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Monitoring of Urban Roadway Safety Hazards from Existing Bus-based Video Imagery: Phase 3

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16. Abstract			
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Safety21 University Transportation Center Report

Project 601: Monitoring of Urban Roadway Safety Hazards from Existing Bus-based Video Imagery: Phase 3

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Abstract

Roadway traffic safety engineers consider crash data to identify locations and times of high hazard risk. While these data and the resulting identifications are valuable, they do not allow for capturing other locations and times prone to hazards where crashes have not occurred yet. Therefore, capturing conditions associated with safety hazards is equally important in pointing safety engineers to roadway locations and times where safety mitigation measures could be taken before crashes occur. Contributors to traffic safety hazards include rapid decelerations and lane changes in the presence of queues and interactions of vulnerable and nonvulnerable vehicles. Traditional traffic data collection methods are constrained in time and space and therefore prone to biased sampling. Taking advantage of video imagery recorded by transit bus-mounted cameras for other purposes offers an opportunity to provide information that can reduce this bias. In this project available, repeated, and extensive imagery recorded by cameras mounted on transit buses operating in regular service is used to identify queues, the presence of high volumes of vulnerable vehicles, and the interactions of vulnerable and nonvulnerable vehicles that could lead to safety hazards. The campus of The Ohio State University roadway network is used as a living lab testbed. The results demonstrate the promise of identifying queuing and mixes of vehicle types over space and time. Further improvements and extensions are discussed.

1. Introduction and Motivation

Roadway traffic safety engineers consider crash data to identify locations and times of high hazard risk. While these data and the resulting identifications are valuable, they do not allow for capturing other locations and times prone to hazards where crashes have not occurred yet. Therefore, capturing conditions associated with safety hazards is important in pointing safety engineers to roadway locations and times where safety mitigation measures could be taken before crashes occur.

Among others, contributors to traffic safety hazards include rapid decelerations and lane changes in the presence of queues and interactions of vulnerable and nonvulnerable vehicles. Phase 1 and phase 2 projects focused on queuing related hazards. This phase 3 extends the queuing related investigation and also investigates the interactions of vulnerable and nonvulnerable vehicles. Regarding the latter, the disparity in size and weight between vulnerable vehicles – scooters, skateboards, bicycles and motorcycles – and nonvulnerable vehicles – sedans, sport utility vehicles, buses and trucks – contributes to the increased risk of accident occurrences that lead to serious injuries and fatalities. A deployment partner commented that near misses of such interactions “happen all the time.” Similarly, and as was highlighted in an The Economist (2024), the increasing size and weight of passenger vehicles is leading to an exponentially increasing risk of injuries to and fatalities of pedestrians and passengers of vulnerable vehicles.

Assessing locations with increased recurring traffic safety hazards requires extensive and regular collection of data on these contributors. Traditional methods entail using sensors at permanent or temporary fixed locations, which is costly and labor intensive and provides limited coverage over space and through time. Moreover, the location of these sensors may be influenced by factors other than optimal sampling, such as requests from well-organized constituencies. Therefore, relying on such data to assess traffic safety hazards to support improved policies and designs could lead to missing high-risk conditions and inequitable outcomes.

Clearly, low cost and extensive, equitable data collection is desirable. Transit buses operate regularly over wide networks. Most agencies have equipped their bus fleet with cameras that record the environment inside and outside buses for liability, security, and safety purposes. Consequently, the imagery is available for other uses at near-zero marginal cost, and the coverage provides comprehensive views that could potentially be used to determine times and locations of regularly occurring safety hazards. Moreover, this imagery has been shown by project investigators to be effective in monitoring traffic volumes across time and space (McCord et al., 2020, 2023, and 2025), information that provides exposure-based context for identifying safety hazards. Furthermore, in the previous phase 1 project, a queue presence and length identification method was developed and evaluated where promising results were obtained. In the previous phase 2 project times and locations of queuing related "hotspots" over a roadway network were identified using imagery recorded by cameras mounted on transit buses in regular operation. In this phase 3 project, the role of infrastructure characteristics on queuing related safety hazards is explored, and the use of transit bus cameras recorded imagery to determine meaningful assessment of vulnerable and nonvulnerable vehicles mix related hazards is investigated.

This project addresses the "Data-driven System Safety" research priority outlined in US DOT Research, Development and Technology Strategic Plan (RD&T Plan). Specifically, the long-term effort relates to the following: (1) "Safe Design" whereby assessing safety hazards that relate to cyclists, scooterists, and motorcyclists and determining the percentage of these vulnerable vehicles involves "Identify[ing] and support[ing] strategies to increase vulnerable road user safety" (see p. 19 of RD&T Plan). (2) "Safety Data" whereby the project focuses on "Develop[ing] safety data collection methods and advance[ing] safety data … to identify and analyze emerging safety issues" and "Improv[ing] safety data systems . . . to improve analy[zing] and identify[ing] emerging safety risks and disparate safety impacts on people and communities" (see p. 19 of RD&T Plan). (3) "Safe Technology" whereby the project involves "Leverag[ing] innovative (nonintrusive, i.e., safe) technologies to monitor, predict, and plan ways to reduce injuries and fatalities among the transportation workforce and traveling public" (see p. 19 of RD&T Plan).

The literature emphasizes the importance of traffic safety monitoring. Some studies address safety aspects related to the presence of pedestrians, cyclists, and motorcyclist in the traffic stream and safety aspects related to work zones (Howarth, 1982; Rouphail and Jovanis, 1987; Marlow, 1990; Jernigan and Lynn, 1995; Tsai, 2011; Mollenhauer et al., 2019; Still and Still, 2019). A few studies refer to the use of imagery for the purpose of monitoring (MacCarley, 1997; Rezaei, 2014; Yang et al., 2018). However, none of the studies address the importance of and ability to achieve time- and space-comprehensive queue presence and vehicle mix data collection for safety hazard monitoring and assessment, which is the focus of this study.

Two investigations are conducted in this study. In one investigation, the role of infrastructure characteristics on queuing related safety hazards is explored by investigating the association between the presence and extent of queuing variables and a set of specific infrastructure characteristic variables. An analysis is also conducted to identify locations where more queuing occurs than explained by these characteristics. In the second investigation, the ability to acquire meaningful information on vulnerable and nonvulnerable vehicle mix related hazards from imagery acquired from cameras mounted on transit buses operating in regular service is explored by summarizing space-time vehicle volumes obtained from the imagery with various indirect metrics and confirming the ability of the metrics to indicate the presence of safety hazards related to vulnerable vehicles and nonvulnerable vehicles interactions.

2. Methodology

2.1 Testbed and Extraction of Vehicle Data from Video Imagery

In a previous study (McCord et al., 2023; McCord et al., 2025), the investigators obtained transit bus-based video imagery to estimate traffic flows across The Ohio State University (OSU) campus and provided summary results to campus planners and operators. The video-based sensing set-up is described in the final report of phase 2 of this project (Mishalani et al., 2025). Video imagery files were downloaded from the Campus Area Bus Service (CABS) buses by the team's outreach partner, OSU's Transportation and Traffic Management (TTM). In previous studies undergraduate and graduate research assistants used a graphical user interface (GUI) to extract data on vehicles passing buses in the opposite direction of the buses' travel direction (McCord et al., 2020).

In this project the GUI is modified to allow for the categorization of vehicles while passing the bus in the opposite direction. The ability to categorize three categories of vehicles was implemented in the modified GUI. The three categories considered in this study are defined as follows:

- Vulnerable vehicles: skateboards, scooters, e-scooters, bicycles, e-bikes, motorcycles, and carts
- Regular vehicles: hatchbacks, sedans, and cross-over sport utility vehicles (SUVs)
- Heavy vehicles: SUVs, passenger tracks, trucks, and buses

As discussed in the final report for phase 2 of this project, the GUI is used to demonstrate the potential of using video imagery recorded by transit bus-mounted cameras. For the approach to be cost-effective for ongoing and frequent monitoring of large networks in practice, it is desirable to automatically identify vehicles in the imagery. Automatic vehicle identification appears feasible given results from research to automatically identify vehicles from mobile video imagery using machine vision methods (Redmill et al., 2023). The automation of vehicle categorization has not been attempted yet by this OSU team. When operational automatic vehicle identification is achieved, the marginal cost of processing the video imagery to extract queuing information would become minimal, as is the present marginal cost of accessing the video imagery which is collected on bus systems for other purposes.

2.2 Queue Identification and Metrics

To identify queues from the video imagery, the automatic queue presence and length determination method developed in the year 1 project (Mishalani et al., 2024) is applied as summarized in the final report of phase 2 (year 2) of the project (Mishalani et al., 2025). Two queue related variables were considered in phase 2 of this project for the purpose of assessing safety risk stemming from hazards associated with queuing. They are the following (Mishalani et al., 2025):

- $PLNQV_i$ = total number of vehicles in all queues identified to have occurred on segment-direction-hour *i* for a given bus pass (a bus traversing a segment-direction)
- $PLNDQ_i$ = number of different queues identified to have occurred on a segment-direction-hour *i* for a given bus pass.

These variables are used in the additional queuing related investigation of this project presented in Section 4.

2.3 Traffic Mix Determination and Metrics

Video imagery is processed using the modified GUI discussed in Section 2.1 to determine the number of vehicles observed from each bus pass in each of the three vehicle categories noted in that section. The numbers of vehicles in each category are then added to determine the total number of vehicles observed on each bus pass. The numbers of vehicles in each category are also summed by category across all bus passes for each segment-direction-hour to determine the percentages of vehicle category for the segment-direction-hour. The methodology developed in a previous study (McCord et al., 2023; McCord et al., 2025) is applied using the total numbers of vehicles on the individual bus passes to estimate the traffic volume for each segment-direction-hour. The calculated percentage of each category is then applied to determine the volume of vulnerable, regular, and heavy vehicles for each segment-direction-hour.

Considering these volumes by vehicle category, the following traffic mix related variables are defined for the purpose of assessing safety risk stemming from the interaction of vulnerable and non-vulnerable vehicles:

- Vul_i = vulnerable vehicle volume for segment-direction-hour *i*
- Non_Vul_i = sum of the regular and heavy vehicle volumes (henceforth referred to as non-vulnerable volume) for segment-direction-hour *i*
- Pct_Vul_i = percent vulnerable vehicles among the total vehicles for segment-direction-hour *i*
- $Prod_i$ = product of Vul_i and Non_Vul_i for segment-direction-hour *i*.

The values of these variables are also normalized to determine relative values of the variable when considering the values across all segment-direction-hours. The normalized vulnerable vehicle volume for segment-direction-hour *i*, $RVVul_i$, is determined for each segment-direction-hour as follows:

$$RVVul_i = \frac{Vul_i - Vul_{min}}{Vul_{max} - Vul_{min}} \quad (1)$$

where Vul_{max} and Vul_{min} are, respectively, the maximum and minimum vulnerable vehicle volumes determined across all segment-direction hours. Naturally, the outcome of this normalization leads to values ranging between 0 and 1. The relative values of the other three variables listed above are similarly determined and denoted by $RVNon\_Vul_i$, $RVPct\_Vul_i$, and $RVProd_i$.

These variables are used in the traffic mix hazard investigation aspect of this project presented in section 5.

3 Data

3.1 Video Imagery Used for Data Extraction

Video imagery recorded on OSU's CABS buses transversing the campus network on October 31, 2024, from 7 am to 7 pm were previously downloaded by TTM, the project's outreach partner, and provided to the project's research team (Mishalani et al., 2025). The roadway segments comprising the campus network previously considered and considered again in this project are shown in Figure 1. The segments are numbered in a manner that distinguishes their direction. The X.1 directions indicate eastbound or northbound traffic, and the X.2 directions indicate westbound or southbound traffic.

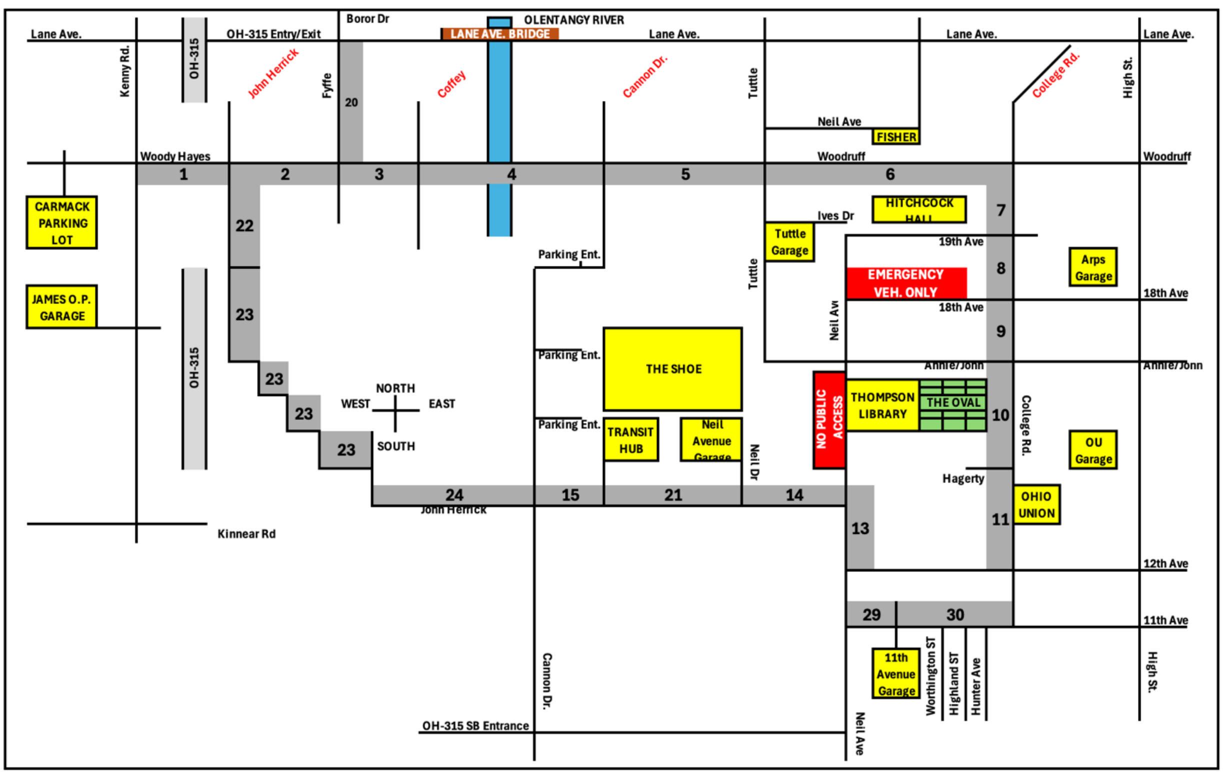

Figure 1: Illustration of OSU campus roadway network and segment numbers

For this project a total of 748 video clips spanning 64.7 hours of imagery were processed semi-automatically using the updated GUI discussed in Section 2.1 by eight undergraduate students and one graduate student. This processing led to the quantification of the variables discussed in Section 2.2, which are the same data used during phase 2 of the project (Mishalani et al., 2025) where the original GUI was applied. It also led to the quantification of the variables discussed in section 2.3 where the modified GUI was applied.

3.2 Infrastructure Characteristics Data

As discussed in Section 1 queuing hotspots were identified across the network during hours of the day in phase 2 of this project. In this study the impact of infrastructure on queuing related safety hazards is explored. This is done by directly considering the roadway infrastructure of the OSU campus, which requires that data on infrastructure characteristics be amassed, the process for which is presented in this section.

The data for road infrastructure of OSU campus is collected by observing each segment on Google satellite imagery and verifying by walking each segment of the network. This includes noting the presence of parking access, traffic control, pedestrian infrastructure, and transit infrastructure in each segment-direction.

The dataset for road infrastructure includes the following variables in an Excel spreadsheet: segment length, access to parking facility or not, type of intersection control, type of mid-segment pedestrian crossing, and type of bus stop on the segment.

Road infrastructure categorical variables are considered with different variations (grouped and ungrouped) as explanatory variables for regression analysis to explore the relationship with queueing variables at the pass level (using $PLNQV_i$ and $PLNDQ_i$ as dependent variables). The ungrouped explanatory variables are defined as follows:

- *Volume*: Hourly volume obtained using the method developed in McCord et al. (2024) associated with a segment-direction-pass
- *Length*: Length of road segment in miles
- *Access Park*: A binary variable with value of 1 if a road segment-direction has left/right turn access to a parking lot/garage and 0 if not
- *Stop-Controlled Intersection*: A binary variable with value of 1 if a road segment-direction has a stop sign control at the downstream end of intersection and 0 if not
- *Uncontrolled Intersection*: A binary variable with value of 1 if a road segment-direction has no control at the downstream end of intersection and 0 if not
- *Traffic Signal*: A binary variable with value of 1 if a road segment-direction has a traffic signal as a control at the downstream end of intersection and 0 if not
- *Signalized Control US*: A binary variable with value of 1 if a road segment-direction has a traffic signal at the upstream (*US*) end of intersection on at least one approach and 0 if not
- *Signalized Mid-Seg Pedestrian Crossing*: A binary variable with value of 1 if a road segment has a signalized mid-segment pedestrian crossing and 0 if not
- *Unsignalized Mid-Seg Pedestrian Crossing*: A binary variable with value of 1 if a road segment has an unsignalized mid-segment pedestrian crossing and 0 if not
- *Mid-Seg Pedestrian Actuated Signal Crossing*: A binary variable with value of 1 if a road segment has a pedestrian actuated signalized mid-segment pedestrian crossing and 0 if not
- *No Mid-Seg Pedestrian Crossing*: A binary variable with value of 1 if a road segment has no mid-segment pedestrian crossing and 0 otherwise
- *Bus Stop No pullout*: A binary variable with value of 1 if a road segment-direction has a bus stop with no pullout and 0 if not
- *Bus Stop with pullout*: A categorical variable with value of 1 if a road segment-direction has a bus stop with a pullout and 0 if not.

- *No Bus Stop*: A categorical variable with value of 1 if a road segment-direction has no bus stop and 0 otherwise

When using the ungrouped variables defined above, the values for type of intersection control (traffic light, stop-controlled, uncontrolled), type of mid-segment pedestrian crossings (signalized, pedestrian-initiated signalized, unsignalized, no crossing), and type of bus stop (with pullout, without pullout, no bus stop) are coded as mutually exclusive for a segment-direction.

Some variables were grouped together to define new binary variables. These are:

- *Bus Stop*: A binary variable with value of 1 if a road segment-direction has a bus stop with no pullout and 0 if the segment-direction has either a bus stop with a pullout or no bus stop
- *Bus Stop One Lane Segments*: A binary variable with value of 1 if a road segment-direction with only 1 lane has a bus stop with no pullout and 0 if the segment-direction has either a pullout or no bus stop
- *Bus Stop Two Lane Segments*: A binary variable with value of 1 if a road segment-direction with 2 lanes has a bus stop with no pullout if the segment-direction has either a bus stop with a pullout or no bus stop
- *Intersection Control*: A binary variable with value of 1 if a road segment-direction has a traffic signal at the downstream intersection and 0 if the segment-direction has either a stop controlled or uncontrolled intersection
- *Mid-Seg Pedestrian Crossing*: A binary categorical variable with value of 1 if a road segment has either a signalized or an actuated crossing and 0 if the segment has an unsignalized crossing or no crossing

4. Queuing Hazard Results

4.1 Introduction and Motivation

In phase 2 of the project (Mishalani et al., 2025) the available, repeated, and extensive imagery recorded by transit bus-mounted cameras for identifying queue presence and length was investigated using the OSU campus as a testbed. The results demonstrate the feasibility of using bus-based imagery to identify queuing over space and time. Specifically, some results confirmed prior expectations based on knowledge of network traffic conditions regarding the presence of hotspots based on travel patterns and infrastructure characteristics, and other results shed light on previously unanticipated hotspots that were explainable after they were identified using the developed methodology.

In the present study the role of infrastructure characteristics on queuing related safety hazards is explored by investigating the association between the presence and extent of queuing variables and a set of specific infrastructure characteristic variables. Expected associations are identified, which further confirms the viability of the developed methodology. Moreover, an analysis of the model residuals is conducted to identify segment-directions where more queuing occurs than explained by known infrastructure characteristics. Such an analysis could point safety experts to roadway segments for further investigation.

In this analysis the infrastructure impact on queuing related safety hazards is conducted at the pass level by considering the variables $PLNQV_i$ and $PLNDQ_i$ defined in Section 2.2 as dependent variables and the infrastructure characteristics variables defined in Section 3.2 as the independent (or explanatory) variables.

4.2 Number of Queued Vehicles

Various regression models were explored to investigate the relationship of $PLNQV_i$ with traffic volumes and road infrastructure variables. The variables used in the final linear regression model for $PLNQV_i$ and the estimation results are presented in Table 1. As seen in this table, all the explanatory variables except *Mid-segment Pedestrian Crossing* are highly significant (p-values much less than 0.01), and all variables' coefficients have positive signs, consistent with expectations that the presence of the represented infrastructure characteristics would increase queuing.

Table 1: Regression Model Estimates for *PLNQV*

Variable	Estimate	t-value	p-value
Intercept	– 1.9902	– 13.240	< 2e-16
Volume (Vehicle per hour per lane)	0.0153	19.216	< 2e-16
Bus Stop One Lane Segments (No Pullout)	0.6939	3.452	0.000562
Bus Stop Two Lane Segments (No Pullout)	2.4939	13.414	< 2e-16
Mid-segment Pedestrian Crossing	0.1302	1.517	0.179659
Intersection Control (Traffic Signal)	0.8018	6.819	1.07e-11
No. of observations = 3,645 Adjusted R^2 = 0.2299			

As indicated by the magnitudes of the estimated coefficients, the model suggests that, among the categorical variables, the impact of *Bus Stop Two Lane Segments (No Pullout)* on queuing is highest, followed by *Intersection Control (Traffic Signal)* and *Bus Stop One Lane Segments (No Pullout)*. Contrary to these findings, one would expect that a bus stop with no pullout would have a greater impact on queuing on a one-lane road than on a two-lane road. The numerical results are possibly a result of a present limitation of the queue estimation approach developed in (Mishalani et al, 2025) where vehicles in two separate lanes could be side by side leading to false positive detection of. It would be useful to improve the automatic queuing identification methodology to allow for a distinction of queuing by lane.

4.3 Number of Different Queues

Various regression models were also explored to study the relationship of the number of different queues $PLNDQ_i$ with volumes and road infrastructure variables. The variables used in the final linear regression equation for $PLNDQ_i$ and the estimation results are presented in Table 2. As seen in this table, the estimated coefficients of all the explanatory variables have positive signs, which is consistent with expectations, and are highly significant (p-values less than 0.01), except *Mid-segment Pedestrian Crossing* which has the expected positive sign but a p-value slightly greater than 0.01 (namely, 0.0161).

Table 2: Regression Model Estimates for *PLNDQ*

Variable	Estimate	t-value	p-value
Intercept	– 0.2741	– 11.529	< 2e-16
***Volume* (Vehicle per hour per lane)**	0.0022	17.711	< 2e-16
***Bus Stop One Lane Segments (No Pullout*)**	0.1374	4.324	0.0000157
***Bus Stop Two Lane Segments (No Pullout*)**	0.4102	13.949	< 2e-16
Mid-segment Pedestrian Crossing	0.0593	2.409	0.0161
Intersection Control (Traffic Signal)	0.1324	7.118	1.31e-12
No. of observations = 3,645 Adjusted R^2 = 0.2198			

Similar to what was found when considering $PLNDV_i$ as the dependent variable, this model implies that the impact of *Bus Stop Two Lane Segments (No Pullout)* on queuing is higher than the impact of *Bus Stop One Lane Segments (No Pullout)*, likely for the reasons discussed above.

4.4 Residual Analysis

To identify locations where more queuing occurs than explained by the factors identified in Section 4.3, the residuals for each of the *PLNDV* and *PLNDQ* models reported above are regressed against segment-direction indicators. The results are shown in Tables 3 and 4 for *PLNDV* and *PLNDQ*, respectively. Segment-direction 10.2 is selected to serve as the reference because the average residual for this segment-direction is the closest to zero for each of the *PLNDV* and *PLNDQ* models.

Table 3: Residuals Regression Model Estimates for *PLNDV*

Variable	Estimate	t-value	p-value
Intercept	0.017486	0.064	0.949067
Segment Direction 1.1	– 1.614872	– 4.091	4.40e-05
Segment Direction 1.2	0.749223	1.928	0.053909
Segment Direction 2.1	0.038440	0.075	0.940566
Segment Direction 2.2	– 1.144365	– 2.235	0.025500
Segment Direction 3.1	– 0.148220	– 0.383	0.701824
Segment Direction 3.2	– 1.331052	– 3.432	0.000606
Segment Direction 4.1	**1.862245**	**4.820**	**1.50e-06**
Segment Direction 4.2	– 0.426029	– 1.105	0.269415
Segment Direction 5.1	**2.225936**	**5.729**	**1.10e-08**
Segment Direction 5.2	**0.879933**	**2.269**	**0.023335**
Segment Direction 6.1	– 0.198227	– 0.519	0.604140
Segment Direction 6.2	**1.269646**	**3.338**	**0.000853**
Segment Direction 7.1	– 1.333734	– 2.604	0.009240
Segment Direction 7.2	– 0.040375	– 0.104	0.917092

Table 3, continued: Residuals Regression Model Estimates for *PLNDV*

Segment Direction 8.1	– 0.384914	– 0.761	0.446456
Segment Direction 8.2	0.446808	1.154	0.248486
Segment Direction 9.1	– 0.092880	– 0.184	0.854235
Segment Direction 9.2	– 0.003452	– 0.009	0.992899
Segment Direction 10.1	0.324050	0.649	0.516394
Segment Direction 11.1	– 0.106771	– 0.216	0.828712
Segment Direction 11.2	– 0.149846	– 0.333	0.739448
Segment Direction 13.1	0.085341	0.168	0.866795
Segment Direction 13.2	– 0.945586	– 1.871	0.061493
Segment Direction 14.1	0.216976	0.429	0.667795
Segment Direction 14.2	– 0.119450	– 0.235	0.814387
Segment Direction 15.1	**0.922921**	**1.979**	**0.047842**
Segment Direction 15.2	0.297561	0.638	0.523386
Segment Direction 20.1	– 1.670139	– 3.692	0.000226
Segment Direction 20.2	– 0.542603	– 1.209	0.226673
Segment Direction 21.1	0.171400	0.339	0.734588
Segment Direction 21.2	– 0.248382	– 0.488	0.625430
Segment Direction 22.1	– 0.719390	– 1.543	0.122938
Segment Direction 22.2	– 0.210047	– 0.455	0.649425
Segment Direction 23.1	– 0.128186	– 0.275	0.783387
Segment Direction 23.2	**1.506830**	**3.232**	**0.001241**
Segment Direction 24.1	– 0.030214	– 0.065	0.948336
Segment Direction 24.2	– 0.796316	– 1.700	0.089224
Segment Direction 29.1	– 0.629200	– 1.237	0.216267
Segment Direction 29.2	– 1.954352	– 3.866	0.000113
Segment Direction 30.1	0.144765	0.286	0.774614
Segment Direction 30.2	– 2.291144	– 4.532	6.03e-06

No. of observations = 3,645
Adjusted R^2 = 0.07711

Table 4: Residuals Regression Model Estimates for *PLNDQ*

Variable	**Estimate**	**t-value**	**p-value**
Intercept	– 0.0183046	– 0.419	0.675459
Segment Direction 1.1	– 0.2329985	– 3.695	0.000223
Segment Direction 1.2	0.1079184	1.739	0.082121
Segment Direction 2.1	0.0676631	0.822	0.411257
Segment Direction 2.2	– 0.1179496	– 1.442	0.149351
Segment Direction 3.1	0.0809794	1.310	0.190349
Segment Direction 3.2	– 0.2110886	– 3.408	0.000662
Segment Direction 4.1	**0.2640629**	**4.279**	**1.93e-05**
Segment Direction 4.2	0.0036313	0.059	0.952996
Segment Direction 5.1	**0.3676197**	**5.924**	**3.44e-09**

Table 4, continued: Residuals Regression Model Estimates for *PLNDQ*

Segment Direction 5.2	**0.1631520**	**2.634**	**0.008475**
Segment Direction 6.1	0.0142993	0.234	0.814853
Segment Direction 6.2	**0.2017805**	**3.321**	**0.000904**
Segment Direction 7.1	– 0.1855241	– 2.268	0.023367
Segment Direction 7.2	0.0103322	0.167	0.867532
Segment Direction 8.1	– 0.0471658	– 0.584	0.559134
Segment Direction 8.2	0.0744767	1.205	0.228430
Segment Direction 9.1	– 0.0044547	– 0.055	0.956003
Segment Direction 9.2	0.0086245	0.139	0.889270
Segment Direction 10.1	0.0837438	1.050	0.293741
Segment Direction 11.1	– 0.0040377	– 0.051	0.959144
Segment Direction 11.2	– 0.0088426	– 0.123	0.902198
Segment Direction 13.1	0.0442463	0.545	0.586108
Segment Direction 13.2	– 0.1395048	– 1.728	0.084098
Segment Direction 14.1	0.0448124	0.555	0.578906
Segment Direction 14.2	– 0.0007955	– 0.010	0.992189
Segment Direction 15.1	**0.1792028**	**2.406**	**0.016157**
Segment Direction 15.2	0.0475412	0.638	0.523238
Segment Direction 20.1	– 0.2262434	– 3.132	0.001752
Segment Direction 20.2	– 0.0439385	– 0.613	0.539865
Segment Direction 21.1	0.0378492	0.469	0.639248
Segment Direction 21.2	– 0.0390642	– 0.481	0.630717
Segment Direction 22.1	– 0.0795611	– 1.068	0.285405
Segment Direction 22.2	– 0.0048624	– 0.066	0.947469
Segment Direction 23.1	– 0.0106297	– 0.143	0.886499
Segment Direction 23.2	**0.1569447**	**2.108**	**0.035135**
Segment Direction 24.1	0.0689153	0.925	0.354792
Segment Direction 24.2	– 0.0190480	– 0.255	0.799044
Segment Direction 29.1	– 0.0616564	– 0.759	0.448022
Segment Direction 29.2	– 0.3095695	– 3.834	0.000128
Segment Direction 30.1	0.0173703	0.215	0.829667
Segment Direction 30.2	– 0.3680775	– 4.559	5.31e-06
No. of observations =3,645			
Adjusted R^2 = 0.06775			

Positive and statistically significant parameters identify segment-directions where more queuing occurs than explained by factors. The segment-directions that satisfy this criterion in either or both of the two sets of model results (see the bold face parameters and p-values in the Tables 1 and 2 where p-values less than or equal to 0.01 are considered indicative of significance where the identified segment-directions from the two models are identical) are 4.1, 5.1, 5.2, 6.2, 15.1, and 23.2. Segment-directions 4.1, 5.1, 15.1, and 23.2 all involved construction activities during the times the videos were recorded, possibly explaining the presence of more queuing than expected otherwise. This finding is consistent with the positive effect of construction on queuing found in the construction related analysis conducted in phase 2 of this project (Mishalani et al., 2025). It is not clear what might explain the positive and statistically significant parameter associated with segment-direction 6.2. It would be worthwhile to investigate possible additional characteristics associated with this segment-direction as part of future research.

5. Traffic Mix Hazard Results

5.1. Assessing Vulnerable and Non-vulnerable Vehicles Mix Hazards Using Indirect Metrics

As discussed previously, the procedure described in Sections 2.1 was used with the imagery obtained over the network of Figure 1 on October 31, 2024 to determine hourly volumes of vulnerable vehicles Vul_i and nonvulnerable vehicles Non_Vul_i (see Section 2.3) for each hour beginning at 7 am (7) through 6 pm (18) and each of the segment-directions presented in Section 3.1. These volumes are shown in the segment-direction vs. hour matrix of Figure 2, where the heat map coloring is based on normalized vulnerable vehicle volumes $RVVul_i$ obtained from Equation (1).

The blanks in the matrix correspond to hours where no vulnerable vehicles were recorded on the segment-direction but where the total volume was small enough that it was sufficiently likely not to observe vulnerable vehicles even though there could in fact be vulnerable vehicles during the hour. Specifically, taken across all bus passes, the data contained 1,165 vulnerable vehicles among the total of 28,154 observed vehicles. From these values, a probability of an observed vehicle being a vulnerable vehicle is assumed to equal 0.04138 (1,165 ÷ 28,154), and the probability of an observed vehicle not being a vulnerable vehicle is therefore assumed to equal 0.95862. The binomial distribution is used to determine the maximum number of vehicles N_v that could be observed such that the probability of observing 0 vehicles is greater than or equal to 0.2 (a somewhat arbitrarily chosen value). That is,

$$Prob(0, N_v; 0.04138, 0.95862) = \left(\frac{N_v!}{0!\,N_v!}\right)(0.04138)^0(0.95862)^{N_v} = (0.95862)^{N_v} \geq 0.2$$

yielding $N_v \leq 38.08$. Therefore, segment-direction-hours where 0 vulnerable vehicles were observed but where there were 38 or fewer total vehicles observed are considered to have total vehicle volumes too small to have confidence that there would be no vulnerable vehicles in the hour. These cells are left blank in the segment-direction by hour-of-day matrices. The predominance of grey and blank cells in Figure 2 indicates that there were relatively low volumes of vulnerable vehicles for most segment-direction-hours, and heat map coloring indicates that only a few locations stand out as having relatively high volumes of vulnerable vehicles and only at certain times of the day.

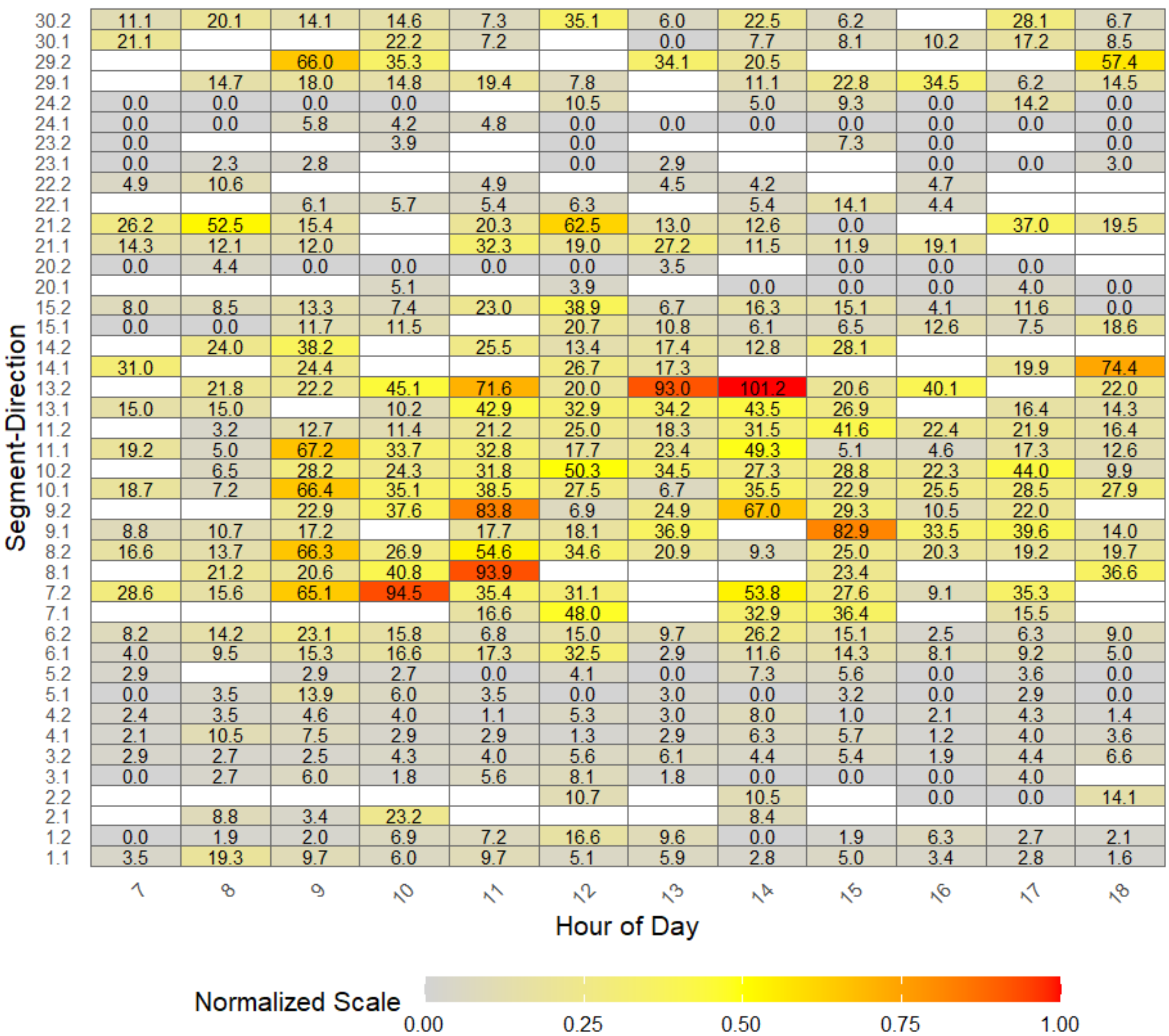

Figure 2: Values of Vul by segment-direction-hour and heatmap formed from $RVVul$

Many of the "hottest" cells in Figure 2 – those that stand out as having high vulnerable vehicle volumes – are seen around midday, beginning during the 10 am (10) hour and ending during the 3 pm (15) hour, and on just a few segment-directions, namely, 7.2, 8.1, 9.1, 9.2, 13.2 and 21.2. This midday period is when students are already on campus making relatively short trips with scooters, skateboards, and bicycles. Segments 7, 8, and 9 are segments with many pedestrian crossings and low vehicle speeds at the northeast part of campus. Students travel in this area to and from campus buildings in the center of the campus and dining locations and dormitories just north of the monitored network. Therefore, it is not surprising to see relatively large volumes of vulnerable vehicles at midday on these segments. At first glance it was surprising to see that segments 7 and 8 only show these high volumes in one direction, and in directions opposite to each other, namely southbound on segment 7 (7.2) and northbound on segment 8 (8.1). However, based on this finding it is speculated that many academic classroom buildings on 19th Ave. on campus (which is not on the monitored network because it is not traversed by CABS buses) is leading to students using vulnerable vehicles on 7.2 (southbound) making right turns (westbound) on 19th Ave. and students using vulnerable vehicles on 8.1 (northbound) making left turns (westbound) on 19th Ave. Nevertheless, it would be interesting to investigate in the future if this pattern persists on other days or if it was an anomaly on the day of data collection.

Segment 13 is a small segment at the south end of the monitored network. Manual observations made for various data collection purposes over the years support that this segment has large volumes of vulnerable vehicles, especially during the midday period. It is noted that 13.2 is the segment-direction with the greatest number of “hot” cells. This was not necessarily expected beforehand, but it is not surprising, given anecdotal observations of the network over the years. Segment 21.2 is also a short, often congested segment on the south end of the monitored network, extending between an exit from a large physical activity center and parking garage to a multi-route bus transit terminal. The relatively large vulnerable vehicle volume on this segment-direction is not currently explainable. It would be worthwhile to determine whether a similarly high volume would be observed on other days, in which case a possible explanation would be vigorously pursued, or this result is an anomaly.

There are also “orangish” cells during the 9 am hour corresponding to segment-directions 7.2, 8.2, 10.1, 11.1, and 29.2. These segment-directions carry traffic toward the center of campus from dormitories, dining locations, and the Ohio Union. The indications of relatively high vulnerable vehicle volumes likely correspond to students using scooters, skateboards, and bicycles at the beginning of heavy class schedules. The relatively heavy volume on segment-direction 14.1 and 29.2 during the 6 pm hour is surprising. This is another example of where it would be interesting to investigate in the future if this pattern persists on other days or if it was an anomaly on the day of data collection.

The percentages of vulnerable vehicles in the traffic streams by segment-direction-hour Pct_Vul_i would be a crude way to capture interactions between vulnerable and nonvulnerable vehicles. These percentages are presented in Figure 3, and the coloring of the heatmap portrayed in the figure is based on the normalized values of the percentages $RVPct\_Vul_i$ (see Section 2.3). Comparing Figure 3 to Figure 2, one can see that, although some segment-direction-hours stand out in the heatmaps in both Figure 3 and Figure 2 – e.g., segment-directions 7.2 during the 10 am hour, 8.1 during the 11 am hour, 8.2 during the 9 am hour, 9.1 during the 3 pm hour, and 9.2 during the 11 am and 2 pm hours – many of the segment-direction-hours that stood out when considering normalized volume in Figure 2 do not stand out in Figure 3. High volumes of nonvulnerable vehicles apparently are masking the relatively large volumes of vulnerable vehicles when considering vulnerable vehicle percentages. Similarly, some segment-direction-hours that did not stand out in Figure 2 appear as “hot” in Figure 3, where relatively lower volumes of nonvulnerable vehicles can accentuate the presence of relatively low volumes of vulnerable vehicle to lead to a relatively large percentage of vulnerable vehicles. The potential for hazardous conditions would seem to be more associated with the magnitude of vulnerable vehicles than with the percentage of vulnerable vehicles in the stream, and subsequent comparisons in this study are made when considering the volume of vulnerable vehicles.

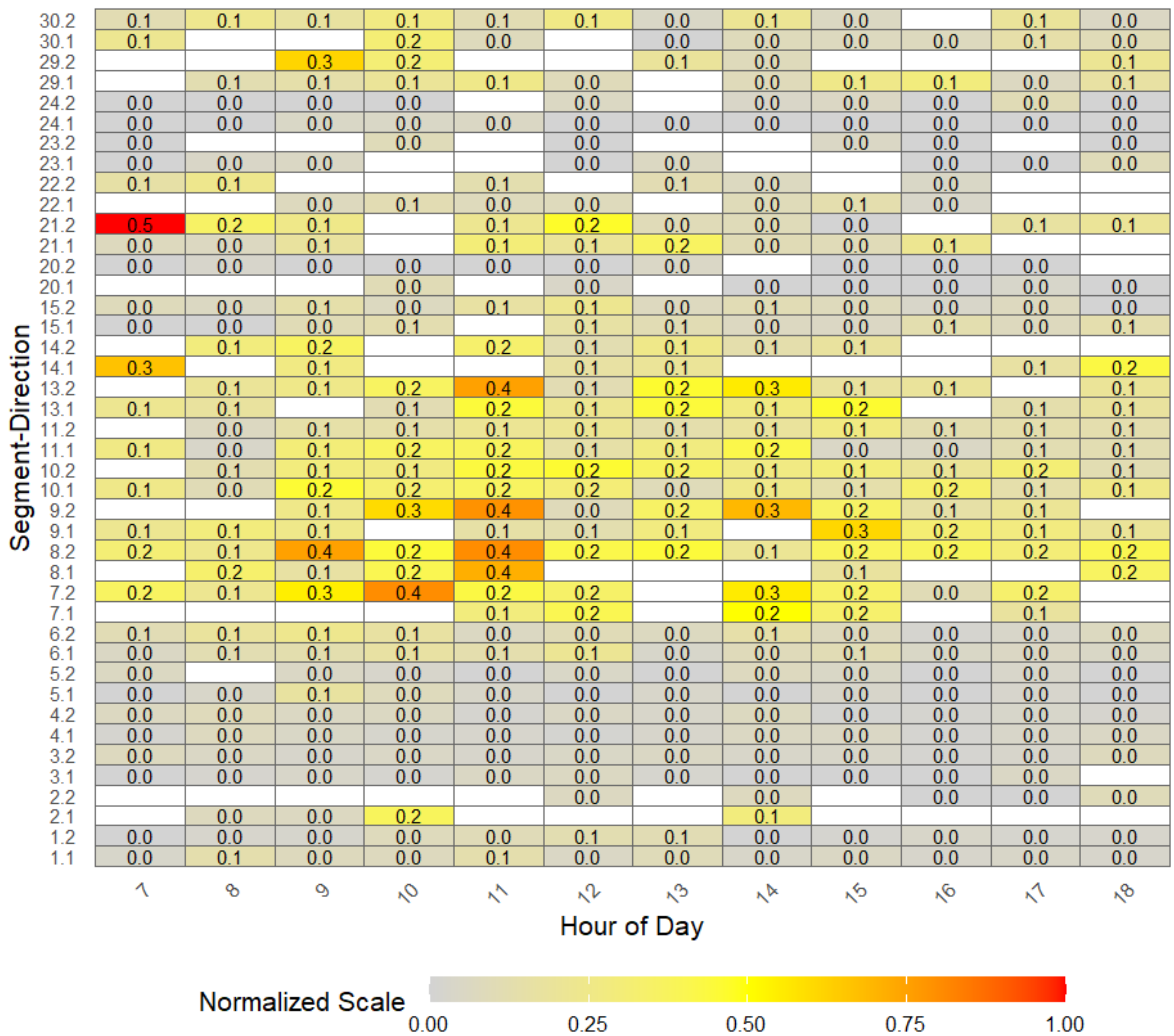

Figure 3: Values of Pct_Vul by segment-direction-hour and heatmap formed from $RVPct\_Vul$

Where both vulnerable and nonvulnerable vehicle volumes are high, the possibility of nonvulnerable vehicles colliding with vulnerable vehicles could be elevated. One approach to capturing this condition is to define thresholds above which the volumes of these vehicle types are considered high. In this study, segment-direction-hours with normalized hourly volumes of vulnerable vehicles $RVVul_i$ greater than or equal to 0.5 *and* normalized hourly volumes of nonvulnerable vehicles $RVNon\_Vul_i$ greater than or equal to 0.5 are considered to indicate this "high-high" condition. The segment-direction vs. hour matrix in Figure 4 indicates with a value of 1 and colored in red the segment-direction-hours where the "high-high" condition occurs – namely, segment-directions 11.1 during the 9 am hour, 13.2 during the 1 pm and 2 pm hours, 14.1 during the 6 pm hour, and 29.2 during the 6 pm hour. These segment-direction-hours all stand out when considering normalized hourly volumes of vulnerable vehicles (Figure 2) but not when considering normalized percentage of vulnerable vehicles (Figure 3), where, as noted previously, the volumes of non-vulnerable vehicles mask the presence of high volumes of nonvulnerable vehicles.

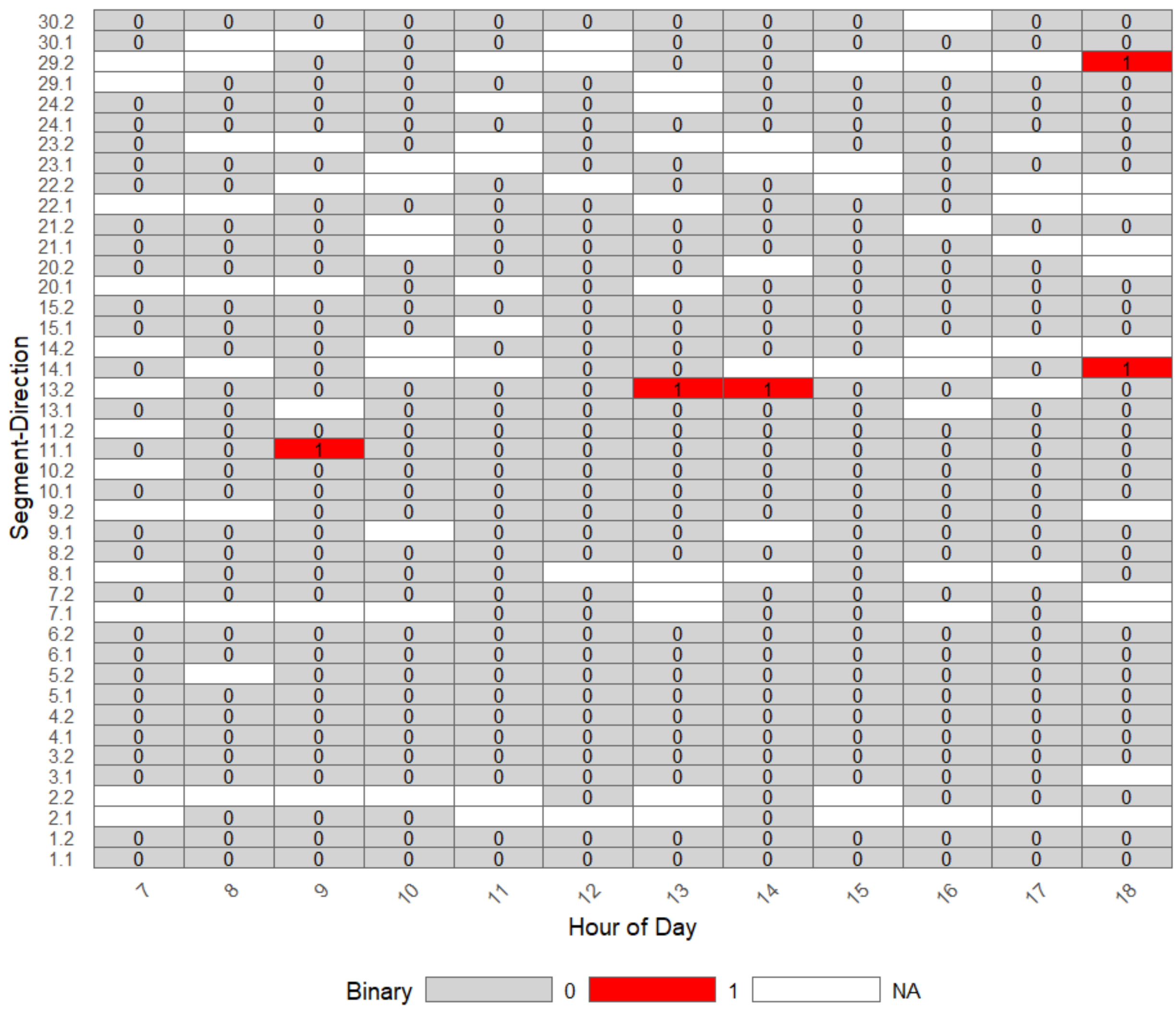

Figure 4: Binary indications of segment-direction-hours where Vul_i and Non_Vul_i surpass respective thresholds

The "threshold approach" leading to Figure 4 requires specification of two thresholds that distinguish large normalized volumes of vulnerable and nonvulnerable vehicles from "not large" normalized volumes. The results portrayed in Figure 4 are derived from arbitrarily setting both thresholds to 0.5. The two thresholds do not need to be equal to each other, and each can vary widely. Moreover, when considering normalized hourly volumes of vulnerable vehicles (Figure 2), additional segment-direction-hours stand out (red "hot" and "orangish") that do not stand out when applying the threshold approach with the selected thresholds of 0.5 (Figure 4). It would, therefore, be helpful to have a continuous metric that indicates when volumes of both vulnerable and nonvulnerable vehicles are high. The product metric defined in Section 2.3 is used in this study, and the values of $Prod_i$ of vulnerable and nonvulnerable vehicle volumes are presented in the cells of the segment-direction by hour-of-day matrix of Figure 5, where the coloring of the heatmap is again based on the normalized value of the metric $RVProd_i$.

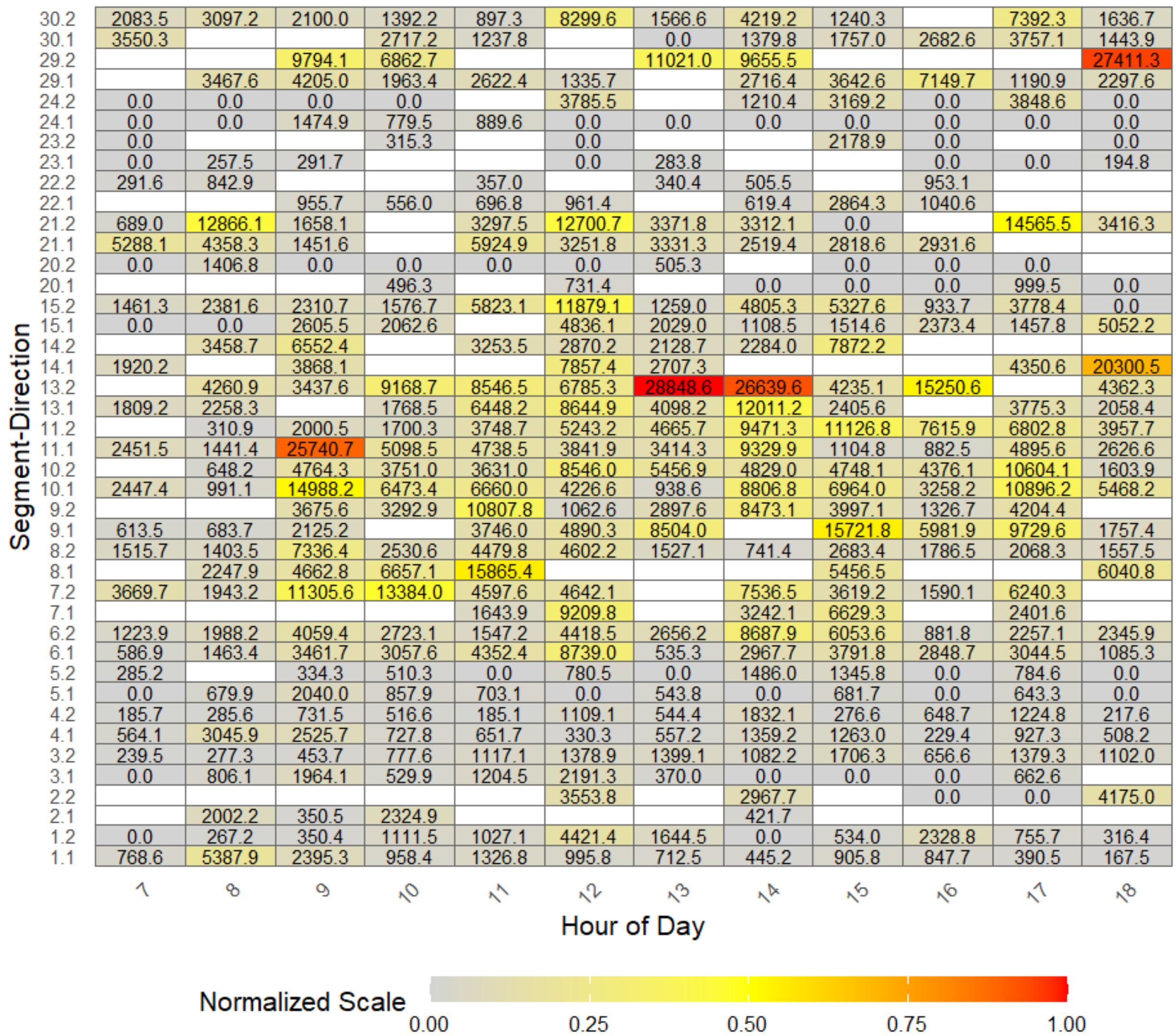

Figure 5: Values of $Prod$ by segment-direction-hour and heatmaps formed from $RVProd$

Comparing Figures 4 and 5, it is seen that the cells where both vulnerable and nonvulnerable vehicle volumes surpass the 0.5 thresholds (Figure 4) also appear as hot when considering the product metric (Figure 5). However, several segment-direction-hour cells – namely, 7.2 during the 10 am hour; 8.1 during the 11 am hour; 9.1 during the 3 pm hour; 10.1 during the 9 am hour;11.1 during the 9 am hour; 13.2 during the 1pm, 2 pm, and 4 pm hours; 14.1 during the 6 pm hour; and 21.2 during the 8 am, 12 pm, and 5 pm hours.; and 29.2 during 6 pm hour – are seen to stand out when using the product metric (Figure 5), whereas they would not be indicated with the thresholds considered above. The product metric provides a richer depiction of possible vulnerable vehicle and nonvulnerable vehicle interactions.

Comparing the results obtained when using the product of vulnerable and nonvulnerable vehicle volumes (Figure 5) to the vulnerable vehicle volumes (Figure 2), segment directions 7.2 and 8.2 during the 9 am hour, 9.2 during the 11 am and 2 pm hours, 13.2 during the 11 am hour, and 19.2 during the 9 am hour were identified above from Figure 2 as having relatively high vulnerable vehicle volumes but not from Figure 5 as having a relatively high product of vulnerable and nonvulnerable vehicle volumes. Conversely, segment-directions 13.2 during the 4 pm hour, and 21.2 during the 8 am and 5 pm hours stand out when considering the product metric (Figure 5), but not when considering volumes of vulnerable vehicles (Figure 2). However, many of segment-direction-hours identified as having relatively high normalized vulnerable vehicle volumes in Figure 2 are also identified as having relatively high values of the normalized product in Figure 5, and similarly for relatively low normalized vehicle volumes and relatively low normalized product values.

5.2 Evaluating the Indirect Metrics through Direct Observations of Hazardous Conditions

To further investigate the hazard-related information derived from the bus-based imagery, an additional analysis is conducted based on directly assessing the presence of safety hazards related to vulnerable vehicles. Specifically, a sample of segment-direction-hours is selected, and the videos of all the bus passes associated with each segment-direction-hour are assessed to identify if a vulnerable vehicle related safety hazard appeared to have occurred during a pass. This subjective assessment is based on considering the proximity in space and time of a mixture of vulnerable and non-vulnerable vehicles and their apparent relative speeds when viewing the video. In addition, the occurrence of unusual maneuvers by either type of vehicle and the presence of pedestrians crossing streets around the same time and in proximity of interacting vehicles are considered. Based on these considerations, each bus pass is classified as either exhibiting one or more safety hazards, whereby the safety hazard indicator variable takes the value 1, or not exhibiting a hazard, whereby the indicator variable takes the value 0.

A total of 61 segment-direction-hours are selected. The number of bus passes associated with these segment-direction-hours is 506, comprising 14% of the total number of passes in the dataset. Among these 506 bus passes, 2.2% are classified as exhibiting one or more safety hazards (i.e., the indicator variable is set to 1). A set of logit models is then estimated considering the safety hazard indicator variable as the dependent viable and the relative values of the metrics considered in Section 5.1 as explanatory variables, one at a time. Tables 5 through 8 show the model estimation results that correspond to explanatory variables used to form Figures 2 through 5, respectively.

Tables 5: Safety Hazard Logit Model Estimates for Explanatory Variable $RVVul$

Variable	Estimate	z-value	p-value
Intercept	– 4.8601	– 8.309	< 2e-16
$\boldsymbol{RVVul}$	2.6894	2.856	0.00429
No. of observations **= 506**			
McFadden's ρ² = 0.0790			

Tables 6: Safety Hazard Logit Model Estimates for Explanatory Variable $RVPct\_Vul$

Variable	Estimate	z-value	p-value
Intercept	– 4.2259	– 9.131	< 2e-16
$\boldsymbol{RVPct\_Vul}$	1.5968	1.456	0.145
No. of observations = 506			
McFadden's ρ² = 0.0187			

Tables 7: Safety Hazard Logit Model Estimates for Explanatory Variable $RVHi\_Mix$

Variable	Estimate	z-value	p-value
Intercept	– 3.9640	– 11.782	< 2e-16
$\boldsymbol{RVHi\_Mix}$	1.6126	1.984	0.0473
No. of observations = 506			
McFadden's ρ^2 = 0.0271			

Tables 8: Safety Hazard Logit Model Estimates for Explanatory Variable $RVProd$

Variable	Estimate	z-value	p-value
Intercept	– 4.6959	– 9.488	< 2e-16
$\boldsymbol{RVProd}$	3.0658	3.300	0.000966
No. of observations = 506			
McFadden's ρ^2 = 0.0876			

All the estimated explanatory variable parameters are positive, as expected. The only model where the estimated coefficient of the explanatory variable is not statistically significant at the 95% confidence level (p-value less than 0.05) is the model where the percentage of vulnerable vehicles $RVPct\_Vul$ is used as the explanatory variable. The p-value of the estimated coefficient is 0.145. This model also has the poorest goodness of fit of the four models, as measured by McFadden's ρ^2. These results support the proposal of Section 5.1 that the percentage of vulnerable vehicles in the traffic stream would likely not be a good indicator of safety hazard.

Of the other three models, the one where the explanatory variable is the binary variable indicating whether the volumes of vulnerable and nonvulnerable vehicles during the segment-direction-hour exceed the thresholds set in Section 5.1 has lowest goodness of fit and highest p-value associated with the estimated coefficient. As discussed in Section 5.1, the positive indications provided by the threshold approach seem to indicate locations and times that are potentially hazardous (once appropriate thresholds are determined), but the approach led to the omission of other locations and times that could be hazardous.

Comparing the model using the metric reflecting the product of vulnerable and nonvulnerable vehicles $RVProd$ as the explanatory variable to the model simply using the volume of vulnerable vehicles $RVVul$, the former has slightly higher goodness of fit and much lower p-value of the estimated coefficient of the explanatory variable, indicating that capturing the potential for interactions between vulnerable and nonvulnerable vehicles is useful in indicating time and locations that require most attention regarding the likely presence of safety hazards associated with vulnerable vehicles. It is noted, however, that determining the value of $RVProd$ requires using the values of the volumes of vulnerable vehicles. As shown in this study, these values, which are not readily available otherwise, can be estimated using video imagery obtained from buses in regular transit service, and these vulnerable vehicle volumes could be a type of useful "by-product" of interest to transportation practitioners.

6. Education and Partner Outreach

Central to the focus of this project is the potential to take advantage of existing imagery obtained from video cameras deployed on transit buses in regular passenger service for purposes other than those for which the cameras are deployed. Doing so eliminates the sensor and platform costs associated with obtaining the imagery. It is worthwhile to impart the concept of using available data for multiple purposes to the emerging generation of transportation engineers.

In addition to graduate (1) and undergraduate (8) students working on this project, this concept was presented in CIVILEN 3700 Transportation Engineering and Analysis during the period covered by this report. CIVILEN 3700 is a core course that most Civil Engineering undergraduate students take. The course introduces various traffic, transit, and roadway topics in a technical and analytical manner. One offering of this twice-per-year course was taught by one of the project PIs in Spring semester 2026 and taken by 81 students. Another offering was taught by an instructor not associated with this project in Autumn semester 2025 and taken by 58 students. In both offerings, the use of available bus-based video imagery for newly developed purposes is presented in a module on the OSU Campus Transit Lab.

This project relied on interactions with OSU's Transportation and Traffic Management (TTM). TTM oversees all campus transportation activities other than parking and traffic signal operations and owns and operates the Campus Area Bus Service (CABS). Longstanding relations between the project investigators and TTM led to TTM's providing the video imagery used in this project. The imagery was recorded by cameras mounted on CABS buses while in regular passenger service. The project investigators meet regularly with TTM management and staff to discuss various activities. The concept of identifying safety hazards and "hotspots" from TTM imagery was discussed during the period covered in this report, and future discussions are expected to continue to increase the practical impact of the project's results and allow user grounded investigations.

7. Conclusion and Future Research

In this study, the OSU campus is used as a living lab testbed to investigate the use of available imagery recorded by transit bus-mounted cameras for identifying locations and times of noticeable queuing and vulnerable and nonvulnerable vehicle interaction. The results demonstrate the promise of using the imagery in identify related safety hazards from which traffic safety engineers could prioritize roadway safety improvements.

For bus video imagery to be valuable in identifying roadway queuing and vulnerable and nonvulnerable vehicle interaction related hazards, it must be shown that *recurring* space-time patterns can be detected. The study reported here investigated patterns that occurred on one specific day. Investigating the ability of the coverage provided by transit buses in regular service to provide such recurring patterns is therefore a pressing area for future investigation.

The hazards identification methods rely on a GUI-based semi-automatic technique to identify vehicles passing camera-equipped buses. For large-scale and efficient identification of safety hazard "hotspots", it is important to develop an automatic machine vision method to replace the semi-automatic technique for identifying vehicles and vehicle types passing camera-equipped buses.

Similarly, it is important to consider other hazards, such as the interaction of pedestrians and vehicles, vehicle speeds and speed variability, and vehicle overtaking.

Of course, determining the increased safety risk associated with the various traffic related hazards is also important. The ultimate impact of the research reported here will be the ability to determine the location and times of roadway traffic conditions that could compromise safety and to do so inexpensively across extensive urban networks by using an existing and widespread source of available data, namely, video imagery obtained from cameras mounted on buses in regular transit service. The ability to systematically determine and monitor hazardous roadway conditions would provide input to policymakers and designers developing measures aimed at reducing the likelihood and severity of traffic and traffic-related accidents.

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