The Potential Safety Benefits of a V2X-Enabled Red Light Running ADAS

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Abstract

This paper introduces a V2X-enabled red light running ADAS as a system that uses signal telemetry forecasts shared over V2X to warn drivers who are approaching a current or impending red light at an excessive speed. The goal of the paper is to forecast the potential safety benefits of such a system for different vehicle classes and ADAS warning modalities. The forecasting approach leverages empirical data on driver red light running intentionality and ADAS response rates gathered from a variety of relevant naturalistic driving studies to identify a subset of RLR crashes that are likely to be prevented by the proposed ADAS. The paper finds that 855 RLR fatalities per year in the United States could be prevented by such an ADAS, which is 70% of the current total number of RLR fatalities. The paper additionally finds that 53 truck-involved RLR fatalities per year could be prevented by retrofitting fleets with the ADAS.

1 Introduction and Objective

1.1 Preventable Tragedies

In 2025, a compact sedan in Georgia ran a red light and collided with a pickup truck, resulting in the deaths of all four occupants of the sedan, aged 15 to 20 (Coosa Valley News, 2025) . In 2018, a semi-truck in Saskatchewan ran a stop sign at almost 60 miles per hour, striking a bus and killing 16 members of the Humboldt Broncos hockey team (Hauer, 2020).

With our increasingly technology-enabled and connected vehicles, we should ask ourselves the question: why do drivers approaching red signals or stop signs at full speed receive no warning from their vehicle?

It is a premise of this paper that it is relatively feasible for a vehicle's internal systems to be aware of the following pieces of information: the vehicle's own location and speed, the location of every traffic signal, and the status (current and predicted) of every traffic signal. It is assumed that the signal status information would be delivered to the vehicle through some form of V2X communication channel. From these pieces of information, it seems feasible for a vehicle's internal systems to determine if the vehicle was approaching a current or impending stop condition at a dangerously high speed, and to warn drivers if such a determination was made.

The hypothetical system envisioned to integrate these pieces of information and deliver these warnings will be called, in this paper, a V2X-Enabled Red Light Running Automated Driver Assistance System, or V2X RLR ADAS for short.

Such a system was recently the subject of a successful technical development and demonstration study at the University of Minnesota (Levin, Sun, He, Zamanpour, & Guo, 2024). However, until now, the potential benefits of such a system have not been quantified.

1.2 Objective

The objective of this paper is to scientifically quantify the potential safety benefits of an Advanced Driver Assistance System (ADAS) that uses signal telemetry data received via V2X together with a vehicle's own mapping and positioning systems to give warnings to drivers for mitigating red light running (RLR) crash risks. The benefits to heavy vehicles and passenger vehicles will be estimated separately.

1.3 ADAS Achievements and Gaps at the Intersection

Advanced Driver Assistance Systems have been reviewed and evaluated for their crash avoidance effectiveness in the real world (Yue, Abdel-Aty, & Wu, 2019). Yue et al. looked at more than 20 different types of ADAS. They found that although ADAS helps for all vehicle types, the benefits are greater for heavy trucks, where crash prevention effectiveness can reach 70%. They broke down ADAS systems into those that target the following crash types: rear-end, lane change, pedestrian, crossing paths, run-off road, and backing crashes. Although RLR crashes are a type of crossing path collision, no ADAS reviewed by the authors directly targets RLR crashes, because such an ADAS is not deployed. Instead, the crossing path ADAS systems reviewed are left turn assist (LTA), which uses forward radar to help judge gaps in oncoming traffic during permissive left turns, and Intersection Movement Assist (IMA), which uses a vehicle's own sensors or connected vehicle data to warn a driver of traffic crossing at 90 degrees. Adjusted for real world conditions, LTA was found to have a crash prevention effectiveness of around 40%, and IMA was found to have a crash prevention effectiveness of around 29% for their respective cross path target types. A new V2X RLR ADAS would be complementary to LTA and IMA in targeting another large subclass of crossing conflicts.

A crash-reconstruction and re-simulation study was used to explore the injury prevention potential of a conceptual intersection-specific ADAS, called I-ADAS (Scanlon, Sherony, & Gabler, 2017). They found that adding I-ADAS to the re-simulation of reconstructed real crashes could prevent as many as 79% of crossing crashes. The effectiveness was highly sensitive to either the amount of warning time, where 3 seconds was much better than 1 second, or the assistance modality, where automatic emergency braking was 2-3 times better than a warning only. The conceptual I-ADAS explored in the Scanlon study relied exclusively on a vehicle's own sensors having direct line of sight to conflicting crossing vehicles. The V2X RLR ADAS explored in the present paper would be a distinctly different and complementary system offering the benefits of earlier warnings based on predicted signal state and providing warning regardless of line-of-sight occlusions.

ADAS can be implemented by Original Equipment Manufacturers (OEMs), or by fleet operators through retrofits with aftermarket solutions. One Italian study investigated the potential safety benefits of retrofitting ADAS into trucks, finding that doing so could save 250 lives annually, which represents about 36% of fatalities from collisions involving at least one heavy truck (Pizzicori, et al., 2025). However, since a red light running ADAS is not widely available at this time, prevention of red-light running crashes was not included in this Italian estimate, suggesting that even more lives could be saved if an ADAS targeting RLR crashes is also retrofitted into truck fleets.

ADAS effectiveness in delivering safety improvements has been substantially reviewed elsewhere, and although it cannot cure all crashes, it is clearly effective at preventing very meaningful numbers of crashes. No widespread ADAS deployments currently target RLR crashes through V2X communication of signal telemetry. The success of other categories of ADAS for both trucks and passenger vehicles suggests that there is merit in exploring the benefits of filling this gap either through OEM or fleet retrofit efforts.

1.4 V2X Communication of Signal Telemetry

Part of the premise of this paper is that it is feasible for a vehicle's internal systems to know the current and predicted phase state of each traffic signal, collectively referred to for the purposes of this paper as *signal telemetry*.

This is distinguished from Signal Phase and Timing (SPaT) data intentionally. Although SPaT data always contains the current state, it may or may not contain the ability to predict when a signal will change. Change predictions in SPaT data are through the optional field *MovementEventTiming.likelyEndTime* in the SAE J2735 standard (SAE International, 2023) . In practice, this optional field is left blank, so SPaT data alone does not establish the feasibility of the information set which is the premise of this paper. Furthermore, many signalized intersections do not yet make any SPaT data available.

Where SPaT is not available, or is insufficient due to exclusion of optional fields, the feasibility of providing signal telemetry over V2X channels inclusive of predicted next signal state and time-to-red relies on external data sources and predictive algorithms This feasibility has been established in several research efforts (Bauer, Ma, & Offermann, 2015) (U.S. Patent No. 10,878,693 B2, 2020).

2 Methodology

The forecasting approach for this paper is to construct a simple modelling equation that predicts the number of lives saved from a V2X RLR ADAS, then to estimate the explanatory variables of the model by applying or transferring reasonable values from the most relevant published research, and finally to apply the model to create forecasts in different scenarios.

2.1 Functional Form of Prediction Model

The prediction model assumes that not every RLR crash can be prevented by the proposed ADAS. Notably, drivers who intentionally run red lights will not likely be affected by an ADAS that warns them of the red light. Therefore, the proportion of drivers by intentionality class is a required input variable. Furthermore, for drivers who are unintentionally running red lights and who may be willing to be helped by an ADAS, some will not successfully respond in time to ADAS warnings, so the successful response rate to a request to intervene is a relevant explanatory variable. The successful response rate to a request to intervene (RTI) from the ADAS is assumed to be dependent on the modality of the RTI, which could be visual only, visual and audible, or activation of emergency breaking. With this in mind, the following predictive functional form and variable definitions are proposed:

$$N_{s,v,m} = C_{s,v} \times I_{s,v} \times R_{s,v,m}$$

Variable	Description
$N_{s,v}$	The number of RLR crash victims of a given severity level (S) and vehicle class (V) forecasted to be prevented by the proposed V2X RLR ADAS.
$C_{s,v}$	The current number of RLR crash victims of a given severity level and vehicle class
I_s	The proportion of RLR crashes of a given severity level with a driver intentionality state that is amenable to targeting by ADAS.
$R_{s,v,m}$	Estimated proportion of RLR crashes, for a given severity level, vehicle class, and request to intervene (RTI) modality where a willing driver will successfully respond to the RTI.

2.2 Sources for Estimates of Explanatory Variables

Current crash data will be sourced from the Fatality Analysis and Reporting System (FARS) with a focus on the United States.

The other explanatory variables are related to human factors. There are a few possible approaches to gathering human factors variables pertaining to driver behavior and performance. This paper draws from the following approaches with prioritization corresponding to the order in which they are listed here. The first approach is Naturalistic Driving Studies which examine real driver behavior mostly from within an instrumented vehicle. The second is observing real driver behavior from outside of vehicles using ITS sensors. The third approach is observing simulated driver behaviour using real humans in driving simulators. The fourth and final approach is observing the outcomes of completely digital simulations with synthetically modeled drivers.

3 Analysis

3.1 Quantification of Red Light Running Fatalities and Injuries by Vehicle Class

Red light running fatalities have increased by 46% between 2018 and 2022 in the United States. Table 1 shows data from the Fatality Analysis and Reporting System (FARS), revealing that in the year 2022, 1272 people died from red light running crashes at signalized intersections.

In 2022, red light running accounted for 30% of signalized intersection fatalities (USDOT, 2025). In addition to these fatalities, an estimated 116,000 people are injured annually in red light running crashes (Levin, Sun, He, Zamanpour, & Guo, 2024).

We will use 1,272 red light running fatalities per year as the total problem of which the system will be able to target and successfully prevent a subset.

Table 1: Red Light Running Fatalities in Context (Source: USDOT 2025, as extracted from FARS)

Year	Traffic Fatalities	Fatalities Involving an Intersection	Fatalities Involving a Signalized Intersection	Fatalities Involving Red-Light Running at a Signalized Intersection	Pedestrian Fatalities Involving a Signalized Intersection	Bicyclist Fatalities Involving a Signalized Intersection	Pedestrian and Bicyclist Fatalities Involving Red-Light Running at a Signalized Intersection
2018	36,835	10,148	3,347	871	817	140	57
2019	36,355	10,273	3,296	856	848	152	62
2020	39,007	10,720	3,577	1,074	792	151	58
2021	42,939	11,799	4,047	1,202	853	154	58
2022	42,514	12,036	4,204	1,272	983	182	84

A previous study used FARS data to conduct a deep analysis of two-vehicle fatal crashes at signalized intersections, including a breakdown by vehicle classification, finding the results in Table 2 below (Subramanian & Lombardo, 2007).

Table 2: Vehicle Classification of Red Light Running Fatalities in the US from 1997 to 2004

Year	Vehicle Type	Vehicles Involved					
		Total		Red-Light Running (Failure-to-Obey Vehicles)		Failure-to-Yield Vehicles	
		Num	%	Num	%	Num	%
1997 to 2004	Cars	12,502	54%	3,300	56%	2,496	71%
	Vans	1,625	7%	436	7%	210	6%
	SUVs	2,310	10%	625	11%	262	7%
	Pickups	3,321	14%	945	16%	328	9%
	Buses	187	1%	22	0%	10	0%
	Motorcycles	1,248	5%	243	4%	73	2%
	Large Trks	1,809	8%	336	6%	105	3%
	Oth/Unk	140	1%	38	1%	16	0%
	Total	23,142	100%	5,945	100%	3,500	100%

Source: Part of Table 40 from (Subramanian & Lombardo, 2007) based on FARS data

From Table 2 we derive three vehicle classes of interest:

- Va will represent all vehicle types that will be targeted by the proposed V2X RLR ADAS, and the category only excludes motorcycles, which would be difficult to equip with the proposed system. Vehicle class Va then accounts for 96% of the total red light running fatalities.
- Vh will represent heavy vehicles of types commonly found in fleets. We include buses and large trucks. Vehicle class Vh accounts for 6 % of the total red light running fatalities.
- Vp will represent passenger vehicles, except motorcycles, and we will include cars, vans, SUVs, and pickup trucks. Vp accounts for 90% of the total red light running fatalities.

We multiply the 2022 total annual fatalities from Table 1 (1272) by the percentage share of fatalities for each vehicle class to get the target number of fatalities for each vehicle class. To get the number of target injuries for each vehicle class, we estimate the number of target injuries for each vehicle class by scaling the corresponding fatal estimate by the ratio of 116,000 annual injuries cited above to the 1272 annual fatalities. This yields the first set of required explanatory variables in Table 3.

Table 3: Forecast Explanatory Variables - Current RLR Victims

Vehicle Class	Current Annual Fatalities (Sf)	Current Annual Injuries (Si)
All targeted vehicles (Va)	$C_{Sf,Va} = 1{,}221$	$C_{Si,Va} = 111{,}360$
Heavy vehicles (Vh)	$C_{Sf,Vh} = 76$	$C_{Si,Vh} = 6{,}960$
Passenger vehicles (Vp)	$C_{Sf,Vp} = 1{,}145$	$C_{Si,Vp} = 104{,}400$

3.2 Quantification of Driver Intentionality States

The USDOT, in guidance on engineering countermeasures to reduce red light running, is careful to distinguish between intentional and unintentional red light running, arguing that engineering efforts are best suited to target the former, while education and enforcement are best for the latter (USDOT, 2009).

Driver intention is impossible to know with certainty. It must be observed from proxies. It is useful to estimate driver intentions because the most effective way to prevent red light running crashes can be different. At the most basic level, we can imagine drivers who would like to stop at all red lights and only violate lights unintentionally. These drivers, unaware that they are about to do something they do not want to do, may respond positively to an alert or warning to stop. At the other extreme we can imagine drivers who want to run red lights on purpose. A warning that the light is red gives them no new information and a request to stop will likely not be heeded.

Understanding intentionality in red light running is also complicated by the dilemma zone problem at change intervals. There are some drivers who may generally not want to run red lights, but their intentions shift after encountering a challenging dilemma zone scenario. Not knowing that a signal change was coming soon, they may have formed an ad hoc expectancy of a right to traverse the intersection in question without stoppage. When the signal changes, they enter a mode of trying to beat the signal change. Others, without forming any views of entitlement, will genuinely be unsure of whether it is better to stop or go, and after some period of hesitation, feel that it is too late to stop and they must commit to the go decision. In both cases, these drivers have an immediate, localized intention that is inconsistent with their more durative, baseline intention.

Multiple papers have explored the decisions making process of drivers at red light rights, including the stop-go decision at phase change, and these studies often attempt to model and predict the outcome of driver decisions in various scenarios. For example, Komol et al. (2022) systematically reviewed 23 such studies, finding that the predictive models generally attain high accuracy levels.

3.2.1 Time in Phase and Relationship to Intentionality

Volpe studied intersections equipped with red light running cameras, finding that more than 50% of red light running occurs within the first 0.5 seconds of a red interval and 94.2% within the first 2.0 seconds of a red interval (RITA / J. A. Volpe NTSC, 2006). If red light running was mainly the product of a general baseline desire to wilfully ignore traffic signals, we would expect it to be more evenly distributed throughout the red interval. The heavy concentration of red light running near onset of the red phase can suggest a predominance of unintentional behavior, or if it was intentional, it was with an intentionality that was disturbed from baseline due to ad hoc expectancies around the phase change.

3.2.2 NDS Data on Intentionality and Distraction

One of the first major naturalistic driving studies was the 100 car NDS (Dingus, et al., 2006). This study involved 100 instrumented cars driving naturally over long periods for a total of 2 million miles. Over the course of those miles, 69 crashes occurred. Humans reviewing video footage from in-car cameras facing the drivers classified the driver as ‘inattentive’ in 78% of these crashes and ‘attentive’ in 22%. Although this pertains to all crash types and not red light running only, ‘inattentiveness’ could be taken as a proxy for intentionality. Someone who crashes because of inattentiveness is a prime candidate for effective intervention by a system that calls their attention to the most relevant hazard.

The 100 Car NDS was followed by the much larger SHRP-2 NDS (Transportation Research Board, 2013). The SHRP-2 NDS had 3100 participants and collected 33 million total miles (Ahemd, Khan, Das, & Dadvar, 2022). This allows for a higher sample size of 166 RLR crashes to be analyzed. A recent report provides a query-based breakdown of the characteristics of the 166 RLR events in SHRP-2 which are relevant to intentionality (Mhalsekar, 2026). That SHRP-2 analysis reveals the information in the following table.

Table 4: Driver Intentionality Coding Distribution in SHRP 2 for Total and Severe Crashes

<table>
<tr><th>Driver Behavior Code</th><th>All Crashes</th><th colspan="2">Severe (L1) Crashes</th></tr>
<tr><td>Signal violation, intentionally disregarded signal</td><td>52 (31.3%)</td><td rowspan="2">2 (33%)</td><td>~12%</td></tr>
<tr><td>Signal violation, tried to beat signal change</td><td>87 (52.4%)</td><td>~21%</td></tr>
<tr><td>Signal violation, apparently did not see signal</td><td>27 (16.2%)</td><td colspan="2">4 (66%)</td></tr>
<tr><td>Total - All violation behavior codes</td><td>166 (100 %)</td><td colspan="2">6 (100%)</td></tr>
</table>

Source: (Mhalsekar, 2026) based on SHRP-2 NDS InSight Platform

Table 4 shows sharp differences based on the severity class of crashes. When all severities are considered, including the many minor outcomes, then completely unintentional perception failures only account for 16.2 % of crashes. However, this figure jumps to 66% when severe crashes are considered (fatalities and injuries). Crashes coded as ‘did not see signal’ are considered amenable to treatment by the proposed ADAS.

Crashes coded as 'tried to beat signal change' are also considered amenable to treatment by the proposed ADAS. Unfortunately, the Mhalsekar analysis aggregates these with 'intentional disregard' crashes when reporting on severe crashes, even though it treats them separately for all crashes. This paper estimates the sub breakdown of these two types by transferring their relative prevalence from the all-crashes breakdown, (e.g. for proportion of severe crashes with behaviour intentional disregard signal, we estimate 33% * 31.3 / (31.3+52.4)). This yields an estimate of 21% of severe crashes related to trying to beat the signal change, which are considered amenable to treatment by ADAS.

The total proportion of serious RLR crashes amenable to treatment by ADAS, not considering vehicle class, is therefore 87%, which is the sum of the 'tried to beat signal change' and 'apparently did not see signal'. With the data available, it is not possible to break this down further between injury crashes and fatal crashes or by vehicle class, therefore 87% will be used for the amenable intentionality estimate for both injury and fatalities.

3.2.3 Selection of Intentionality Estimates for Forecast Input

We have reviewed data on time in phase for RLR behavior in general, distraction data on crashes in general from the 100 CAR NDS, and driver intentionality data in severe RLR crashes from the SHRP-2 NDS. The results are summarized in Table 5. For the purpose forecasting input, we will use the data derived from the SHRP-2 NDS because it is most specifically related to serious RLR crashes. The other data sources (Volpe and the 100 Car NDS) are less specifically related to our research question. These other data sources are used here as 'sanity' checks, and it is reassuring that the selected amenable intentionality proportion of 87% sits almost exactly in the middle of the data from Volpe and the 100 Car NDS.

Table 5: Review and Selection of Estimate for Intentionality Proportion Amenable to Treatment

Source of Intentionality Inference	Proportion of Total Crashes Amenable to Treatment (IST)	Proportion of Fatal and Injury Crashes Amenable to Treatment
Based on Proportion of RLR events within first 2 seconds of phase from Volpe	$I_{St} = 94.2\ \%$	n/a
Based on Proportion of Crashes with Distracted Drivers in 100 Car NDS	$I_{St} = 78\ \%$	n/a
Based on Intentionality States in Total and Serious RLR Crashes in SHRP-2	$I_{St} = 68.6\%$	$I_{Si} = I_{Sf} = 87\%$ (selected for fatal and injury forecasts for all vehicle classes)

3.3 Response Rates to ADAS Warnings and Guidance

Even for drivers whose intentions are open to being helped by an ADAS, it is not a given that the warning or information conveyed by the ADAS will be successful in evoking the desired driver response. Some drivers may be too deeply distracted to be engaged by the ADAS. Other drivers may simply be too slow in processing and reacting to information from the ADAS.

For this reason, when forecasting benefits of the proposed ADAS we will include empirical data on successful response rates to ADAS requests to intervene.

Yan, Li, and Xu (2015) used a high fidelity driving simulator to studied driver response to audio red light warnings, finding that audible warnings of a red or impending red light reduced crashes in the simulator by 84.3%.

A USDOT / NHTSA study investigated driver response rates to an ADAS providing forward collision warning (FCW) on a test track (Kiefer, Cassa, Flannagan, Jerome, & Palmer, 2005). Response rates were investigated as a function of whether the warning modality was audio and visual, or visual only. In this trial, emergency braking interventions by a supervising passenger with safety brakes was used as a proxy for crash outcomes, and a reduction in these emergency interventions is a surrogate for possible crash reductions from the ADAS. Based on these surrogates, the study found that dual modality warnings from FCW ADAS (audible plus visual) can reduce forward collisions by 48%, while single modality warnings (visual only) can reduce forward collisions by a slightly more modest 42%.

Another USDOT / NHTSA project used a 4-week naturalistic driving study (NDS) design to investigate the effectiveness of ADAS in producing desired driver responses following a request to intervene (RTI) (Russell, Blanco, Atwood, Shaudt, & Fitchett, 2018). This study found an 80.5% successful driver response rate to ADAS RTIs and a complementary 19.5% no response rate. In cases of successful response, the mean time to first response was 0.94 seconds (S.E. = 0.09 s). First response might simply be a glance at the instrument panel or a firmer grip on the steering wheel. The mean time to intervention (the action called for by the RTI to reduce risk) was 1.79 seconds (S.E. = 0.11 s).

The three studies mentioned above agree that ADAS systems can successfully evoke responses in a meaningful proportion of drivers. However, the studies diverge somewhat in the magnitude of this proportion. We are inclined to use the result of 80.5% from the NDS study because it is most representative of real-world conditions. However, this study looked at audible RTIs only, and it is not a given that a V2X RLR ADAS will use an audible tone. The simulation study cited above found that visual only warnings had an effect that was 12.5% lower (1 - 42/48) than the dual modality warnings. For this reason, we will use two response rates in our forecasts. Forecasts for dual modality warning scenarios will use a response rate of 80.5%, while forecasts for visual only warnings will use a response rate of 80.5% X (1 - 0.125) = 70%.

3.4 Forecasts

The following forecasts in Table 6 are based on the application of the explanatory variable estimates to the forecast model functional form. They show the estimates of the annual expected fatalities and injuries that can be prevented through the proposed V2X RLR ADAS, broken down by vehicle class and the ADAS warning modality. We forecast that the ADAS will prevent 855 fatalities and 77,991 injuries per year if deployed at all signalized intersections and vehicles in the United States with a dual modality warning. If a visual only warning modality is used, the fatality prevention estimates are slightly lower. For heavy vehicles, the system has the potential to prevent 53 fatalities and 4,874 vehicles.

Table 6: Annual Fatal and Injury Reduction Predictions for V2X RLR ADAS

	Modality: Audio and Visual		Modality: Visual Only	
Vehicle Class	**Annual Fatalities Prevented**	**Annual Injuries Prevented**	**Annual Fatalities Prevented**	**Annual Injuries Prevented**
All targeted vehicles (Va)	855	77,991	744	67,818
Heavy vehicles (Vh)	53	4,874	46	4,239
Passenger vehicles (Vp)	802	73,117	697	63,580

4 Conclusions

The deployment of various ADAS in recent years has resulted in demonstrable safety gains. However, no widely used ADAS is targeting RLR crashes. This is a major gap in the ADAS field, since RLR crashes account for more than 1200 annual fatalities and represent about 30% of all fatalities at signalized intersections.

By combining a vehicle's own GPS systems with signal telemetry data shared to a vehicle over V2X channels, it is feasible for OEMs or third party fleet retrofitters to construct an ADAS that warns vehicles which are approaching a current or impending stop condition at too high of a speed. This paper has scientifically estimated the potential road safety benefits of such an ADAS by applying empirical research on driver intentionality states and response rates to ADAS requests to intervene. We found that up to 855 RLR fatalities can be prevented per year, which is 70% of the current total number of RLR fatalities.

Because implementing the proposed system can make such a dramatic impact towards vision zero, a variety of stakeholders, such as vehicle regulators, OEMs, fleet retrofitters, signal owners, and ITS providers should begin working together urgently to bring V2X RLR ADAS to life.

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