantial variation in average gaps between the eight busiest intersections, ranging from 4.4 to 7.7 s, although the sample sizes were quite small for most of these intersections.*
- ***Intersection type (number of intersecting roads):*** *For LTAP-OD, average gaps were longer at 4-way intersections (5.1 s, 0.3 – 5.1 s,* n = 27*) than side streets (4.9 s, 3.6 – 6.5 s,* n = 11*) and 3-way intersections (4.6 s, 3.9 – 5.1 s,* n = 4*), but the effect was small. For all scenarios combined there was no effect between 3- and 4-way intersections.*

The difference between specific intersections is a good demonstration that gaps are intersection dependent, but it is less clear what variables underlie the differences, and intersection type does not seem to be the answer. It seems likely that other factors, such as traffic density, the number of lanes of oncoming traffic to cross, or the speed of oncoming traffic may be more important than the number of intersecting roads. The fact that most of the data came from one particular type of driving environment—the generally well-marked and wide roads in Ann Arbor, and not, say, the irregular and narrow roads of Boston—limits the generalizability of these results.

- ***Age:*** *There was no effect of age overall in the baseline data, and only a small effect for certain scenarios—but the direction of this effect varied between scenarios. Conclusions were limited by sample size. There was likewise no strong effect of age in the crash-database data.*

This analysis provides little evidence of age effects for baseline driving or crashes. Some of this may be due to the relatively small sample size and the lack of balance between age groups. There was a slight tendency for the crashes with very short gap sizes to involve more older or younger than middle-aged drivers, but the effect was only stronger for LTAP-LD and less so for LTAP-OD. This might reflect the greater difficulty of making left turns among those with less experience or cognitive decline, and we know that older drivers are more likely to be in crashes [69] and are more prone to poor gap selection [56, 70]. Both of those would make smaller gap selection among older drivers easier to believe. But the weak effects are more in line with Bougler et al. [17], who found no age-related difference for LTAP-ODs.

Bougler et al. also saw no difference in gender when looking at LTAP-OD, though, which differs from this study.

- ***Gender:*** *Men turned into gaps that were on average smaller (5.4 s, range = 3.6 – 7.5 s,* n *= 31) than those into which women turned (6.5 s, 3.9 – 10.9 s,* n *= 23)—a medium effect. The same pattern was true for all scenarios individually.*

  There was no effect of gender in the crash database.

The moderate gender effect seen here is consistent with two simulator studies [77, 78] that also found longer median gap times for women than for men for LTAP-OD scenarios.

- ***Light:*** *No effect for day versus night, though this analysis was hampered by a small number of events at night. Results were inconsistent for crashes.*
- ***Weather:*** *No effect for clear versus adverse, though this analysis was also hampered by an almost complete lack of events in adverse weather.*
- ***Road surface:*** *Average accepted gaps in baseline were shorter on dry roads (6.0 s) than on slippery roads (6.5 s) for all scenarios combined, though the opposite was found for LTAP-OD, which had longer dry gaps (5.0 s) than slippery (4.6 s).*

  There were medium and large effects in the crash database, but only for LTAP-LD and SCP-R, and the direction of these effects were different, and there too, sample sizes were small.

Environmental conditions showed no strong effects in baseline, but this was largely due to a lack of events under worse conditions (night time, adverse weather, slippery road). There was a small tendency for longer gaps on slippery road conditions, but the same effect was found for rejected gaps, suggesting that gap availability may again be a confounding factor since environmental factors may determine how many drivers are on the road, with people avoiding the roads in bad weather. Furthermore, this result contradicts a study by Rakha et al. [81], who found gaps to increase for left turns as rain intensity decreases.

The results in the crash database for environmental conditions are inconsistent and the small sample sizes mean that single data points have a strong influence on the direction of the effects—so little stock should be put in them.

In 1994 one in five LTAP crashes occurred on wet, snowy, or icy pavement, where traction may have been low and braking less effective [20]. Taking traction into account could make warnings more accurate by including the stopping and acceleration time needed by the turning vehicle under the current circumstances.

- ***Distraction:*** *There was no effect overall. There was a small effect for LTAP-OD, in which drivers tended to drive into* longer *gaps when distracted (mean = 5.2 s, range = 4.0 – 6.2 s,* n *= 7) than when not (4.9 s, 3.6 – 6.6 s,* n *= 32), and a large effect for RTIP, with drivers turning into* shorter *gaps when distracted (6.0 s, 2.5 – 7.9 s,* n *= 5) than when not (7.2 s, 5.0 – 9.4 s,* n *= 19, but the sample sizes were small (for example, the size of the effect for RTIP was largely due to a single gap of 2.5 s accepted by a distracted drivers).*

The crash database events showed no strong patterns (just a weak effect for shorter gaps while distracted for LTAP-LD).

There was little evidence of an effect of distraction in either baseline or crash events. We might have expected distracted drivers to include a few shorter gaps than those who were paying attention—although nothing too short since by definition these were all normal driving without collisions or emergency maneuvers. Indeed, if making a turn through oncoming traffic is so dangerous that they often result in collisions, then the baseline study, which by definition omitted collisions, would not include most distraction events (or only events with less-severe distraction). According to the GES, distraction was a causal factor in about 21 and 20 percent of LTAP-OD crashes at signalized and unsignalized intersections, respectively, from 2004 to 2008 [84].

The distraction analysis was hampered by a shortage of events with distracted drivers, and the two scenarios with adequate events to test showed opposite patterns: in LTAP-OD, gaps were longer for distracted drivers and for RTIP they were shorter. The effect in RTIP was largely due to a single driver with a short gap, though, so in general these results are not strong enough to support any conclusions. The in-vehicle cameras also had inadequate resolution to check for eye glances to the periphery, which would have been needed to spot cognitive distraction.

The lack of an effect of distraction in the crash data may be due partly to police reporting, with drivers not accurately reporting whether or not they were distracted, since, unlike the baseline analysis, their distraction status was not being evaluated by video monitoring. But the primary issue, like for baseline, is insufficient sample size.

In all IMA scenarios, the vehicle began stopped or nearly stopped. LTAP-OD events included some turns made without stopping and these were binned separately from the LTAP-OD turns from stopped if the speed never dipped below 4 mph.

- ***Speed:*** *Crossings from stopped generally followed the same pattern, accelerating at about the same rate from about 4 – 5 mph at the beginning of the maneuver. The average length of acceleration varied, though: 10 seconds later, the average speed varied from 11.5 mph for SCP-L (*n *= 25 events) to 31.2 mph for RTIP (*n *= 36). Both LTAP-OD turns from stopped and without stopping had converged to about the same speed (15.4 and 13.3 mph, respectively) by that point.*

Speeds were fairly consistent and should be useful for setting test procedure protocols, at least for turns from stopped for IMA and for all turns for LTAP-OD.

The speeds from the crash data are messier for several reasons: They are measured at a lower resolution (once every second or every half second rather than every tenth of a second); they may include turns without stop for all scenarios; they are from all types of roads from all over the country, rather than just Ann Arbor and Washington, DC; and, crucially, they may include evasive maneuvering, such as increasing the speed or braking, if the driver noticed the oncoming vehicle. Nonetheless, they followed a roughly similar trajectory in most scenarios, though in some cases the average speeds were different; e.g., the LTAP-LD maneuvers were at about half the speed during crash events as in the baseline.

- ***Throttle:*** *The median delay between brake release and throttle application for baseline crossings from a stop was 0.5 s and ranged from 0.2 to 0.6 s for individual scenarios.*

Release of the brakes is not enough to indicate a driver's intent to initiate a turn or start the crossing maneuver from stopped since the driver most likely also has to open the throttle to accelerate. Green [89] estimates that, when making an unplanned stop, the movement time from throttle to brakes (the reverse movement) takes about 0.2 s when the driver is alert and aware that a reaction may be needed. When the need to react is unexpected, Green increases the expected movement time to 0.3 s. Contrasted with the 0.6 s delay observed in this study by drivers accelerating into a turn, this suggests that drivers may allow the vehicle to rest or coast at a slow speed before turning or crossing after releasing the brakes and before applying the throttle. As a result, throttle application may be needed as a complement to brake release to predict the start of a turn.

The observed delay from throttle application to the opening of the gap had a median of 0.8 s and ranged from 0.1 to 1.1 s by scenario. It is tempting to interpret these delays as acts of anticipation, with the driver accelerating before the gap opens because they must first traverse the distance to the zone of collision. However, such an interpretation would depend on throttle being an independent measure from gap start when in fact we determined gap start based on yaw rate, which necessarily follows throttle application after a small delay since the vehicle requires time to accelerate.

In addition to illustrating the difficulty in identifying precisely when gaps start, the throttle-to-gap delays were used in the collision analysis to enable better comparison with baseline data. This was needed due to the different methods of estimating gap start used for each: in baseline, gaps were estimated as when the vehicle started to move; in the CDS they were estimated by throttle application. To make the measures more equivalent, the median delay from throttle application to gap start observed in the baseline was subtracted from the gap-start times in the CDS cases.

- ***Acceleration:*** *For the first 2 seconds of acceleration from stopped (starting when vehicle speed exceeded 4 mph), for all scenarios combined, drivers accelerated by a median of 1.8 m/s^2 (mean = 1.8 m/s^2, range = 0.6 – 3.3 m/s^2,* n *= 106). Individual scenario medians ranged from 1.7 m/s^2 for LTAP-OD to 2.3 m/s^2 for LTIP.*
- ***Steering wheel angle:*** *At the beginning of turns, average steering wheel angle varied from 55.0 degrees for LTAP-OD (cross without stop) (*n *= 24) to 112.6 degrees for LTIP (*n *= 11). At the maximum point of turn, it varied from 138.8 degrees for LTAP-OD (cross without stop) to 195.0 degrees for LTAP-OD.*

Acceleration and steering wheel angle should also be useful for setting test procedure protocols, at least for turns from stopped for IMA and for all turns for LTAP-OD.

- ***Turn signal:*** *Turn signal use was at 81 percent for all turning scenarios, and ranged from 50 percent for LTIP to 96 percent for LTAP-OD.*

The overall percentage of turn-signal use was not far from the 75-percent rate estimated by Ponziani [83]. That said, the high use of turn signals in several scenarios may also be affected by the fact that all of the drivers were taking part in a safety-related experiment in which their behavior was being monitored and, as a result, they may be more safety conscious than the average driver. It is also possible that there are regional differences across the country in turn-signal use.

Although the high use of turn signals in some scenarios offers some justification for warning systems that require turn signal activation to issue alerts, there seems to be little use in knowing *when* the driver activated the signal. This is because the timing is complicated by time spent waiting for vehicles ahead, for oncoming traffic, or for changing traffic lights.

5.2 Key Findings for Developers

Several of the findings in this study have potential relevance for the design of crossing-path collision warning and avoidance systems. Foremost is the finding that, in line with previous research, gap size remains a good indicator of driver behavior. The utility of other variables, such as the moderate gender effect observed here, is dependent upon the details of how a developer designs and implements the application to warn and suppress nuisance alerts.

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Appendix A: Full Literature Review

This appendix expands the summary of the literature review in Section 2.

In some cases, the following sections are broken down by scenario type, but much of the information is relevant to intersection crossings in general and, in those cases, the different scenarios are discussed together.

Modeling How Drivers Cross Intersections

This section adds to Section 2.1.1, outlining algorithmic steps for making various intersection crossings.

SCP – Signalized. Tijerina et al. [99] describe how the ideal driver would negotiate a signalized intersection during an SCP.

1. Detect the presence of the intersection during an approach and slow down.
2. Detect and interpret the signal status correctly.
3. Estimate, when the light changes from green to amber, if it is safe to proceed through the intersection.
4. Anticipate sudden deceleration from lead vehicle.
5. Detect the presence of cross traffic.
6. Recognize crash hazards posed by cross traffic, perhaps by estimating the speed and distance of the approaching vehicles.
7. Identify vision obstruction problems and attempt to overcome such problems.
8. Watch for and anticipate other traffic or pedestrians that may cause a cross traffic vehicle to suddenly stop in the SV travel lane.

SCP – Unsignalized. The process for an unsignalized intersection is similar [100] and is visualized in Figure 45.

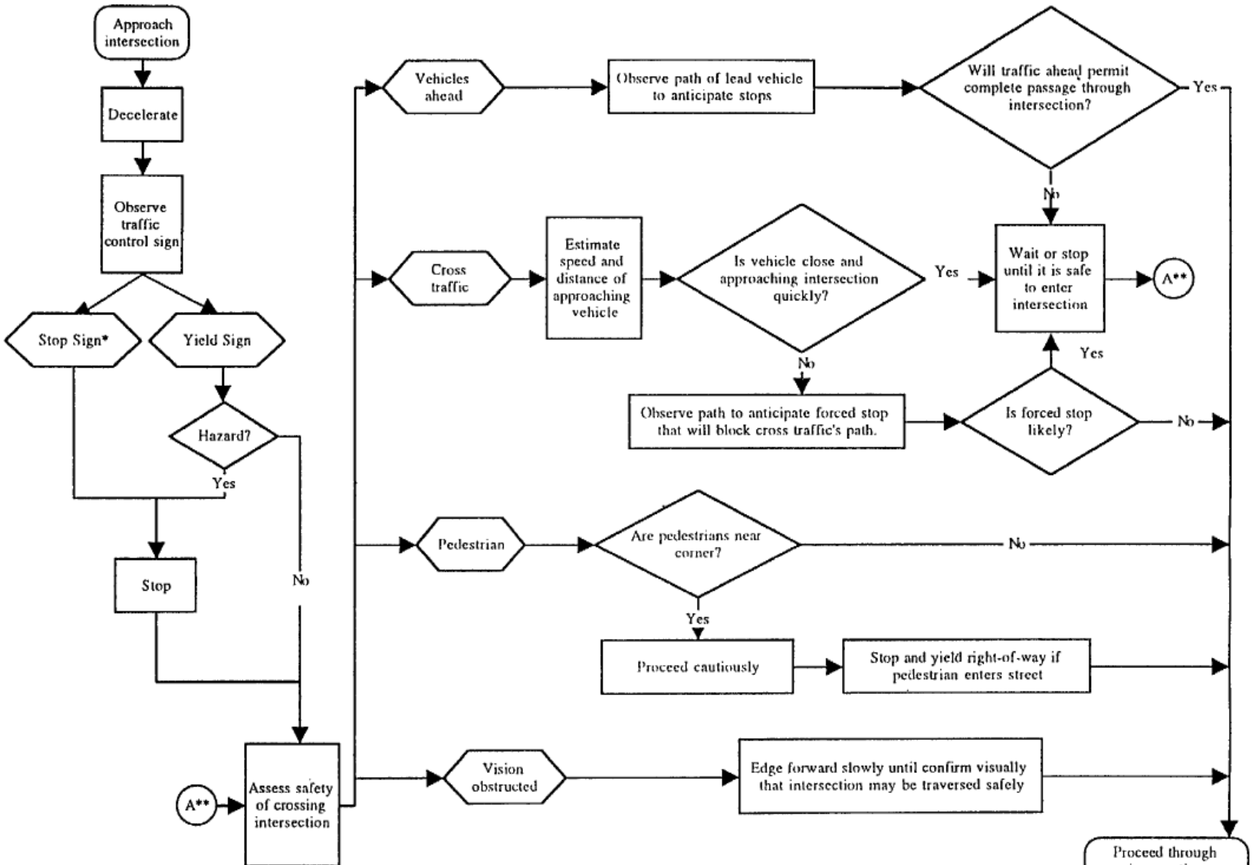
1. Detect the presence of the intersection during an approach.
2. Correctly identify signage.
3. Anticipate sudden deceleration from lead vehicle.
4. Detect the presence of cross traffic.
5. Recognize crash hazards posed by cross traffic, perhaps by estimating the speed, acceleration, and distance of the approaching vehicles.
6. Watch for and anticipate other traffic or pedestrians that may cause a cross traffic vehicle to suddenly stop in the SV travel lane.
7. Identify problems that might obstruct the driver's vision and attempt to overcome such problems.
8. Stop the vehicle.
9. Estimate when it is safe to proceed through the intersection.

The authors list the following metrics as necessary for a SCP crash-avoidance algorithm.

- Driver brake reaction time
- Vehicle machinery delays
- Distance from vehicle to stop line
- Distance from stop line to the leading edge of the first travel lane
- Lane number
- Travel lane width
- Vehicle speed and acceleration
- Speed of oncoming vehicle and acceleration
- Approach direction of oncoming vehicle
- Intersection width

They note that "it is likely that the CAS algorithm will require multiple set points. Alternative set points should be systematically assessed to determine how set points (such as population 50th percentile braking deceleration versus individual average deceleration) influence driver acceptance and performance. This is an analytical exercise to refine the system design iteratively" (p. 50).

LTAP-OD. The steps involved in a typical left turn are listed by Chovan et al. [20] in the left column of Table 2. These steps are adapted from a flowchart by McKnight and Adams [101], which is recreated in Figure 46. Finally, another model is presented more recently by Shladover et al. [54] in Figure 47.



* Includes implied stops such as a four-way stop at a disabled signal head.
** The circled letter A's represent a feedback loop

Figure 45. Driver Behavior for SCP at Unsignalized Intersections From Chovan et al.

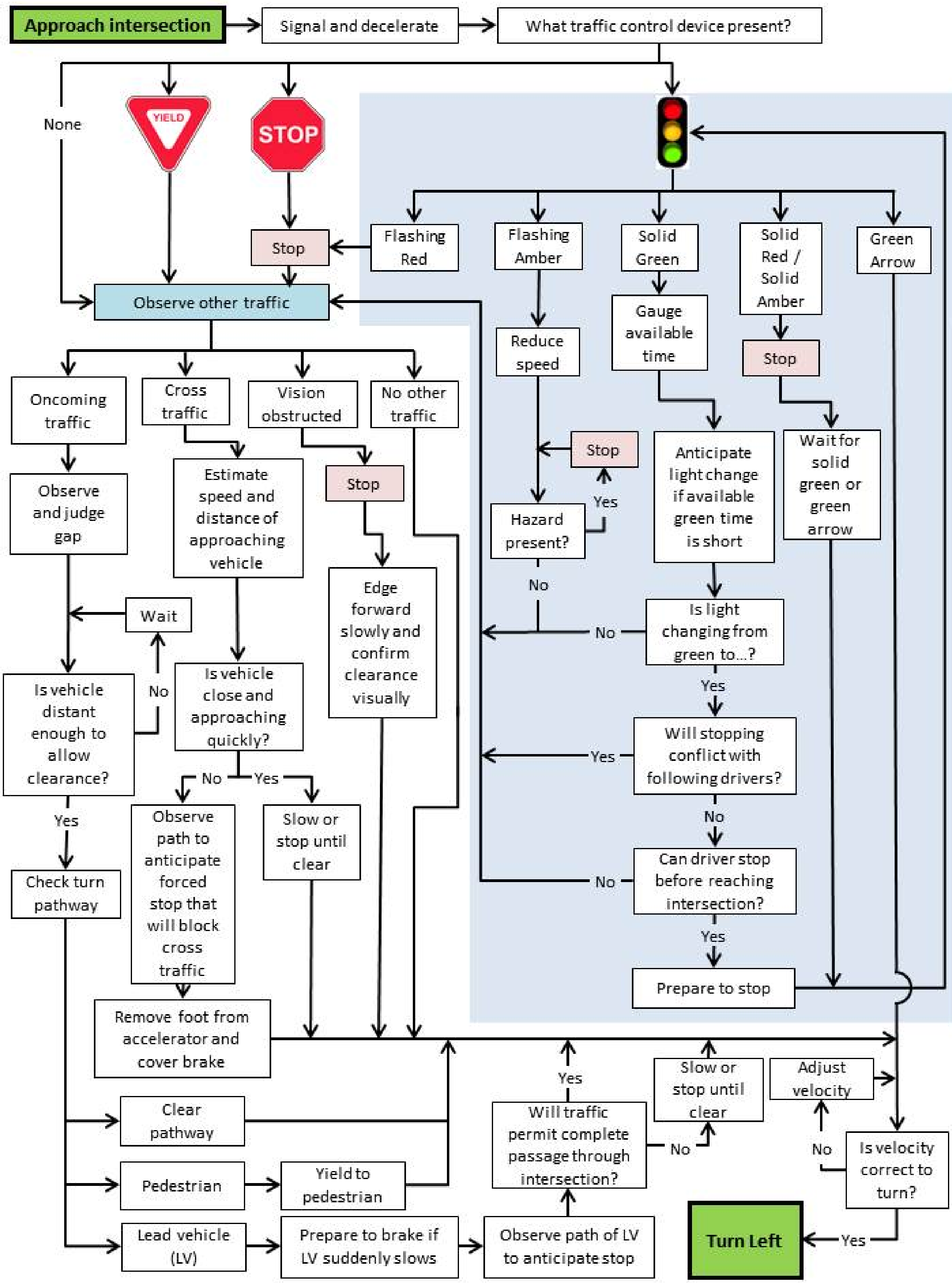


Figure 46. Driver Behavior for LTAP, Adapted From McKnight & Adams via Chovan et al.

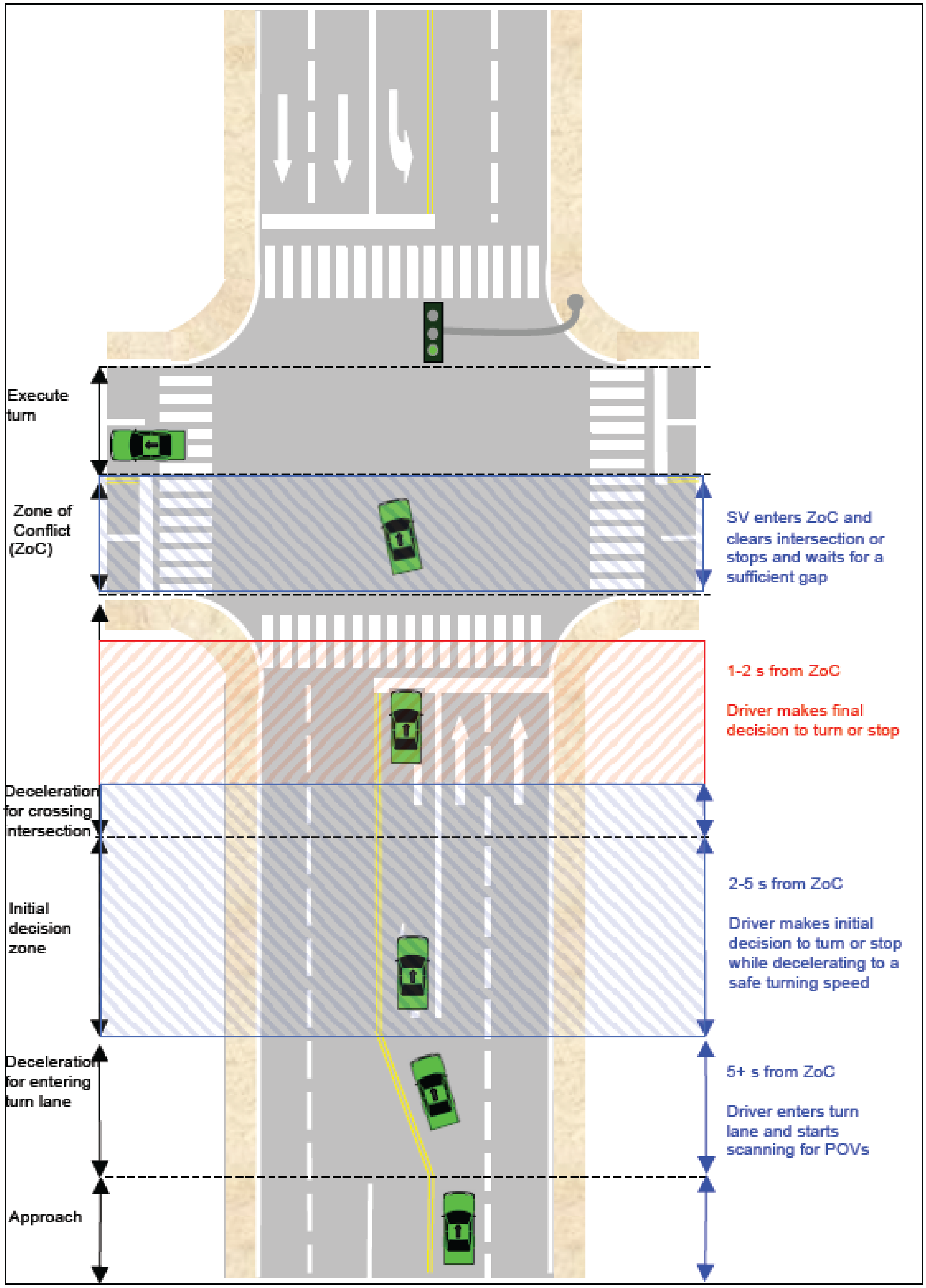


Figure 47. Typical Left-Turn Scenario

Further Work on LTAP-OD Gap Lengths

In the Berkeley FT, Bougler et al. [17] characterized lags when the driver turned with or without slowing down (Table 31). [9] In these cases, a negative difference means the driver will clear the ZOC before the oncoming vehicle, and positive that the oncoming vehicle would clear the ZOC first (the positive lags in time are due to cases where the oncoming vehicle was accelerating while very close to the ZOC). Bougler et al. [17] found strong overlap in the Berkeley FT between the mean lag when the driver turned (4.3 s ± 3 s standard deviation) and the mean lag when they did not (0.5 s ± 2.5 s).

Table 31. Lags for Turns

	Parameter	Min.	Max.	Mean	SD
Without Slowing	POV Distance to ZOC (m)	49.0	113.0	85.6	18.1
	POV time to ZOC (s)	4.3	16.0	8.0	2.7
	SV Distance to ZOC (m)	10.0	50.0	23.1	11.6
	SV Time to ZOC (s)	2.1	6.3	3.8	1.1
	Lag in time (s)	-12.3	1.4	-4.3	3.1
	Lag in distance (m)	-98.0	-20.0	-62.5	24.2
Slowing	POV Distance to ZOC (m)	18.0	82.0	54.9	20.8
	POV time to ZOC (s)	2.8	8.5	5.2	1.6
	SV Distance to ZOC (m)	27.0	62.0	39.7	11.4
	SV Time to ZOC (s)	3.2	6.7	4.9	1.0
	Lag in time (s)	-2.7	2.6	-0.3	1.3
	Lag in distance (m)	-42.0	19.0	-15.3	18.8

The RFS Test by Bougler et al. [17] was more limited in that it presented the driver with a more idealized situation—perpetually green light, no pedestrians, only one oncoming vehicle—and so unsurprisingly the gaps observed were narrower in range, with only 3 seconds between zero and 100 percent of drivers turning.

Shladover et al. [54] continued the work begun by Bougler et al. [17], conducting a pilot study at the Richmond Field Station (RFS Test 2). The pilot study used an infrastructure-based warning application that based alerts on a metric called predicted post-encroachment time (PPET). For the purpose of this review, the PPET is roughly equivalent to the definition of lag given above (and used by Bougler et al. 2008): it measures the spare time a turning vehicle has before an oncoming vehicle reaches the ZOC. An onboard display was then rigged to show the current estimated PPET to the driver (Figure 48).

In order to calibrate what warning urgency level should go with what PPET, Shladover et al. built up a database of turning times for different PPETs at a series of intersections using radar (see Figure 9, below). Figure 49 shows that scale along with the percent of drivers (SV is the subject vehicle or driver making the turn) that would make the turn at a given PPET. The highest threat-level threshold was set at 1.5 s, since they observed less than 5 percent of drivers to turn with smaller PPETs during the data collection phase.

[9] In other places, e.g., Nowakowski [113], the authors have referred to this particular definition of lag as "trailing buffer" or "predicted post-encroachment time," PPET. This definition of lag is different than the definition used in some other studies, where it is taken to mean the distance between the front bumper of the turning vehicle and the front bumper of the approaching vehicle. There are many different measurements used to characterize gaps, which illustrates the importance of correctly translating data before interpreting or merging data from other studies as well as the need for an agreed-upon set of definitions.

Figure 48. Example of a PPET Display

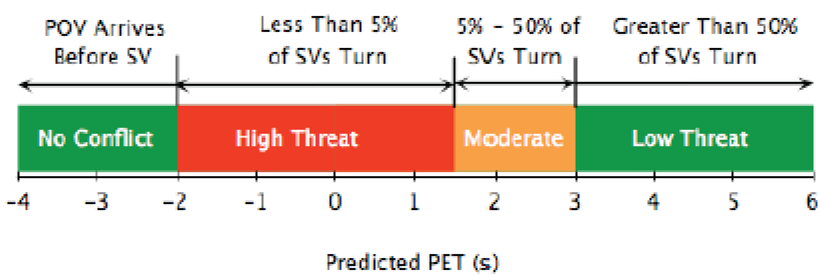


Figure 49. Graduated LTAP-OD Scale Based on PPET

Finally, observations of 67 left turns at an intersection on the University of Minnesota campus were found to include 212 gap events [102]. The average accepted gap was 9.4 s long (SD = 7.7 s), but with a range of 3.8 – 60.8 (no ceiling was set on gap length). Rejected gaps were on average 1.9 s in length (SD = 1.3 s), with a range of 0 – 7.3 s.

Speed

The following profiles show idealized speed profiles for a variety of approaches (Figures 50, 51, 52, 53, and 54).

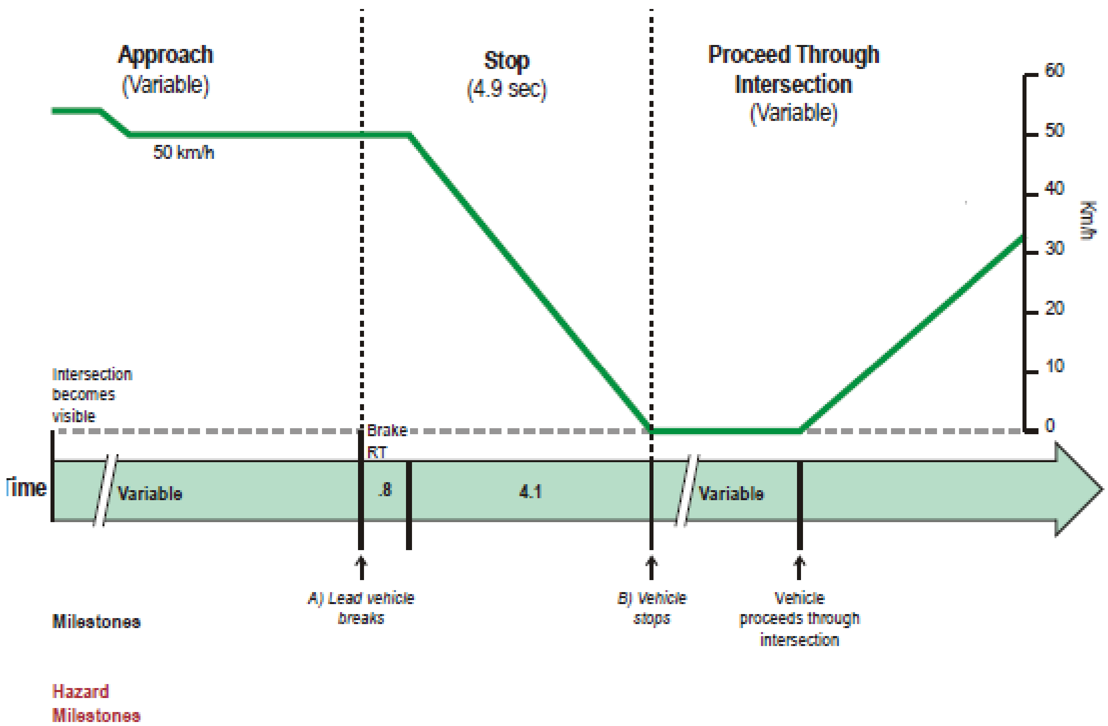


Figure 50. Timeline of Straight Crossing After Red Light

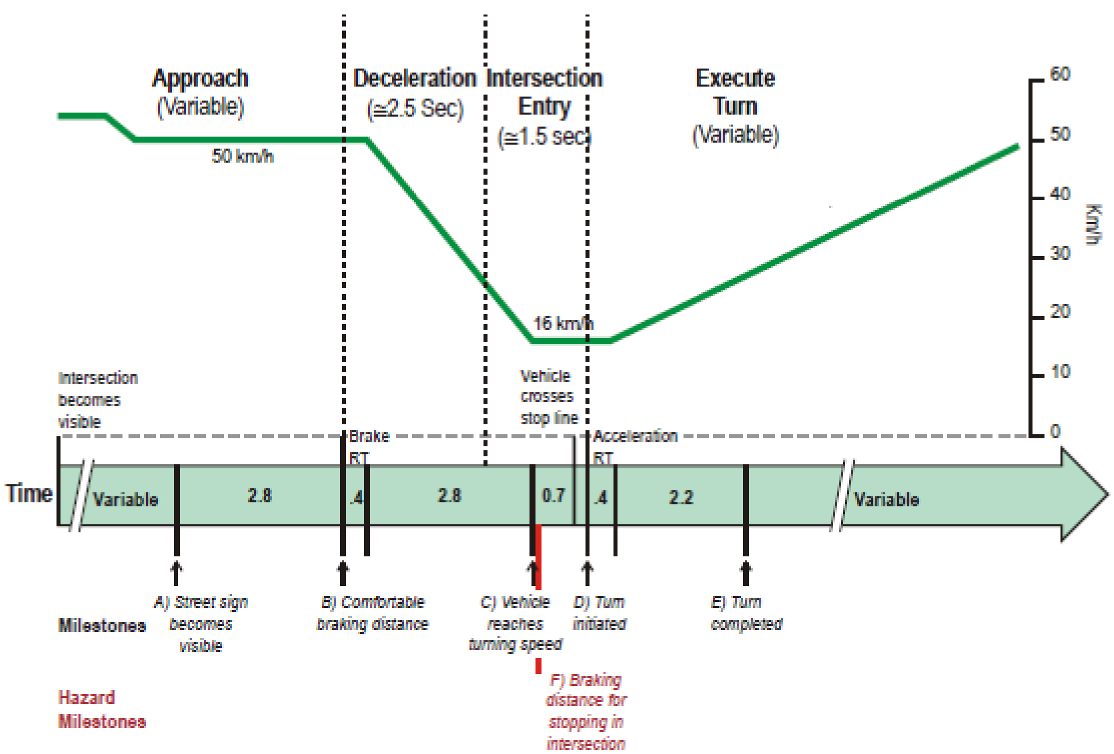


Figure 51. Timeline of Right Turn on Green Light

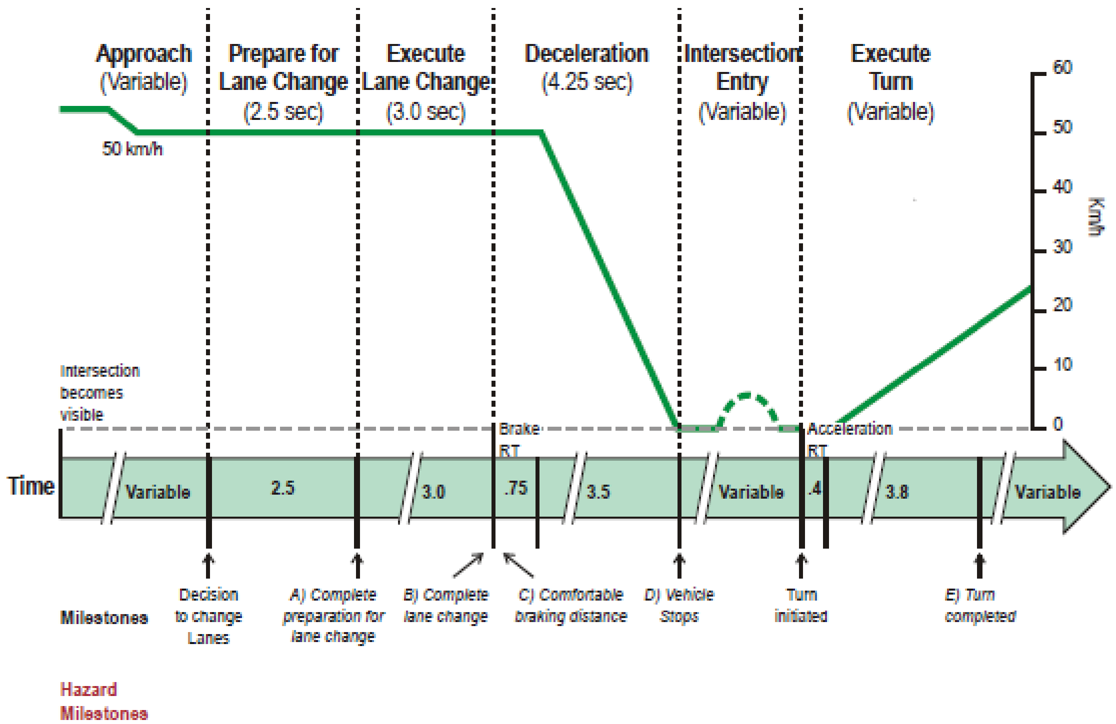


Figure 52. Timeline of Right Turn on Yellow Light

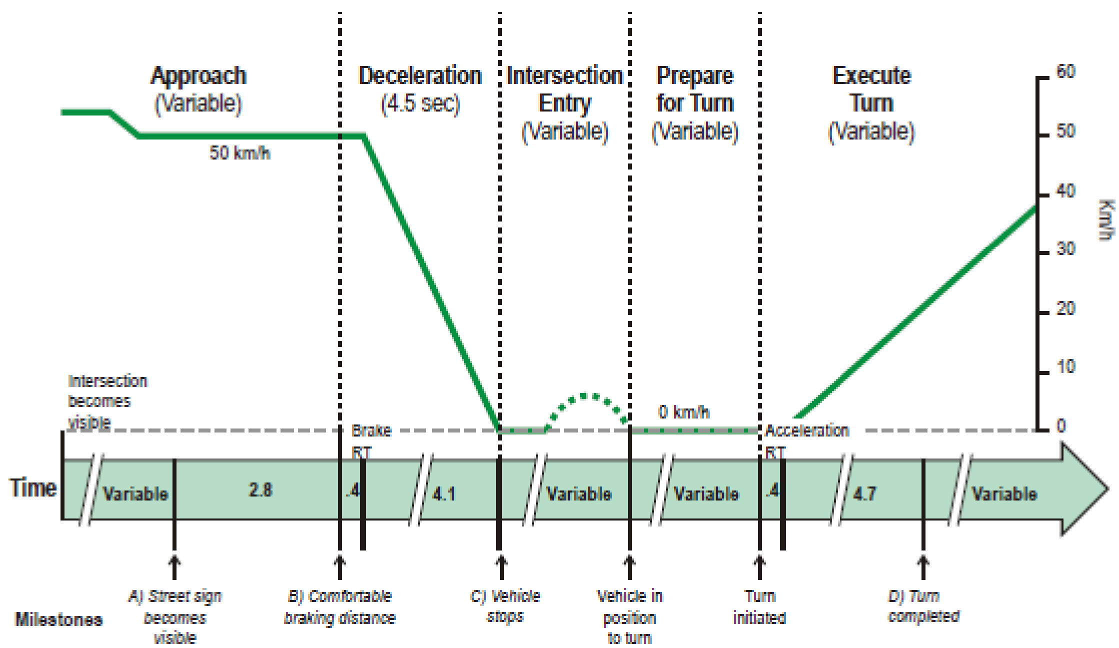


Figure 53. Timeline of Left Turn on Green Light

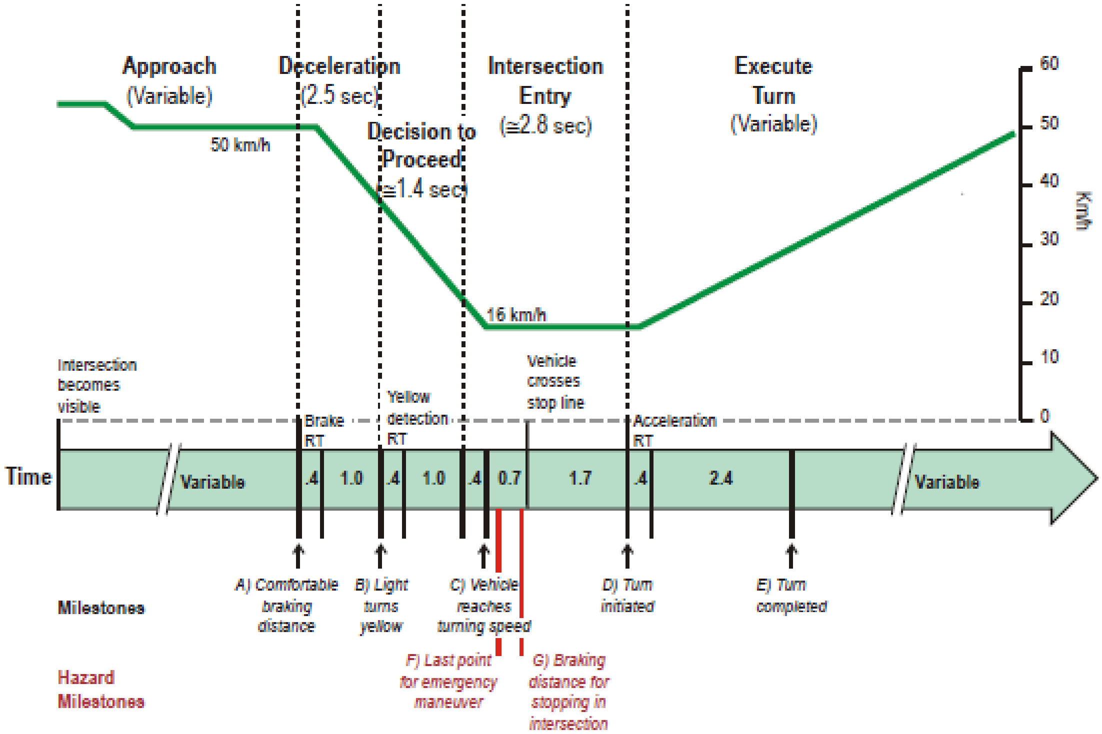


Figure 54. Timeline of Left Turn on Yellow Light

Using Eye and Head Movement to Infer Driver Intent

There is a rich and expanding literature on using modeling and machine-learning algorithms to infer driver intent based on a variety of different inputs. Although some studies, such as Salvucci et al. [103], have developed algorithms for identifying driver actions using just vehicle data, others, such as, Oliver and Pentland [104], incorporate video data gathered from onboard cameras showing the driver. Specifically, Oliver and Pentland used data on driver movement including head movement and eye gaze direction in conjunction with cameras showing the surrounding traffic and with vehicle sensors giving brake status, gear, steering wheel angle, speed, and acceleration throttle. Multiple other studies use head motion, especially to predict lane-changing behavior [105, 106], but lateral head movement may be particularly relevant to IMA maneuvers as well, where it is performed to check for cross traffic.

Further details and information are available for lane-changing studies [107], gaze tracking [108], and for driver-behavior modeling in general [109, 110, 111]. Other parts of the driver may be observed as well, e.g., hand and foot position [112].

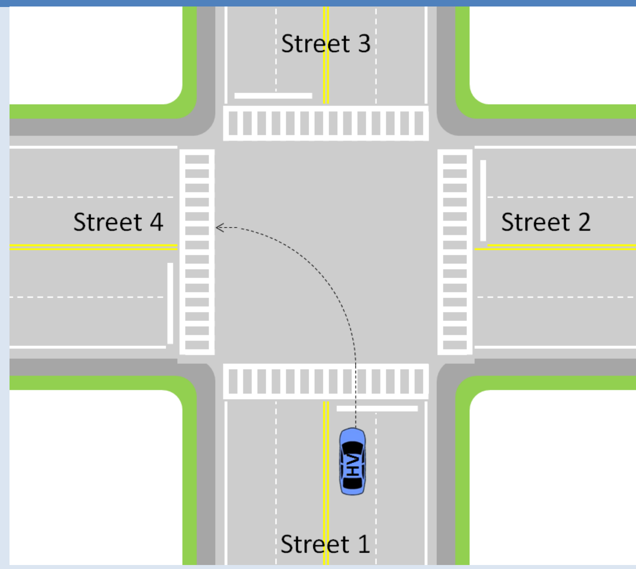
Appendix B: Video Coding Guide

The parameters recorded during manual video review of events from the Safety Pilot and Driver Adaptation databases are listed in the table below. In the table, the following terms are used.

- OV is the oncoming vehicle.
- HV is the host vehicle, or the vehicle being studied.
- Collision zone is the area on the road where the paths of the OV and HV cross.
- LTA is the Left Turn Assist.
- IMA is the Intersection Movement Assist.

Variable	Definition
Comments	Any additional comments may be used to denote uncommon occurrences
Crossing Lanes	The number of lanes dedicated for travel in the direction opposite to the one the HV is coming from. A dedicated turning lane does not count towards this value.
Dedicated Turning Lane	Measures if the vehicle is turning from a lane that is designated as Left Turn Only. Default value is NULL. • TRUE • FALSE
Driver Distracted	Is the driver distracted by something, e.g., cell phone, talking to passengers with eyes off road, singing, eating, falling asleep, etc.? Default value is NULL. • TRUE • FALSE
First Opportunity to Turn	The timestamp of the driver's first opportunity to initiate a maneuver; could be: 1. The time when the front wheels of the HV reach the solid white stop line at the entrance to the intersection 2. The time when the HV becomes the first car in line to go 3. The time when the OV waited for to pass has passed 4. HV must wait for line of cars to pass before the driver can reject or accept a different gap 5. The timestamp should be at whichever of the 3 events occurs closest to the start of the maneuver, itself 6. If the driver has the opportunity to go since before the video began, then the First Opportunity to Go should be the first timestamp in the video 7. May be different values when describing rejects/accepts of multiple threats
Glare	Measures if a glare is affecting the vision of the driver. Glare can be directly from the sun, reflection off of another vehicle, headlights, etc. Default value is NULL. • TRUE • FALSE
Go, No go, etc.	• GO (HV accepts a gap and turns left in front of an oncoming vehicle) • NO GO (HV rejects a gap and turns left after an oncoming vehicle has passed) • NON-CONFLICT • NA

Variable	Definition
HV Initial Location	Where the HV is initiating a maneuver from • MAIN ROAD (HV initiates maneuver from a major road) • SIDE STREET (HV initiates maneuver from a side street or similar) • OTHER
HV Maneuver	• FORWARD • TURN LEFT • TURN RIGHT • OTHER
HV Reaches/Clears Collision Zone	The time when the front of the HV first enters the collision zone / when the rear of the HV exits the collision zone.
Intersection Approach Type	Describes the vehicle movement immediately before the beginning of the turn: • Stop then Go from Stop Line: HV is stopped at the stop line of the intersection, and begins turning from that position • Stop then Go from Inside Intersection: HV is stopped past the stop line and in the intersection, and begins turning from that position • Rolling Speed: Vehicle initiates turn at a speed below 11 mph • Full Speed: Vehicle initiates turn at a speed of 10 mph or greater
Intersection Type	Describes the geometry of the intersection: • 3-WAY • 4-WAY • SIDE STREET (HV turns onto a side street or into a parking lot) • OTHER (some other type of intersection)
Lighting	The cameras have bad contrast, and will make images appear darker than they really are (account for this as best as possible) • LIGHT (daytime, dusk, dawn, overcast) • DARK (nighttime)
Obstruction	Measures if the driver's view is obstructed by anything, e.g., another vehicle, a bush, ice on windshield, etc. Default value is NULL. • TRUE • FALSE
OV Initial Location	Describes where the OV is located in relation to the HV at the start of the turn (see figure below): • In front (Street 3) • Left Side (Street 4) • Right Side (Street 2) • Behind (Street 1)

Variable	Definition
	
OV Lane Number	Lane 1 is the inside lane (closest to the yellow line). Lane numbers increase by 1 as you move towards the outside edge of the road.
OV Maneuver	Describes the OV's movement at the start of the HV's turn: • Turning left • Turning right • Moving forward • Stopped • Accelerating
OV Reaches Intersection	The time when the front wheels of the OV reach the stop line of the intersection
OV Reaches/Clears Collision Zone	The time when the front of the OV reaches the collision zone / when the rear of the OV clears the collision zone
Road Surface	Assume road is slippery if precipitating, more reflective (but be sure not to confuse reflection of an overcast sky on the asphalt as moisture on the road) • DRY • SLIPPERY
Start of Maneuver	Timestamp of when the driver begins the maneuver. For turning in Safety Pilot, it is when the absolute value of the yaw > 2. For turning in Driver Adaptation, it is when the vehicle has positive speed and steering wheel angle > 50. For when the driver proceeds straight, it is when they accelerate and/or cross the white intersection line
Traffic Control Device	Describes the type of traffic signal used at the intersection: • LIGHTS (standard red/yellow/green or flashing yellow arrow) • STOP SIGN • UNSIGNALIZED (none for the turn; may occur at a side street)
Travel Lanes	The number of lanes dedicated for travel in the direction the HV is coming from. A dedicated turning lane does not count towards this value.
Turn Signal	Measures if the driver uses their turn-signal to signify a turn. Default value is NULL. • TRUE • FALSE
Weather	• CLEAR • ADVERSE (precipitation, fog, etc.)

Appendix C: Brake and Throttle Timing

This section provides additional baseline data from Section 3.3.6.

Figures 55 – 59 show the relationship between brake and throttle use in relation to the timing of the gap for all but the LTAP-OD scenario.

Red rectangles indicate brake activation and the thickness of the horizontal blue lines indicates percentage throttle depression. Black brackets indicate the gap into which the driver turned, starting with their first opportunity to turn (judged during video review and used to synchronize the different events) and ending when the oncoming vehicle reached the collision zone. The angle brackets (< and >) indicate when the vehicle was in the collision zone. Not all vehicles in Safety Pilot reported throttle data and events with no throttle were dropped.

For more information and for the LTAP-OD data, see Section 3.3.6.

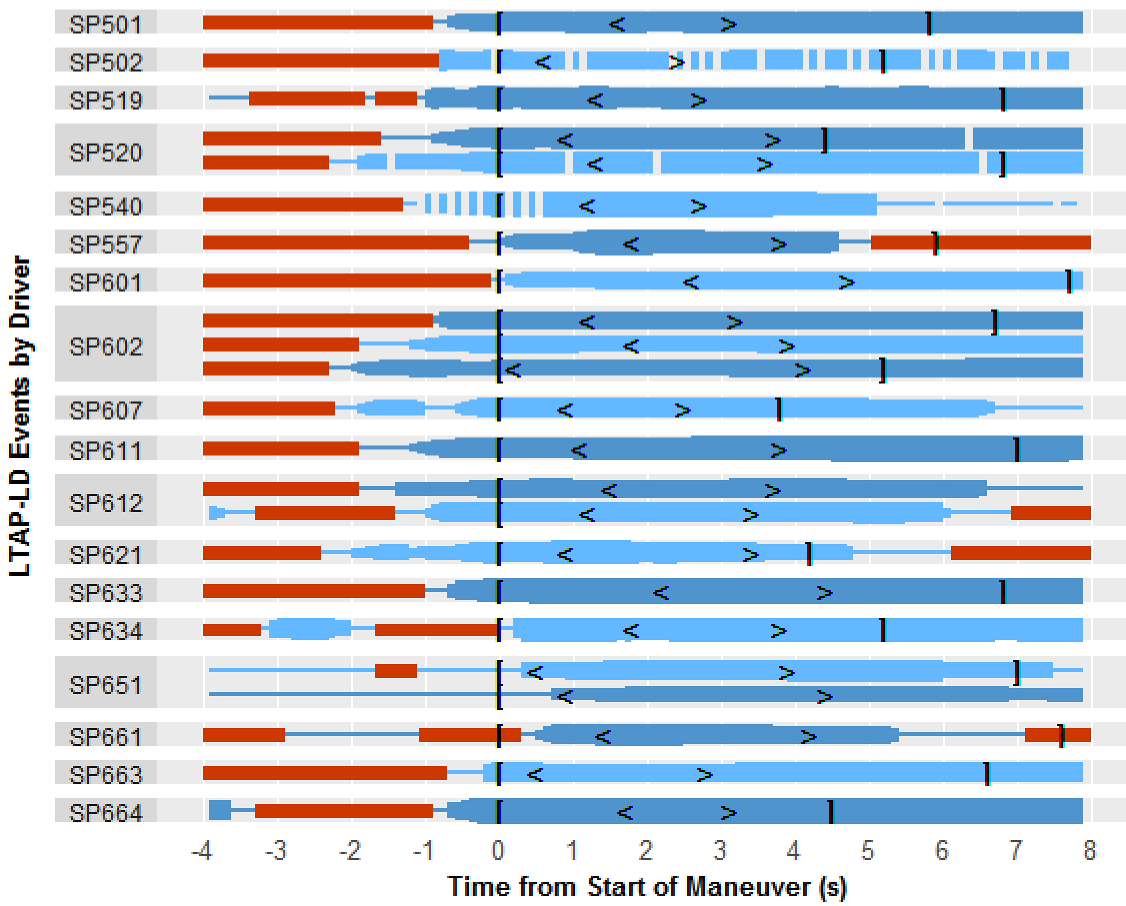


Figure 55. Brake and Throttle for Individual LTAP-LD Events

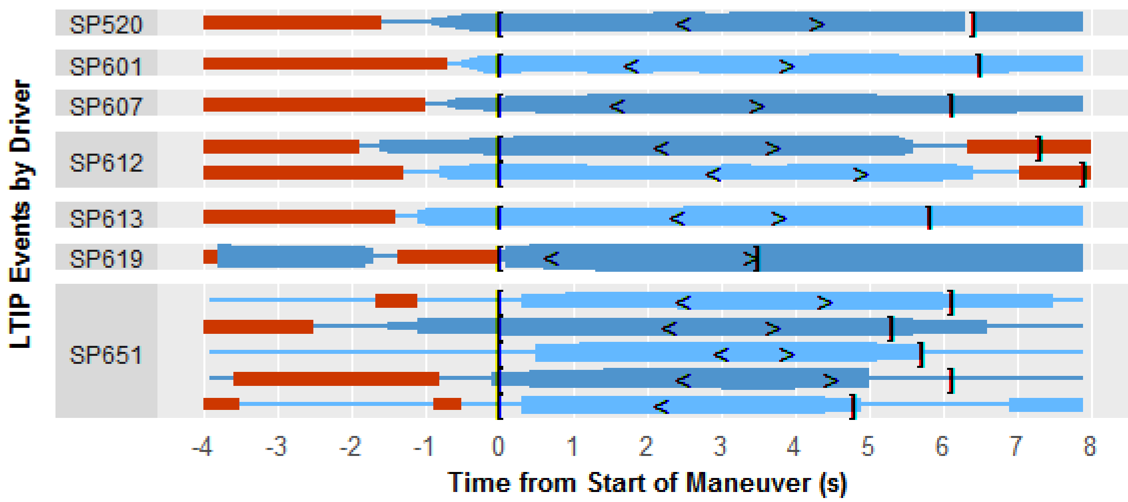


Figure 56. Brake and Throttle for Individual LTIP Events

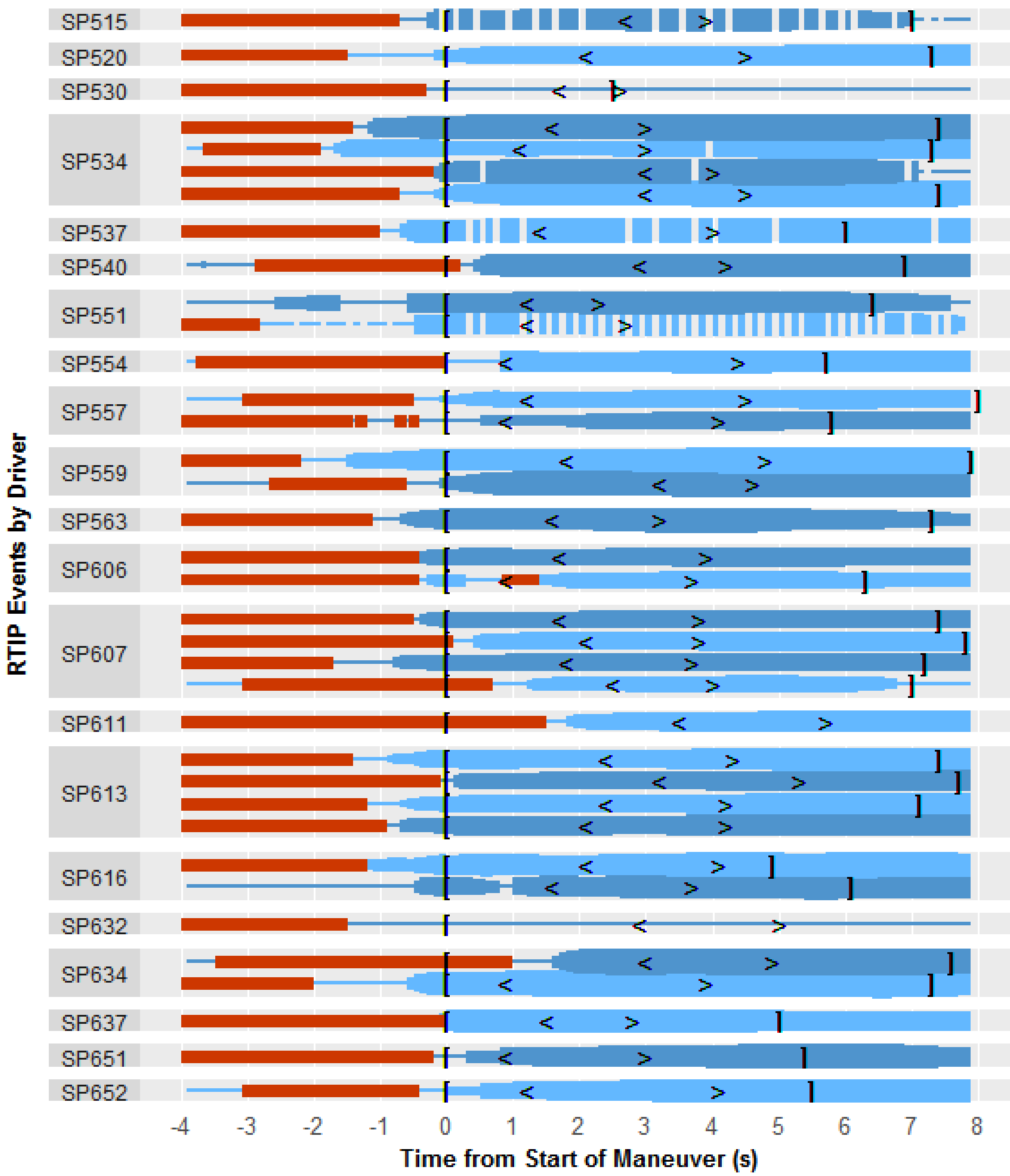


Figure 57. Brake and Throttle for Individual RTIP Events

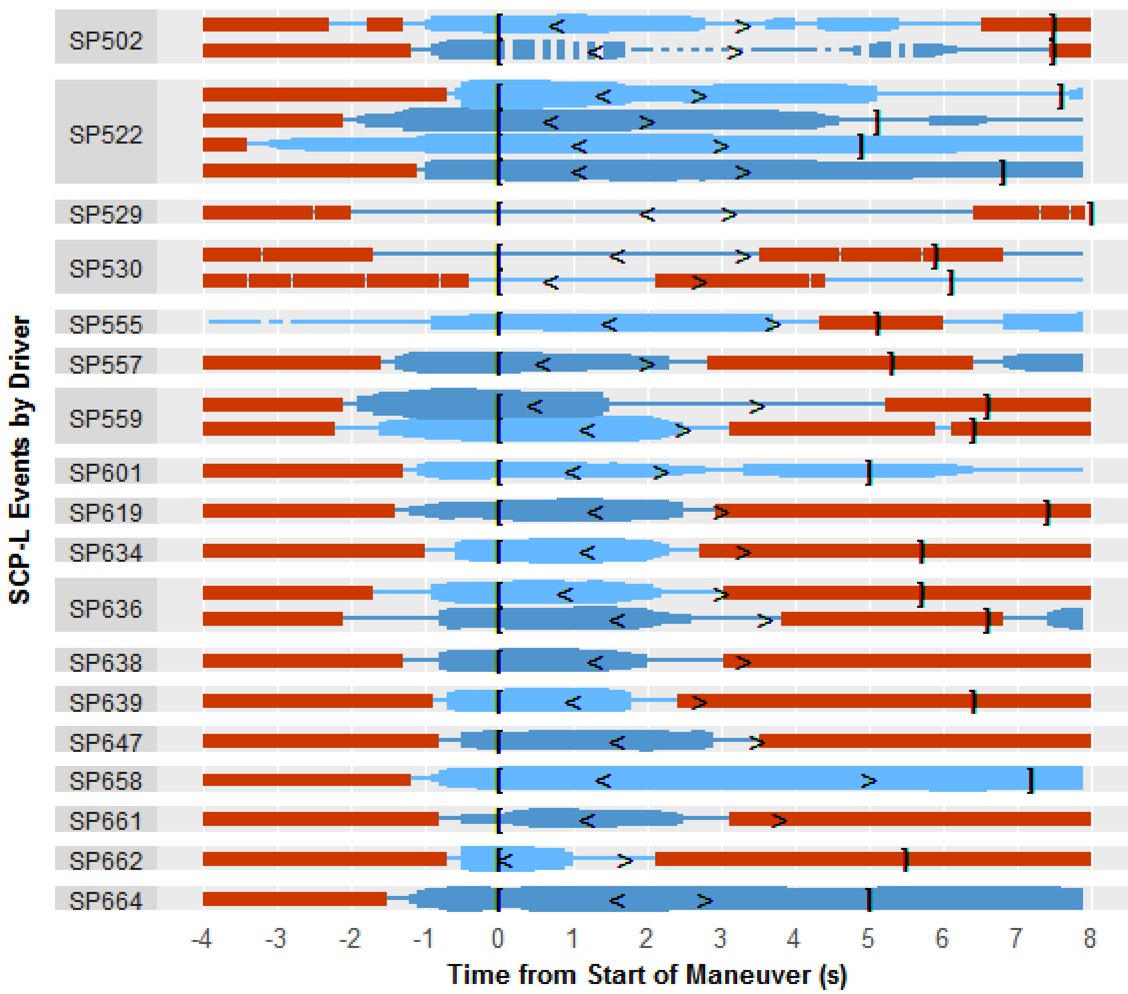


Figure 58. Brake and Throttle for Individual SCP-L Events

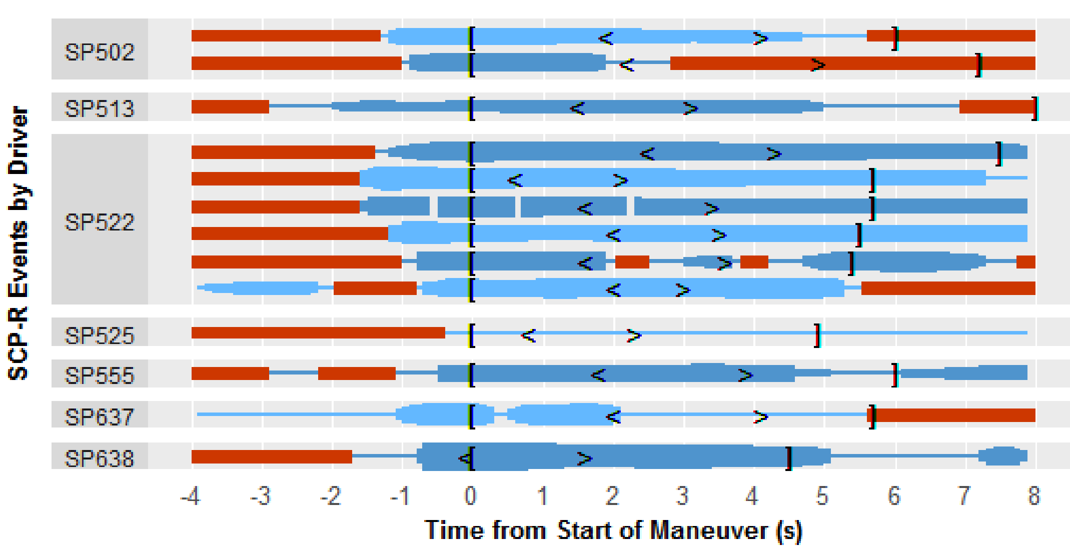


Figure 59. Brake and Throttle for Individual SCP-R Events

The delay between brake release (the last time the brakes were on before the start of the maneuver) until the first application of throttle to over 4.5 percent is given in Table 32 and graphed below in Figure 60, where the green bars in the fore indicate by-driver averages, and the gray bars in the background the individual events. The vertical blue lines indicate the median by driver and the gray lines indicate the median by event (the gray lines are sometimes hidden behind the blue ones). LTAP-OD turns made without stopping are omitted.

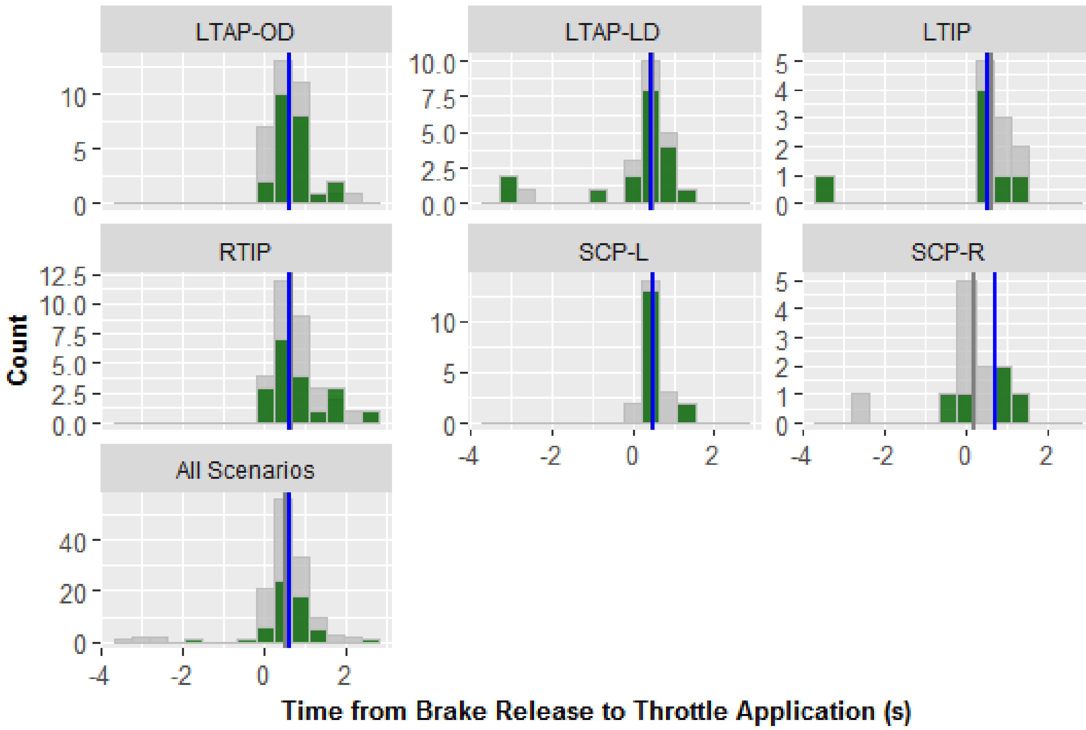


Figure 60. Length of Delay From Brake Release to Throttle Application

Table 32. Length of Brake and Throttle Application (Based on By-Driver Averages)

Scenario	Delay from brake release to throttle application			Delay from throttle application to gap start		
	Mean (s)	Median (s)	*n*	Mean (s)	Median (s)	*n*
LTAP-OD (from stopped)	0.7	0.6	34	1.4	1.0	28
LTAP-LD	0.1	0.5	22	1.1	1.0	18
LTIP	0.4	0.6	11	1.1	0.7	7
RTIP	0.8	0.6	32	0	0.1	19
SCP-L	0.5	0.5	21	0.9	0.9	16
SCP-R	0.2	0.2	11	1.1	1.1	6
All Scenarios	0.5	0.5	131	1.0	0.8	60

Figure 61 shows the distribution of these delays, with the orange bars in the foreground indicating by-driver averages, and the gray bars in the background the individual events (these are not stacked bar graphs). The median is indicated for driver averages by the vertical red lines and for individual events by the gray lines (for some scenarios the gray lines are hidden behind the red ones). Table 32 above provides further details.

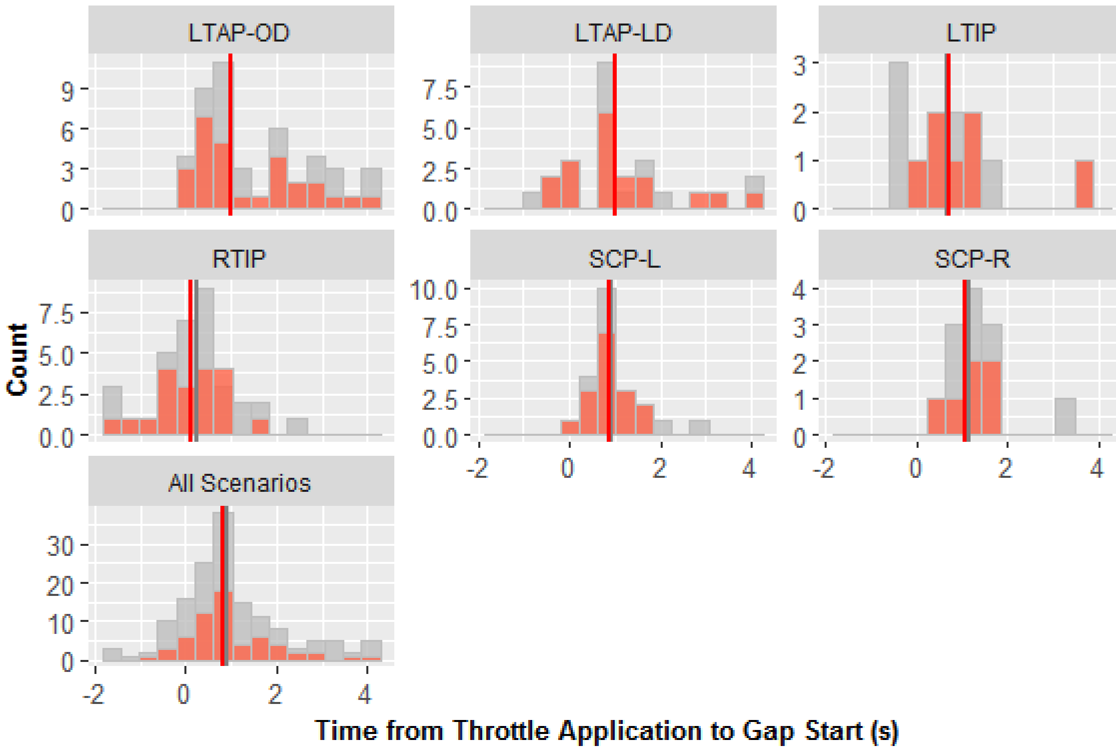


Figure 61. Length of Delay From Throttle Application to Gap Start

Appendix D: Acceleration

This section provides additional baseline data from Section 3.3.5.

Acceleration values for the first 2 seconds of those turns were plotted as a function of the size of the gap in Figure 62. The areas shaded grey around the regression lines indicate the 95 percent CI for the line (i.e., were you to repeat the experiment, you could be 95 percent certain its shaded area would include the true regression line).

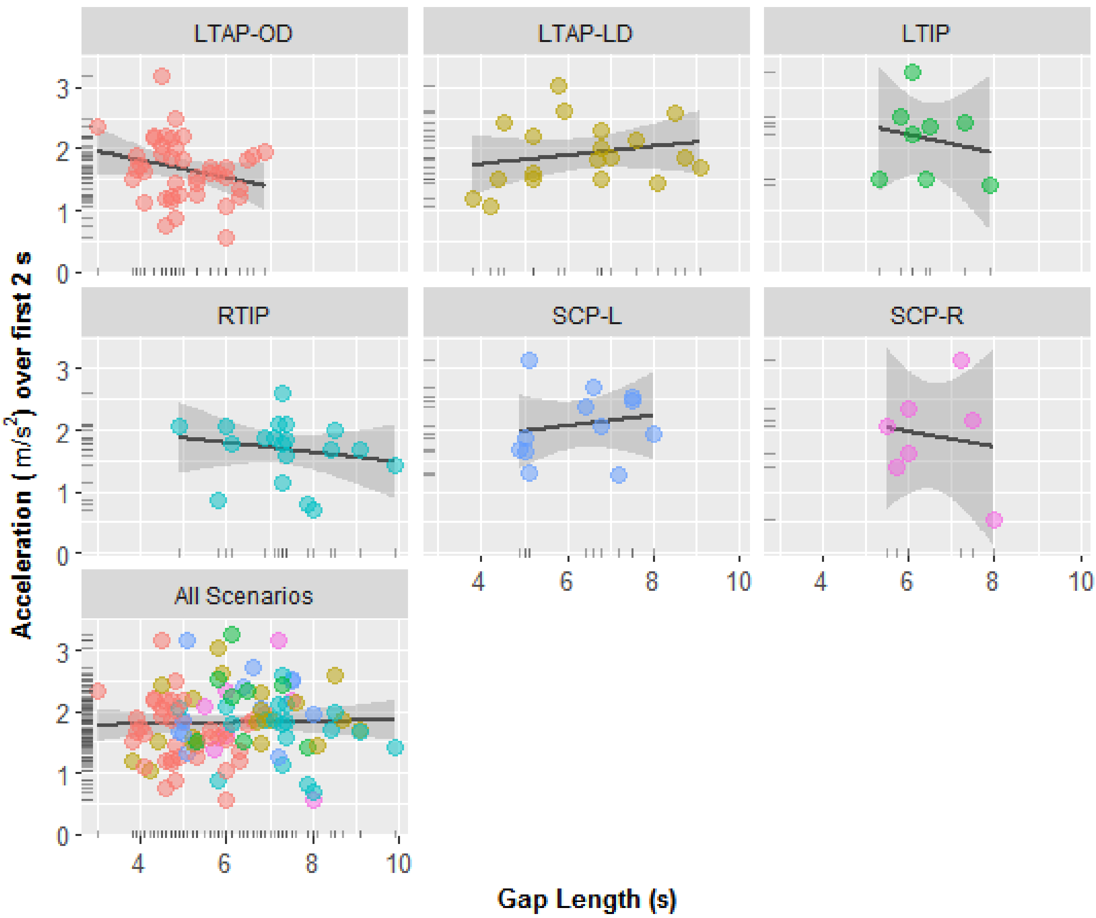


Figure 62. Gap Length by Acceleration Over the First 2 Seconds of Turn From Stopped

Appendix E: Intersection Geometry

This section provides additional baseline data from Section 3.3.8.

Table 33 and Figure 63 below show gap sizes by traffic control device. If events at stop signs are dropped and only lights and no-signal events are compared for LTAP-OD, there is a small effect (BS comparison, $d = 0.2$, 95 percent CI: 0 – 0.91; insufficient drivers for a WS comparison, $n = 3$). There was no effect for gaps where drivers waited instead of turning (BS comparison, $d = 0.3$, 95 percent CI: 0 – 1.2; no drivers had gap-reject events at both levels so a WS comparison was not possible).

(For the other scenario types, the analysis was run with lights dropped, comparing uncontrolled intersections to those with stop signs, but unfortunately there were insufficient events for analysis.)

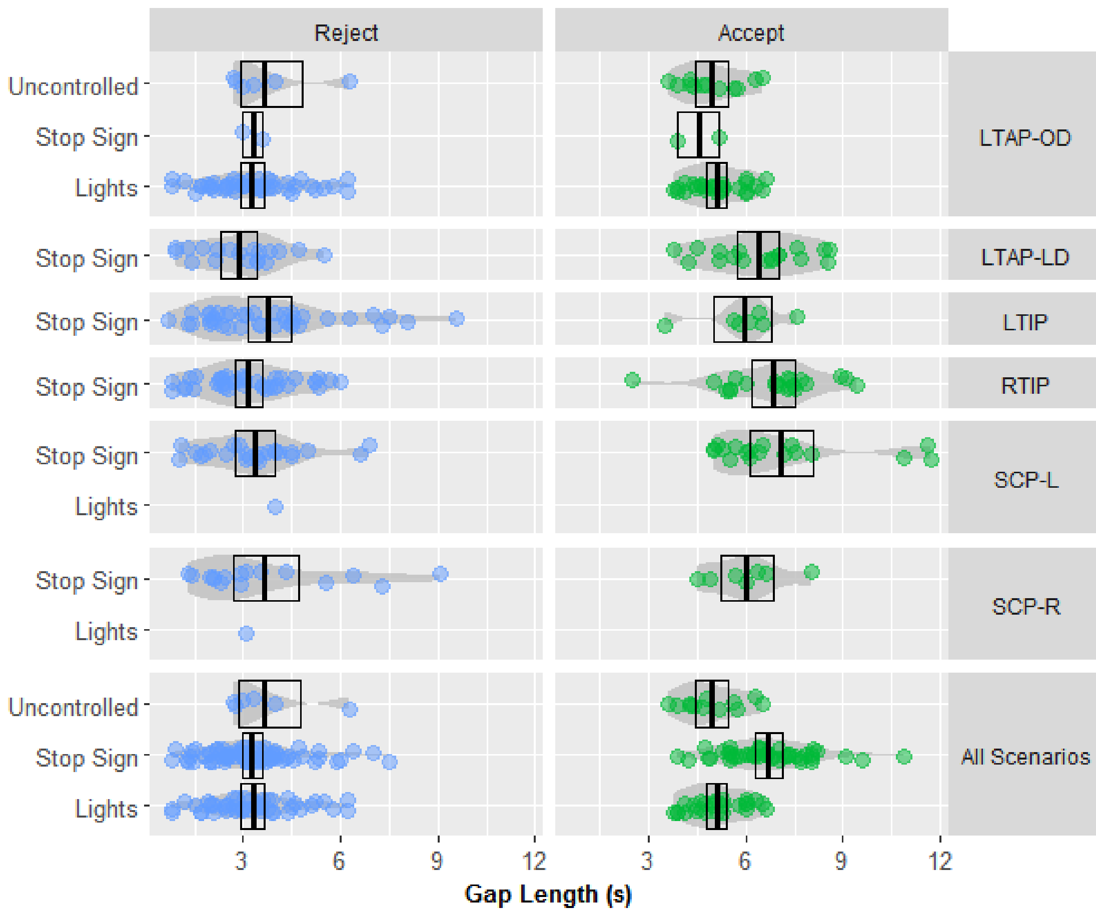


Figure 63. Gap Lengths Compared by Traffic Control Device

Table 33. Length of Gaps When Drivers Turned for Different Traffic Control Devices

Gap	Scenario	Traffic Control D.	Mean	SD	Range	*n*	Effect Size
Accepted	LTAP-OD	Lights	5.1	0.8	3.8 – 6.6	26	Insufficient *n*
		Uncontrolled	4.9	0.9	3.6 – 6.5	12	
		Stop Sign	4.6	0.9	3.9 – 5.2	2	
	LTAP-LD	Stop Sign	6.4	1.5	3.8 – 8.6	18	Insufficient *n*
	LTIP	Stop Sign	5.9	1.3	3.5 – 7.6	7	Insufficient *n*
	RTIP	Stop Sign	6.8	1.6	2.5 – 9.4	21	Insufficient *n*
	SCP-L	Stop Sign	7.1	2.2	5.0 – 11.7	18	Insufficient *n*
	SCP-R	Stop Sign	6.0	1.2	4.5 – 8.0	7	Insufficient *n*
	All Scenarios	Uncontrolled	4.9	0.9	3.6 – 6.5	12	-
		Stop Sign	6.7	1.4	3.9 – 10.9	45	
Rejected	LTAP-OD	Lights	3.3	1.3	0.8 - 6.2	48	Insufficient *n*
		Uncontrolled	3.7	1.4	2.7 - 6.3	6	
		Stop Sign	3.3	0.4	3 - 3.6	2	
	LTAP-LD	Stop Sign	2.9	1.3	0.9 – 5.5	19	Insufficient *n*
	LTIP	Stop Sign	3.8	2.1	0.7 – 9.6	38	Insufficient *n*
	RTIP	Stop Sign	3.2	1.4	0.8 – 6.0	39	Insufficient *n*
	SCP-L	Lights	3.6	-	3.6 – 3.6	1	Insufficient *n*
		Stop Sign	3.5	1.7	1 – 7.3	30	
	SCP-R	Lights	3.1	-	3.1 – 3.1	1	Insufficient *n*
		Stop Sign	3.7	2.3	1.3 – 9.1	16	
	All Scenarios	Lights	3.3	1.3	0.8 – 6.2	49	-
		Uncontrolled	3.7	1.4	2.7 – 6.3	6	
		Stop Sign	3.3	1.3	0.8 – 7.5	74	

Table 34 shows the rejected gap sizes by intersection ID (for accepted gaps, see Table 15).

Table 34. Rejected Gap Lengths for Individual Intersections

Scenario	Intersection	Mean	SD	Range	*n*	Effect Size
LTAP-OD	31	2.7	-	2.7 – 2.7	1	Medium (BS) η^2 = 0.13 (90% CI: 0 – 0.2)
	35	2.9	0.8	1.8 – 4.4	13	
	30	3.0	1.6	0.8 – 5.2	15	
	32	3.0	1.4	0.8 – 5.7	21	
	37	3.5	0.6	3.0 – 3.9	2	
	36	3.8	1.4	2.5 – 6.2	6	
	33	4.3	1.1	3.0 - 6.2	9	
LTAP-LD	12	0.9	-	0.9 – 0.9	1	Large (BS) η^2 = 0.66 (90% CI: 0.1 – 0.7)
	16	1.7	0.5	1.4 – 2.0	2	
	3	4.0	0.9	3.2 – 5.5	5	
	14	2.6	1.2	1.2 – 3.4	3	
	7	2.8	0.7	2.2 – 3.5	3	
LTIP	111	1.8	-	1.8 – 1.8	1	Small (BS) η^2 = 0.04 (90% CI: 0 – 0.3)
	2	2.3	0.9	1.1 – 3.5	9	
RTIP	8	3.2	1.6	2.1 – 4.4	2	No effect
	14	3.2	0.8	2.5 – 4.4	4	
	4	3.3	1.8	1.2 – 7.9	12	
	21	3.7	1.6	1.3 – 5.3	6	
SCP-L	108	1.5	0.4	1.1 – 1.9	3	Medium (BS) η^2 = 0.18 (90% CI: 0 – 0.4)
	18	2.7	-	2.7 – 2.7	1	
	4	3.4	1.7	1.0 – 6.9	16	
SCP-R	13	3.1	2.0	1.3 – 6.4	5	Small (BS) η^2 = 0.06 (90% CI: 0 – 0.4)
	108	4.4	4.1	2.0 – 9.1	3	
All Scenarios	12	0.9	-	0.9 – 0.9	1	Small (BS) η^2 = 0.11 (90% CI: 0 – 0.1)
	2	2.3	0.9	1.1 – 3.5	9	
	31	2.7	-	2.7 – 2.7	1	
	18	2.8	1.9	1.4 – 4.1	2	
	108	2.8	2.6	0.8 – 9.1	10	
	35	2.9	0.8	1.8 – 4.4	13	
	8	3.0	0.9	2.1 – 3.9	3	
	16	3.0	1.4	1.7 – 5.0	4	
	30	3.0	1.6	0.8 – 5.2	15	
	32	3.0	1.4	0.8 – 5.7	21	
	111	3.0	1.5	2.1 – 4.7	3	
	13	3.1	2.0	1.3 – 6.4	5	
	118	3.1	1.9	1.3 – 5.6	4	
	4	3.2	1.5	0.9 – 7.9	33	
	7	3.5	1.3	1.6 – 4.9	9	
	37	3.5	0.6	3.0 – 3.9	2	
	36	3.6	1.4	2.1 – 6.2	7	
	21	3.7	1.4	1.3 – 5.3	7	
	3	4.1	1.6	2.2 – 7.1	9	
	14	4.2	2.1	1.2 – 7.3	8	
	33	4.3	1.1	3.0 – 6.2	9	

Figure 64 and Table 35 show gap sizes by intersection type.

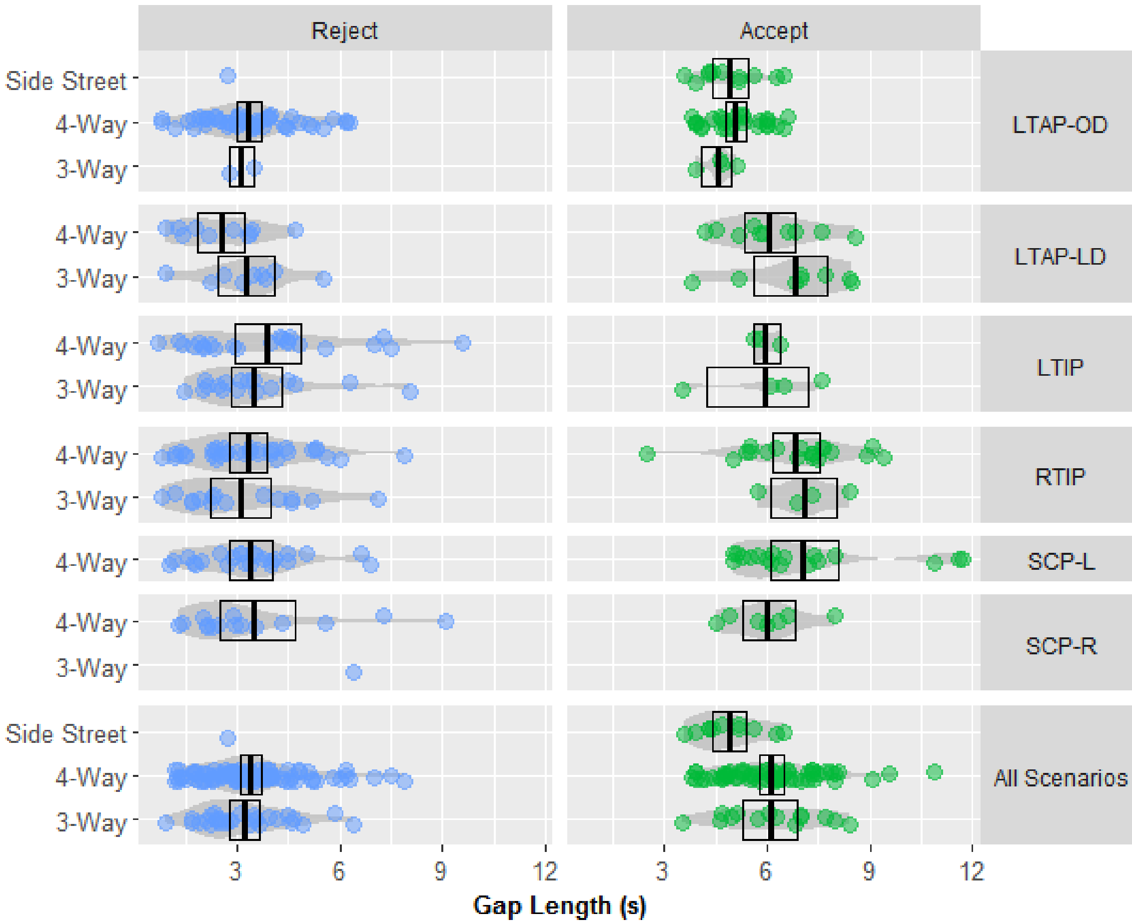


Figure 64. Gap Lengths Compared by Intersection Type

Table 35. Gap Lengths Compared by Intersection Type

Gap	Scenario	Intersection Type	Mean	SD	Range	n	Effect Size
Accepted	LTAP-OD	3-Way	4.6	0.5	3.9 – 5.1	4	Small (BS) η^2 = 0.04 (90% CI: 0 – 0.1)
		4-Way	5.1	0.9	3.8 – 6.6	27	
		Side Street	4.9	0.9	3.6 – 6.5	11	
	LTAP-LD	3-Way	6.8	1.6	3.8 – 8.5	8	Small (BS) d = 0.5 (95% 0 – 1.6)
		4-Way	6.1	1.4	4.2 – 8.6	10	
	LTIP	3-Way	5.9	1.7	3.5 – 7.6	4	No effect
		4-Way	5.9	0.4	5.6 – 6.4	3	
	RTIP	3-Way	7.1	1.1	5.7 – 8.4	4	No effect
		4-Way	6.8	1.6	2.5 – 9.4	19	
	SCP-L	3-Way	-	-	-	-	Insufficient n
		4-Way	7.1	2.2	5.0 – 11.7	18	
	SCP-R	3-Way	-	-	-	-	Insufficient n
		4-Way	6.0	1.2	4.5 – 8.0	7	
	All Scenarios	3-Way	6.1	1.4	3.5 – 8.4	14	No effect
		4-Way	6.1	1.5	3.8 – 10.9	60	
Rejected	LTAP-OD	3-Way	3.1	0.5	2.8 – 3.5	2	Insufficient n
		4-Way	3.3	1.3	0.8 – 6.3	52	
		Side Street	2.7	-	2.7 – 2.7	1	
	LTAP-LD	3-Way	3.3	1.3	0.9 – 5.5	9	Medium (BS) d = 0.6 (95% 0 – 1.7)
		4-Way	2.5	1.2	0.9 – 4.7	10	
	LTIP	3-Way	3.5	1.7	1.4 – 8.1	17	No effect
		4-Way	3.9	2.3	0.7 – 9.6	23	
	RTIP	3-Way	3.1	1.8	0.8 – 7.1	15	No effect
		4-Way	3.3	1.6	0.8 – 7.9	33	
	SCP-L	3-Way	-	-	-	-	Insufficient n
		4-Way	3.4	1.5	1.0 – 6.9	24	
	SCP-R	3-Way	6.4	-	6.4 – 6.4	1	Insufficient n
		4-Way	3.5	2.2	1.3 - 9.1	15	
	All Scenarios	3-Way	3.2	1.3	0.9 – 6.4	29	No effect
		4-Way	3.4	1.4	1.2 – 7.9	91	

Appendix F: Gender and Age

This section provides additional data from Sections 3.3.9 (baseline) and 4.3.4 (crash database).

Table 36 and Figures 65 and 66 show baseline gap sizes by age group. For each age group, the rows are broken down further by gender.

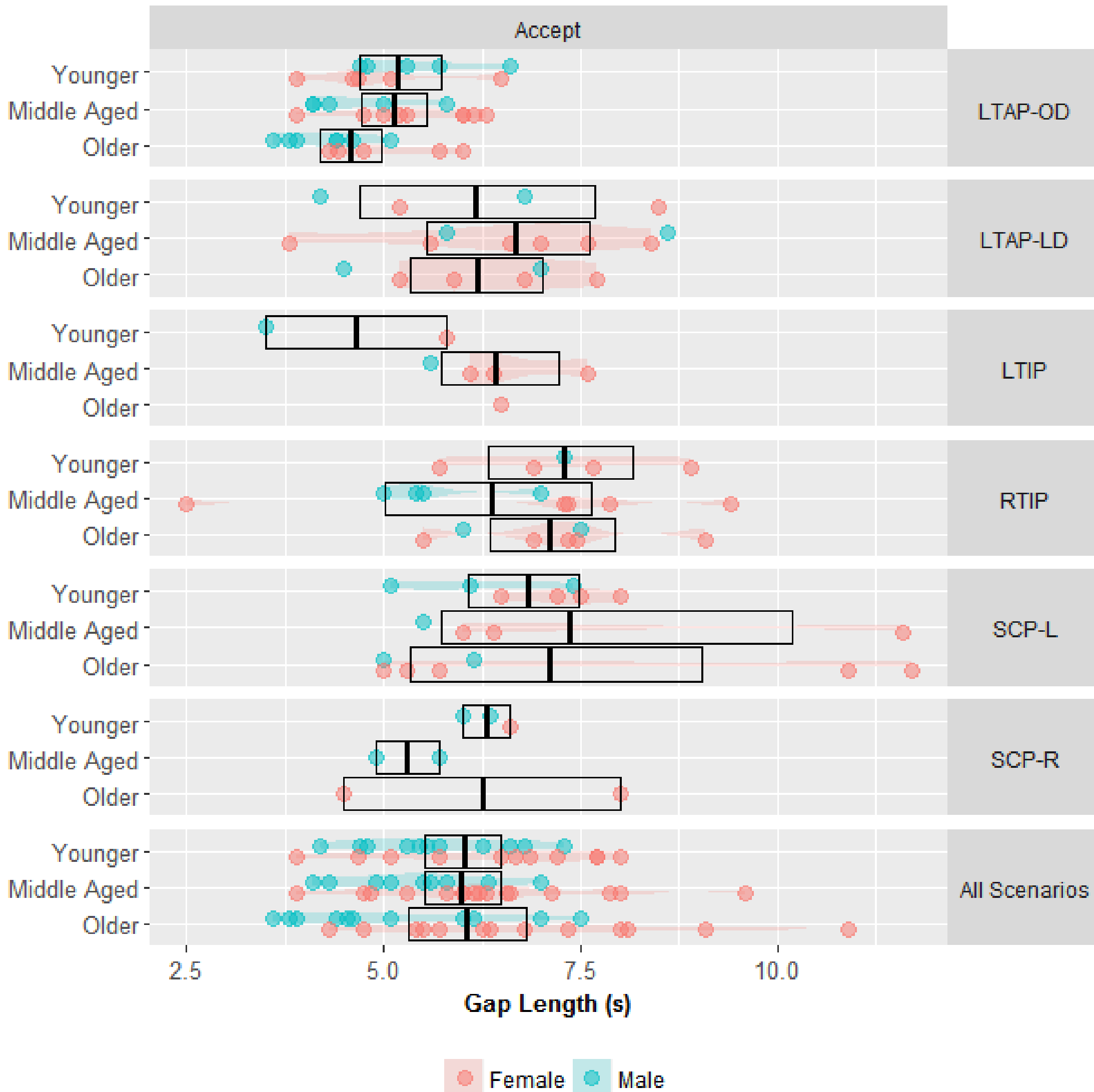


Figure 65. Accepted Baseline Gap Lengths Compared by Age Group

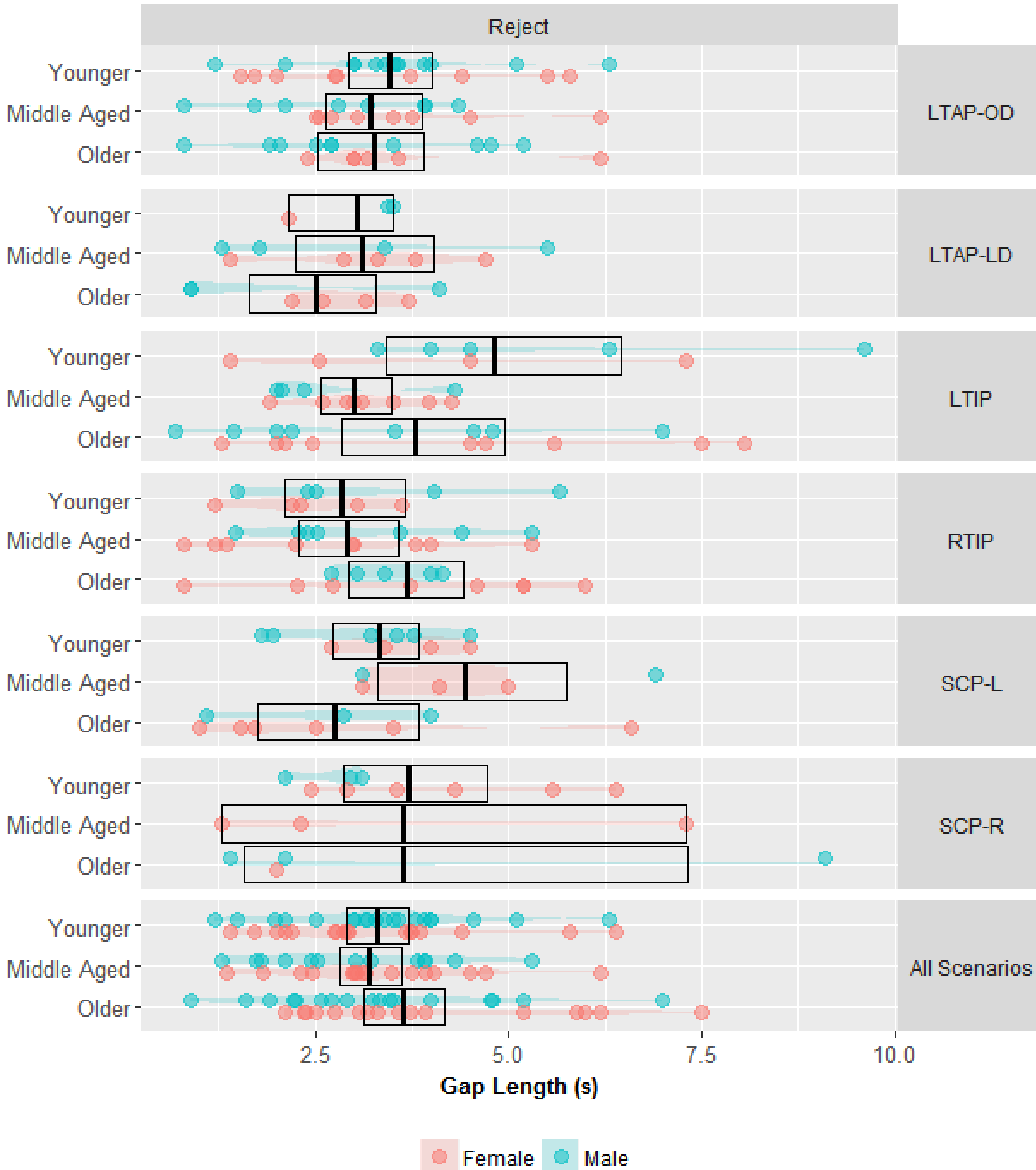


Figure 66. Rejected Baseline Gap Lengths Compared by Age Group

Table 36. Baseline Gap Lengths Compared by Age Group

Gap	Scenario	Age Group	Mean		SD	Range	*n*	Effect Size
			Weighted	Unweighted				
Accepted	LTAP-OD	Younger	5.2	5.2	0.9	3.9 – 6.6	10	Small (BS) η^2 = 0.11 (90% CI: 0 – 0.3)
		Mid. Aged	5.1	5.0	0.8	3.9 – 6.3	14	
		Older	4.6	4.6	0.7	3.6 – 6.0	12	
	LTAP-LD	Younger	6.2	6.2	1.9	4.2 – 8.5	4	Small (BS) η^2 = 0.03 (90% CI: 0 – 0.2)
		Mid. Aged	6.7	6.8	1.6	3.8 – 8.6	8	
		Older	6.2	6.1	1.2	4.5 – 7.7	6	
	LTIP	Younger	4.6	4.6	1.6	3.5 – 5.8	2	Insufficient *n*
		Mid. Aged	6.4	6.2	0.9	5.6 – 7.6	4	
		Older	6.5	6.5	-	6.5 – 6.5	1	
	RTIP	Younger	7.3	7.3	1.2	5.7 – 8.9	5	Small (BS) η^2 = 0.07 (90% CI: 0 – 0.2)
		Mid. Aged	6.4	6.3	2.0	2.5 – 9.4	9	
		Older	7.1	7.0	1.2	5.5 – 9.1	7	
	SCP-L	Younger	6.8	6.7	1.0	5.1 – 8.0	7	No effect
		Mid. Aged	7.4	6.8	2.8	5.5 – 11.6	4	
		Older	7.1	6.6	2.9	5.0 – 11.7	7	
	SCP-R	Younger	6.3	6.4	0.3	6.0 – 6.6	3	Insufficient *n*
		Mid. Aged	5.3	5.3	0.6	4.9 – 5.7	2	
		Older	6.2	6.2	2.5	4.5 – 8.0	2	
	All Scenarios	Younger	6.0	6.0	1.2	3.9 – 8.0	22	No effect
		Mid. Aged	6.0	5.9	1.3	3.9 – 9.6	25	
		Older	6.0	5.9	1.8	3.6 – 10.9	24	
Rejected	LTAP-OD	Younger	3.5	3.4	1.4	1.2 – 6.3	22	No effect
		Mid. Aged	3.2	3.2	1.3	0.8 – 6.2	16	
		Older	3.3	3.3	1.4	0.8 – 6.2	16	
	LTAP-LD	Younger	3.0	2.8	0.8	2.1 – 3.5	3	Small (BS) η^2 = 0.05 (90% CI: 0 – 0.2)
		Mid. Aged	3.1	3.1	1.5	1.3 – 5.5	9	
		Older	2.5	2.4	1.3	0.9 – 4.1	7	
	LTIP	Younger	4.8	4.7	2.5	1.4 – 9.6	9	Small (BS) η^2 = 0.11 (90% CI: 0 – 0.3)
		Mid. Aged	3.0	2.9	0.9	1.9 – 4.3	12	
		Older	3.8	3.8	2.3	0.7 – 8.1	17	
	RTIP	Younger	2.8	2.8	1.3	1.2 - 5.6	10	Small (BS) η^2 = 0.07 (90% CI: 0 – 0.2)
		Mid. Aged	2.9	2.9	1.4	0.8 – 5.3	16	
		Older	3.7	3.6	1.4	0.8 – 6.0	13	
	SCP-L	Younger	3.3	3.4	0.9	1.8 – 4.5	10	Medium (BS) η^2 = 0.17 (90% CI: 0 – 0.4)
		Mid. Aged	4.4	4.5	1.6	3.1 – 6.9	5	
		Older	2.8	2.7	1.8	1.0 – 6.6	9	
	SCP-R	Younger	3.7	3.5	1.5	2.1 – 6.4	9	No effect
		Mid. Aged	3.6	3.6	3.2	1.3 – 7.3	3	
		Older	3.6	3.1	3.6	1.4 – 9.1	4	
	All Scenarios	Younger	3.3	3.5	1.3	1.2 – 6.4	37	Small (BS) η^2 = 0.02 (90% CI: 0 – 0.1)
		Mid. Aged	3.2	3.2	1.1	1.3 – 6.2	30	
		Older	3.7	3.5	1.6	0.9 – 7.5	33	

Figure 67 and Table 35 show gap sizes by gender for CDS cases (crash database). For each gender, the rows are further broken down into age group to show how age groups varied within the gender groups (to reveal any confounding effects).

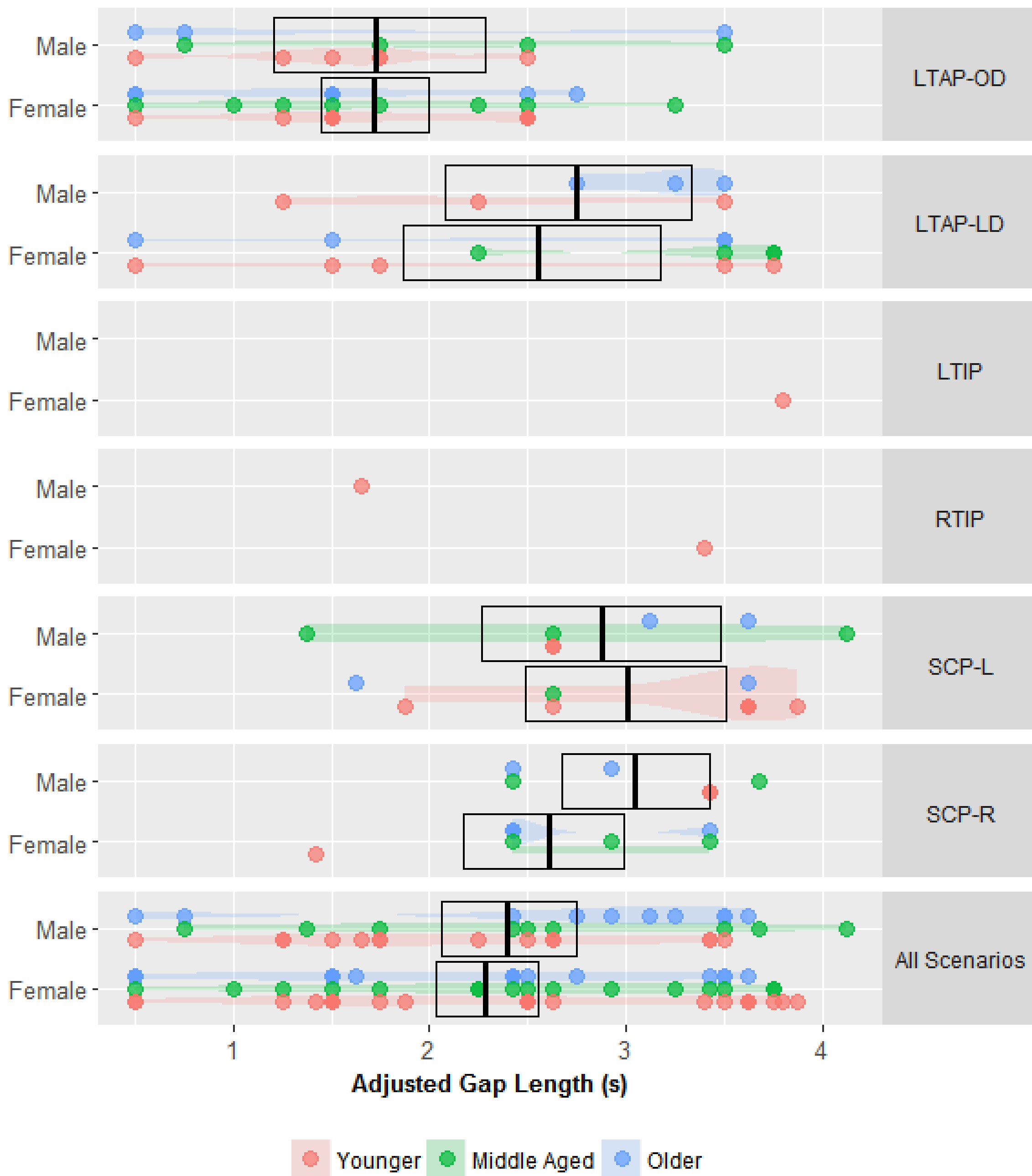


Figure 67. Adjusted CDS Accepted Gap Lengths by Gender

Table 37. Adjusted CDS Accepted Gap Lengths by Gender

Events	Scenario	Gender	Mean Weighted	Mean Unweighted	SD	Range	*n*	Effect Size (*d*, 95% CI)
All Data	LTAP-OD	Female	1.7	1.7	0.8	0.5 – 3.2	27	No effect
		Male	1.7	1.8	1.0	0.5 – 3.5	13	
	LTAP-LD	Female	2.6	2.6	1.3	0.5 – 3.8	13	No effect
		Male	2.8	2.8	0.9	1.2 – 3.5	6	
	LTIP	Female	3.8	-	-	3.8 – 3.8	1	Insufficient *n*
	RTIP	Female	3.4	-	-	3.4 – 3.4	1	Insufficient *n*
		Male	1.6	-	-	1.6 – 1.6	1	
	SCP-L	Female	3.0	-	0.8	1.6 – 3.9	9	No effect
		Male	2.9	-	0.9	1.4 – 4.1	7	
	SCP-R	Female	2.6	-	0.7	1.4 – 3.4	8	Medium (BS) 0.72 (0 – 2.4)
		Male	3.0	-	0.5	2.4 – 3.7	6	
	All Scenarios	Female	2.3	2.3	1.0	0.5 – 3.9	59	No effect
		Male	2.4	2.4	1.0	0.5 – 4.1	33	
2008 – 2011	LTAP-OD	Female	1.7	-	0.8	0.5 – 2.5	13	Small (BS) 0.27 (0 – 1.7)
		Male	1.5	-	1.0	0.5 – 2.5	3	
	SCP-R	Female	2.9	-	0.6	2.4 – 3.4	4	Medium (BS) 0.69 (0 – 0.5)
		Male	2.6	-	0.3	2.4 – 2.9	3	
	All Scenarios	Female	2.3	-	1.0	0.5 – 3.6	24	No effect
		Male	2.1	-	0.9	0.5 – 3.1	9	
2012 – 2014	LTAP-OD	Female	1.7	-	0.7	0.5 – 3.2	14	No effect
		Male	1.8	-	1.1	0.5 – 3.5	10	
	SCP-R	Female	2.3	-	0.6	1.4 – 2.9	4	Large (BS) 2.44 (0 – 5.7)
		Male	3.5	-	0.1	3.4 – 3.7	3	
	All Scenarios	Female	2.3	-	1.1	0.5 – 3.9	35	No effect
		Male	2.5	-	1.1	0.5 – 4.1	24	

Figure 68 and Table 38 show gap sizes by age group for CDS cases (crash database). For each age group, the rows are further broken down into gender to show how gender varied within the age groups (to reveal any confounding effects).

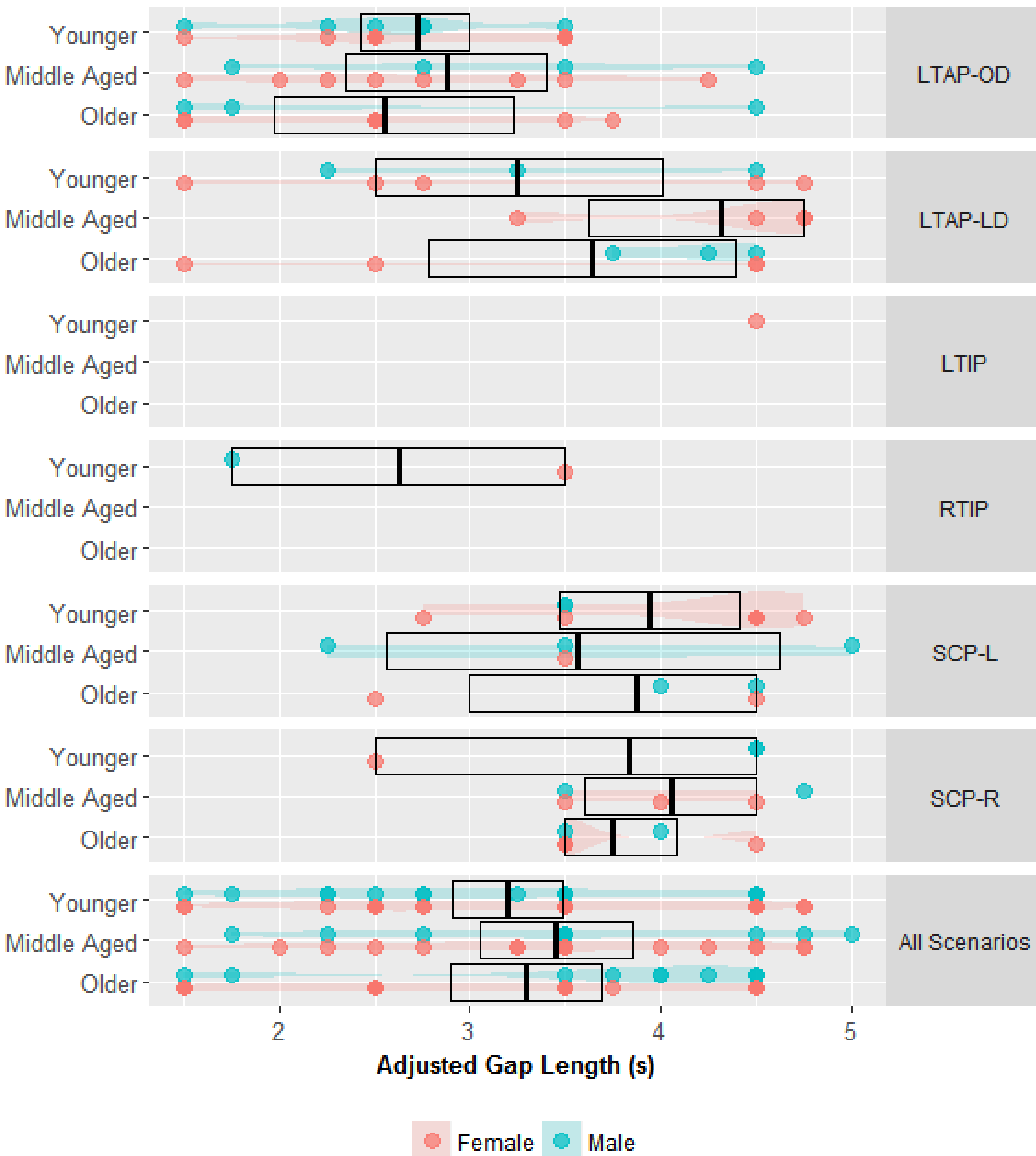


Figure 68. Adjusted CDS Accepted Gap Lengths by Age Group

Table 38. Adjusted CDS Accepted Gap Lengths by Age Group

Events	Scenario	Age Group	Mean		SD	Range	*n*	Effect Size
			Weighted	Unweighted				
All Data	LTAP-OD	Younger	1.7	1.7	0.7	0.5 – 2.5	18	Small (BS) η^2 = 0.02 (90% CI: 0 – 0.1)
		Mid. Aged	1.9	1.9	1.0	0.5 – 3.5	12	
		Older	1.6	1.6	1.1	0.5 – 3.5	10	
	LTAP-LD	Younger	2.2	2.3	1.2	0.5 – 3.8	8	Medium (BS) η^2 = 0.13 (90% CI: 0 – 0.3)
		Mid. Aged	3.3	3.3	0.7	2.2 – 3.8	4	
		Older	2.6	2.7	1.2	0.5 – 3.5	7	
	LTIP	Younger	3.8	-	-	3.8 – 3.8	1	Insufficient *n*
	RTIP	Younger	2.5	-	1.2	1.6 – 3.4	2	Insufficient *n*
	SCP-L	Younger	3.1	2.9	0.7	1.9 – 3.9	8	Small (BS) η^2 = 0.04 (90% CI: 0 – 0.2)
		Mid. Aged	2.7	2.7	1.1	1.4 – 4.1	4	
		Older	3.0	3.0	0.9	1.6 – 3.6	4	
	SCP-R	Younger	2.8	2.4	1.2	1.4 – 3.4	3	Small (BS) η^2 = 0.05 (90% CI: 0 – 0.2)
		Mid. Aged	3.0	3.0	0.6	2.4 – 3.7	5	
		Older	2.7	2.7	0.4	2.4 – 3.4	6	
	All Scenarios	Younger	2.3	2.2	1.0	0.5 – 3.9	40	No effect
		Mid. Aged	2.5	2.5	1.0	0.5 – 4.1	25	
		Older	2.3	2.4	1.1	0.5 – 3.6	27	
2008 – 2011	LTAP-OD	Younger	1.8	-	0.8	0.5 – 2.5	10	Small (BS) η^2 = 0.03 (90% CI: 0 – 0.2)
		Mid. Aged	1.5	-	1.4	0.5 – 2.5	2	
		Older	1.5	-	0.8	0.5 – 2.5	4	
	All Scenarios	Younger	2.0	-	0.9	0.5 – 3.6	15	Small (BS) η^2 = 0.06 (90% CI: 0 – 0.2)
		Mid. Aged	2.3	-	1.0	0.5 – 3.4	6	
		Older	2.4	-	1.0	0.5 – 3.6	12	
2012 – 2014	LTAP-OD	Younger	1.6	-	0.4	1.2 – 2.5	8	Small (BS) η^2 = 0.04 (90% CI: 0 – 0.2)
		Mid. Aged	2.0	-	0.9	0.8 – 3.5	10	
		Older	1.6	-	1.3	0.5 – 3.5	6	
	All Scenarios	Younger	2.4	-	1.0	0.5 – 3.9	25	No effect
		Mid. Aged	2.5	-	1.1	0.8 – 4.1	19	
		Older	2.2	-	1.2	0.5 – 3.6	15	

Appendix G: Environmental Conditions

This section provides additional baseline data from Section 3.3.10.

Figure 69 and Table 39 show gap sizes by lighting condition.

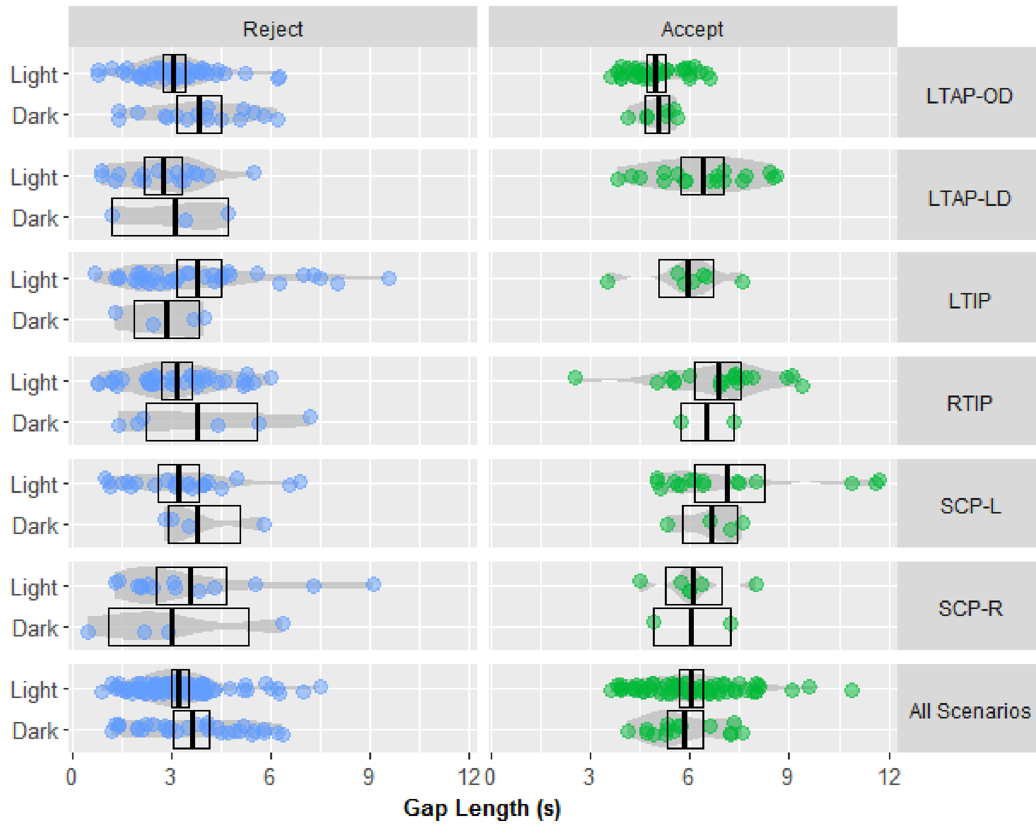


Figure 69. Gap Lengths Compared by Lighting

Table 39. Gap Lengths Compared by Lighting

Gap	Scenario	Lighting	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
Accepted	LTAP-OD	Dark	5.0	0.5	4.1 – 5.6	7	No effect
		Light	5.0	0.9	3.6 – 6.6	34	
	LTAP-LD	Dark	-	-	-	-	Insufficient *n*
		Light	6.4	1.5	3.8 – 8.6	18	
	LTIP	Dark	-	-	-	-	Insufficient *n*
		Light	5.9	1.3	3.5 – 7.6	7	
	RTIP	Dark	6.5	1.1	5.7 – 7.3	2	Insufficient *n*
		Light	6.9	1.6	2.5 – 9.4	19	
	SCP-L	Dark	6.7	1.0	5.3 – 7.6	4	Small (BS) 0.21 (0 – 1.5)
		Light	7.1	2.3	5.0 – 11.7	16	
	SCP-R	Dark	6.1	1.6	4.9 – 7.2	2	No effect
		Light	6.1	1.1	4.5 – 8.0	6	
	All Scenarios	Dark	5.8	1.1	4.1 – 7.6	15	No effect
		Light	6.1	1.5	3.6 – 10.9	66	
Rejected	LTAP-OD	Dark	3.9	1.5	1.4 – 6.2	17	No effect
		Light	3.1	1.2	0.8 – 6.3	46	
	LTAP-LD	Dark	3.1	1.8	1.2 – 4.7	3	Small (BS) 0.28 (0 – 1.7)
		Light	2.8	1.2	0.9 – 5.5	17	
	LTIP	Dark	2.9	1.2	1.3 – 4.0	4	Small (BS) 0.45 (0 – 1.5)
		Light	3.8	2.1	0.7 – 9.6	37	
	RTIP	Dark	3.8	2.3	1.4 – 7.2	6	No effect
		Light	3.2	1.4	0.8 – 6.0	38	
	SCP-L	Dark	3.8	1.4	2.8 – 5.8	4	Small (BS) 0.34 (0 – 1.5)
		Light	3.3	1.6	1.0 – 6.9	23	
	SCP-R	Dark	3.0	2.5	0.5 – 6.4	4	Small (BS) 0.24 (0 – 1.5)
		Light	3.6	2.3	1.3 – 9.1	14	
	All Scenarios	Dark	3.6	1.6	1.2 – 6.4	32	Small (BS) 0.27 (0 – 0.7)
		Light	3.3	1.3	0.9 – 7.5	90	

Figure 70 and Table 40 show gap sizes by weather condition.

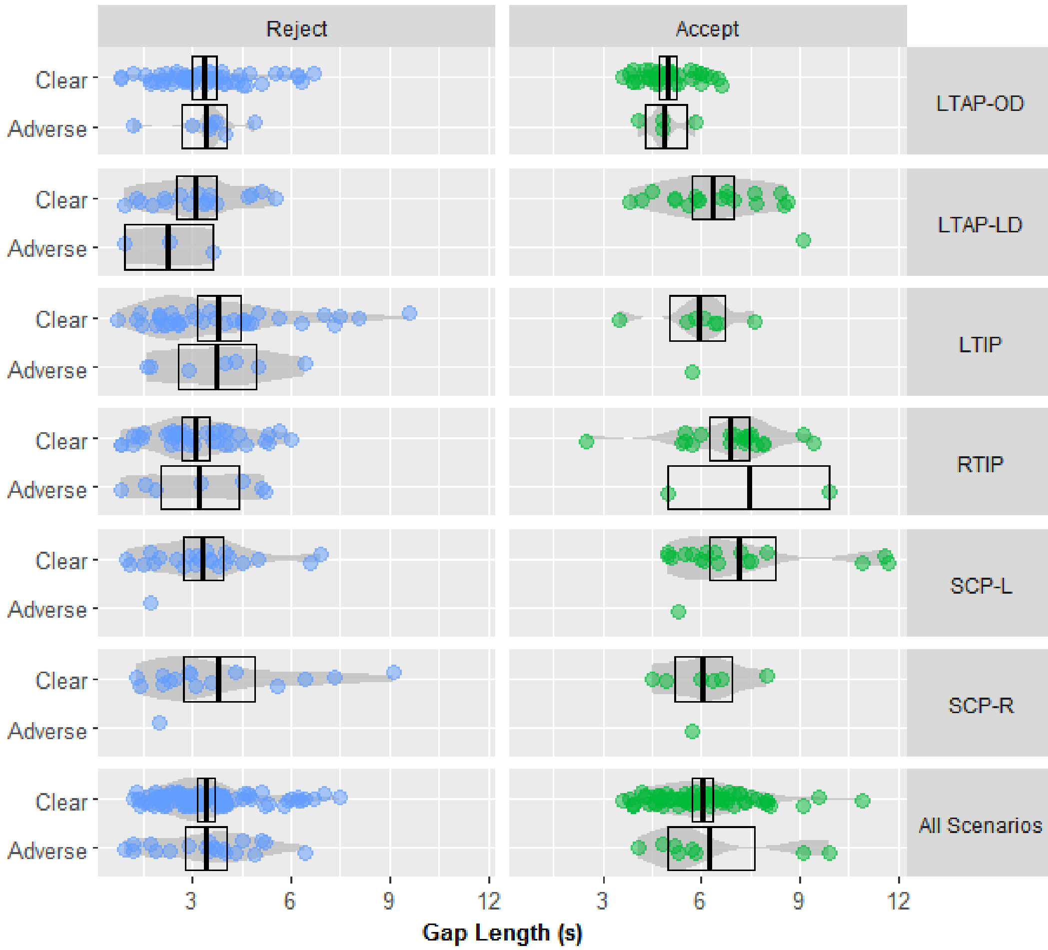


Figure 70. Gap Lengths Compared by Weather

Table 40. Gap Lengths Compared by Weather

Gap	Scenario	Weather	Mean	SD	Range	*n*	Effect Size (*d*, 95% CI)
Accepted	LTAP-OD	Adverse	4.9	0.7	4.1 – 5.8	4	No effect
		Clear	5.0	0.8	3.6 – 6.6	35	
	LTAP-LD	Adverse	9.1	-	9.1 – 9.1	1	Insufficient *n*
		Clear	6.3	1.5	3.8 – 8.6	18	
	LTIP	Adverse	5.7	-	5.7 – 5.7	1	Insufficient *n*
		Clear	5.9	1.3	3.5 – 7.6	7	
	RTIP	Adverse	7.5	3.5	5.0 – 9.9	2	Insufficient *n*
		Clear	6.9	1.5	2.5 – 9.4	20	
	SCP-L	Adverse	5.3	-	5.3 – 5.3	1	Insufficient *n*
		Clear	7.2	2.2	5.0 – 11.7	17	
	SCP-R	Adverse	5.7	-	5.7 – 5.7	1	Insufficient *n*
		Clear	6.1	1.3	4.5 – 8.0	6	
	All Scenarios	Adverse	6.2	2.1	4.1 – 9.9	8	No effect
		Clear	6.0	1.4	3.6 – 10.9	70	
Rejected	LTAP-OD	Adverse	3.4	1.1	1.2 – 4.9	8	No effect
		Clear	3.4	1.4	0.8 – 6.7	52	
	LTAP-LD	Adverse	2.3	1.4	0.9 – 3.6	3	Medium (BS) 0.62 (0 – 2.0)
		Clear	3.1	1.3	0.9 – 5.5	18	
	LTIP	Adverse	3.7	1.8	1.6 – 6.4	7	No effect
		Clear	3.8	2.1	0.7 – 9.6	36	
	RTIP	Adverse	3.2	1.8	0.8 – 5.2	7	No effect
		Clear	3.1	1.4	0.8 – 6.0	38	
	SCP-L	Adverse	1.7	-	1.7 – 1.7	1	Insufficient *n*
		Clear	3.3	1.5	1.0 – 6.9	23	
	SCP-R	Adverse	2.0	-	2.0 – 2.0	1	Insufficient *n*
		Clear	3.8	2.3	1.3 – 9.1	15	
	All Scenarios	Adverse	3.4	1.5	0.9 – 6.4	20	No effect
		Clear	3.4	1.4	1.2 – 7.5	97	

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