Accident Analysis and Prevention 145 (2020) 105544

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

A Bayesian modeling framework for crash severity effects of active traffic management systems

Zulqarnain H. Khattak[a,*], Michael D. Fontaine[b]

[a] Oak Ridge National Laboratory, Oak Ridge, TN 37830, United States
[b] Virginia Transportation Research Council, 530 Edgemont Rd, Charlottesville, VA 22903, United States

ARTICLE INFO

Keywords:
Active traffic management
Safety
Injury severity
Bayesian modeling
Variable speed limit
Lane control signals

ABSTRACT

Transportation agencies utilize Active traffic management (ATM) systems to dynamically manage recurrent and non-recurrent congestion based on real-time conditions. While these systems have been shown to have some safety benefits, their impact on injury severity outcomes is currently uncertain. This paper used full Bayesian mixed logit models to quantify the impact that ATM deployment had on crash severities. The estimation results revealed lower severities with ATM deployment. Marginal effects for ATM deployments that featured hard shoulder running (HSR) revealed lower likelihoods for severe and moderate injury crashes of 15.9 % and for minor injury crashes of 10.1 %. The likelihood of severe and moderate injury crashes and minor injury crashes reduced by 12.4 % and 8.33 % with ATM without HSR. The models were observed to be temporally transferable and had forecast error of 0.301 and 0.304 for the two models, revealing better performance with validation data. These results have implications for improving freeway crash risk at critical locations.

1. Introduction

A quarter of all traffic fatalities and injuries in the United States occurred on freeways according to United States Department of Transportation (USDOT, 2017). Likewise, crashes are the fourth leading cause of death in the United States (Kochanek et al., 2014). As a result, transportation agencies are finding new approaches to mitigate safety issues on freeways. Traffic agencies utilize active traffic management (ATM) systems to dynamically manage recurrent and non-recurrent congestion real time (Iteris, 2011; Khattak et al., 2018b; Kuhn et al., 2017). ATM encompasses a broad array of technological solutions (Iteris, 2011) that attempt to increase the efficiency of transportation facilities by dynamically managing traffic based on fluctuating demand and varying traffic conditions. An ATM system may be composed of a variety of different components, including:

- Variable speed limits (VSLs) provide dynamic speed limit advisories to drivers on overhead gantries (Boateng et al., 2019). VSLs use an automated algorithm for determining the desired posted speed limits using speed data collected from sensors. The data are then smoothed and processed to create transitions into and out of congestion. The goal of VSLs is to harmonize traffic, reducing variation of speeds approaching congestion. This may reduce turbulence in the traffic stream and reduce end of queue crashes.
- Lane control signals (LCSs) (Khattak et al., 2020) are deployed on overhead gantries to provide advance lane utilization information to drivers in the event of incidents and work zones. The intent of LCS is to encourage drivers to vacate closed lanes further in advance of the location of a blockage.
- Dynamic hard shoulder running (HSR) utilizes information on existing traffic conditions to dynamically open and close the shoulders to travel. As congestion forms at a site, the shoulder is opened as a travel lane to add additional capacity. When volumes dissipate, the shoulder is returned to use as an emergency refuge.

While several studies (Cheng et al., 2018; Dutta et al., 2019; Hourdos and Zitzow, 2014) have analyzed the safety impact of ATM systems, the impact of ATM on crash severities is still unclear. This paper seeks to fill this gap by investigating the impact of ATM on crash severity and whether those impacts are different for sites with and without HSR.

2. Literature review

Although the ATM has been analyzed for crash frequency effects in the past (Cheng et al., 2018; Dutta et al., 2019; Hourdos and Zitzow, 2014), the crash severity effects of ATM have not been investigated thoroughly. The studies of ATM and crash severity modeling are

* Corresponding author.
E-mail addresses: khattakzh@ornl.gov, zk6cq@virginia.edu (Z.H. Khattak).

https://doi.org/10.1016/j.aap.2020.105544
Received 23 December 2019; Received in revised form 1 March 2020; Accepted 4 April 2020
Available online 24 July 2020

provided in this section.

2.1. ATM safety studies

Several studies have examined the safety effects ATM deployments in North America and Europe, with many focused on VSL deployments. One study (Bham et al., 2010) used one year of before and one year of after data to analyze the safety effects of VSLs deployed on I-270/I-255 in St. Louis County, Missouri using the naïve before-after and Empirical Bayes (EB) method. The study found a crash reduction of 3–8 % with VSL deployment. Another study (Hourdos and Zitzow, 2014) examined the safety effectiveness of VSLs on I-94 in Minneapolis using 6 months of before after deployment data, but found no changes in crashes. The safety effects of VSLs on Interstate 5 in Washington were assessed using an observational EB before-after analysis using 9787 crashes that occurred over 6 years (Pu et al., 2017). The results revealed a 29 % decrease in total crashes after VSL implementation. More recently, empirical traffic data from the Whitemud Drive network in Canada (Cheng et al., 2018) was utilized to analyze crash risk on freeways. The study did not provide a crash modification factor, but did find that corridor performance with a congestion based VSL reduced crash likelihood and congestion. (Dutta et al., 2019) analyzed the safety effects of an ATM deployment that included advisory VSLs, lane use control, and dynamic HSR on I-66 using the EB method with 2 years of post-deployment data. They observed a 4% and 6% reduction in total and rear end crashes across the corridor. ATM segments with HSR were observed to produce 31 %–38 % reductions in crashes, while no reductions were observed on sections without HSR.

A European study (Aron et al., 2013) analyzed the safety impact of a dynamic HSR in Paris, France. The study used an observational before-after method and found a statistically insignificant reduction of 8% in weaving section crashes. A reduction of 3% was observed for the whole section segment with HSR, but this was not significant. (Sparmann, 2006) analyzed VSL signs installed on a network of 12 miles in Hessen, Germany, and observed a reduction of 27–29 % in crashes with heavy material damage and personal damage. Another study (De Pauw et al., 2017) analyzed a congestion based VSL deployed on a Belgian freeway using an EB before-after analysis. Injury crashes were reduced by 18 %, fatal injury by 6%, rear-end by 20 %, and single vehicle crashes by 15 %.

2.2. Crash severity modeling

The literature provides a variety of crash severity modeling approaches that have been applied depending on data requirements and the outcomes expected. Crashes are analyzed using Ordered logit or probit models (Haleem et al., 2015; Liu et al., 2015; Obeng, 2011; Zhao and Khattak, 2015; Kockelman and Kweon, 2002; Quddus et al., 2002) since crashes have an ordered nature. However, multinomial logit (Fan and Hale, 2014; Nataliya and Mannering, 2009; Zhao and Khattak, 2015) are sometimes estimated without taking the ordered nature into account. Likewise, generalized logit models (Abegaz et al., 2014; Hu and Donnell, 2010; Zeng et al., 2019) and random parameters ordered probit models (Anarkooli et al., 2017; Jalayer et al., 2018; Khattak et al., 2019a) have also been used. Other studies (Holdridge et al., 2005; Hu and Donnell, 2010; Mehta and Lou, 2013; Wu et al., 2013) used nested logit to account for unobserved heterogeneity.

Ye and Lord (2014) suggested that the performance of severity models depend on specific conditions and the sample size requirements increase while moving from ordered probit to logit models with random parameters. Readers interested in methodological issues and appropriate methods for various type of datasets are encouraged to refer to (Savolainen et al., 2011; Mannering and Bhat, 2014). Further, recent studies have focused on Bayesian modeling (Ahmed et al., 2018; Xie et al., 2018; Khattak et al., 2019b).

2.3. Summary of literature

While the crash frequency impact of ATM strategies has been analyzed, the impact of ATM strategies on individual levels of injury severities has not been studied. It is therefore, imperative to analyze the crash severity outcomes resulting from an ATM deployment. Furthermore, the impact of various ATM components on injury severity has also not been investigated.

3. Objective and scope

This study investigated the individual level of injury severities resulting from ATM deployment using a case study of I-66 in Virginia. The injury severity models for the ATM system were developed using a before-after methodology. The study is referred as before-after in the sense that crash severity was analyzed before and after deployment of ATM on the same sites as opposed to using comparison sites across different corridors. This study answers the following questions:

1 How are crash severities affected by the presence of ATM?
2 How are crash severities affected by additional factors along with the presence of ATM?
3 Are there any significant differences in severity effects across sites with and without dynamic HSR?
4 Is model estimation for ATM deployment improved by the Bayesian framework?
5 Are the models temporally transferable?

The safety impact of ATM was determined by calibrating crash severity models using the full Bayesian framework. The impact of ATM systems with and without HSR was also analyzed to assess any difference in the impact on injury severity since HSR has been observed to create larger reductions in crash frequency in past studies. Knowledge of crash severity impact resulting from deployment of ATM systems could be beneficial to agencies seeking to invest in ATM.

4. Data and site description

An ATM system was deployed on 13 miles of I-66 in Northern Virginia between September 2015 and spring 2018. I-66 connects the Virginia suburbs with Washington, D.C, and the route is a heavily congested during peak periods. While the ATM was active, a total of 22 gantries spaced an average of 0.6 miles apart were present. The gantries were used to implement advisory VSLs, lane control signals, and HSR. The characteristics of each segment of the route, including the ATM treatments present, are summarized in Table 1. Prior to ATM activation, HSR operated using static time of day operation, with shoulders open to travel during the AM peak (5:30 – 11:00 AM) in the EB direction and during the PM peak (2:00 – 8:00 PM) in the WB direction on weekdays. Following ATM activation, the shoulders continued to be opened in the aforementioned times, however they operated dynamically during other times when congestion formed. The ATM system was removed in early 2018 due to a managed lane construction project. Readers interested in additional details on ATM implementation are encouraged to refer to several recent studies (Piljin Chun and Fontaine, 2016; Dutta et al., 2018). A total of 12 segments from both eastbound and westbound direction with ATM deployment were utilized in this study. ATM deployments are rare across the country, which makes it difficult to utilize multiple segments like traditional safety studies. However, this has no impact on the model accuracy since model accuracy is dependent on total number of observed crashes.

One of those studies (Dutta et al., 2019) analyzed the operational and safety effects of the I-66 ATM deployment. Significant improvements in travel time in the off-peak periods, including weekends, was observed, while improvement was not observed during the peak period in the peak direction. The lack of operational improvement in the peak

Table 1
ATM segment characteristics (Chun and Fontaine, 2016).

Segment #	Location	Length (mi)	2016 AADT	ATM Strategies	Road Features
1	US 29 (Exit 52) to VA 28 (Exit 53)	1.3	EB = 67,000, WB = 66,000	VSL, LCS	• HOV-2 on left lane (Operating hours 5:30-930 – 9:30 am EB and 3:00 – 7:00 pm EB)
2	VA 28(Exit 53) to VA 286(Exit 55)	1.9	EB = 80,000, WB = 81,000	VSL, LCS	• HOV-2 are not dynamic
3	VA 286 (Exit 55) to US 50(Exit 57)	2.6	EB = 64,000 WB = 61,000	VSL, LCS	• Four lanes in each direction
4	US 50 (Exit 57) to VA 123(Exit 60)	1.9	EB = 92,000 WB = 92,000	VSL, LCS, HSR	• HOV-2 on left lane (Operating hours 5:30 – 9:30 am EB and 3:00 – 7:00 pm EB)
5	VA 123(Exit 60) to VA 243(Exit 62)	2.1	EB = 93,000 WB = 86,000	VSL, LCS, HSR	• HOV-2 are not dynamic
6	VA 243(Exit 62) to I 495(Exit 64)	3.2	EB = 81,000 WB = 86,000	VSL, LCS, HSR	• Three lanes and shoulder lane in each direction

periods was likely due to the prior static time of day usage of HSR, so no additional capacity was added during peak periods once ATM was activated. Across the entire corridor, small reductions (4–6 percent) in total, multiple vehicle, and rear end crashes were observed with the ATM deployment. Interestingly, most of the safety benefits were associated with HSR sections (31–38 % crash reductions on HSR segments), which were offset by small changes in the ATM sections without HSR.

Data from 2011 to 2018 collected from the Virginia Department of Transportation (VDOT) were used to develop crash severity models on this corridor. The before deployment period consisted of data between January 2011 and August 2015, while the after period consisted of data between December 2015 and February 2018. The first 3 months of post activation data was discarded so that the data would not be skewed by the initial adjustment period. This study site had a pre-existing static HSR operation where the shoulder was open during specific time of day periods in the before period. Since the study sought to isolate the effects of using dynamic HSR, the data corresponding to the static HSR operational hours from both before and after period were removed to create a true comparison between no HSR to ATM with HSR. This study focused on basic freeway sections, and crashes within the interchange influence areas were removed from the data.

The before-after approach was used since there was substantial data available to calibrate severity models. The before-after approach here refers to injury severity analysis before and after deployment of ATM systems on the same sites rather than using comparison sites across different corridors. In safety modeling (FHWA, 2016; AASHTO, 2010), studies where group of sites with a feature or countermeasure are compared to another group of sites with similar characteristics but without that feature or countermeasure are termed as cross-sectional, while studies where crashes or severities before and after deployment of countermeasure are compared on the same site are termed as before-after studies. The before-after method has significant benefits over a comparison group approach since those comparison sites may have differing characteristics from the ATM deployment locations, leading to biased estimates. Past studies have also noted such limitations (Elvik, 2002) and favored before-after method. Since geometrics, AADT, and driver related factors served as confounding factors for the models, the before-after with comparison group method was neglected so as to not account for confounding effects twice (Elvik, 2002). The inventory files from VDOT and Google Earth observation were utilized to collect information on average annual daily traffic (AADT), freeway lanes, and speed limits.

The research sought to identify ATM's impact on crash severity levels while considering the worst injury sustained. The severities are recorded using the KABCO scale as fatal (K), incapacitating injury (A), visible injury (B), no apparent injury with some pain (C), and property damage only (O). Incapacitating injuries are serious injuries which may involve broken bones, and wounds. On the other hand, swellings and bruises sustained in crashes are moderate injuries and termed as non-incapacitating. When the occupant complains but has no apparent injury, it is termed as minor injury

The descriptive statistics are provided in Table 2 while summary statistics for the categorical data are provided in Table 3. A total of 7179 crash records were used in this analysis. Out of these crashes, the before ATM deployment data had 4656 crashes, and the after-deployment data had 2523 crashes. The segments where ATM was deployed without dynamic HSR had 1731 crashes before and 1084 crashes after the ATM was deployed. Segments that had dynamic HSR had 1805 crashes before and 1439 crashes after the ATM deployment when all crashes during the static time of day HSR periods were discarded.

The number of lanes present in each direction varied between 3 and 4 lanes, with a mean of 3.96. Based posted speed limits varied between 55 and 60 mph in both periods, averaging 57.2 mph in the before period and 56.7 mph in the after period. These speed limits are base posted regulatory speeds and not the reduced VSLs for ATM cases.

Table 2
Descriptive statistics of data.

Category	Variable	Level	Mean	St. deviation	Min	Max
Roadway Characteristics	Presence of Guard Rail	Yes	0.03	0.17	0	1
	Average Annual Daily Traffic (veh/day)	< 40,000	0.07	0.25	0	1
		40000 − 70000	0.18	0.38	0	1
		> 70,000	0.75	0.43	0	1
	Presence of Horizontal Curve	Yes	0.12	0.33	0	1
Temporal Effects	AM Peak EB (1 if between 5:30 − 11:00)	Yes	0.21	0.40	0	1
	Midday (1 if between 11:00 − 14:00)	Yes	0.12	0.32	0	1
	PM Peak WB (1 if between 14:00 − 18:00)	Yes	0.34	0.48	0	1
Crash Type	Angle (1 if angle)	Yes	0.07	0.25	0	1
	Rear end (1 if rear end)	Yes	0.26	0.44	0	1
	Sideswipe (1 if sideswipe)	Yes	0.09	0.29	0	1
	Animal Involvement (1 if animal involved)	Animal related	0.10	0.09	0	1
Pavement Condition	Wet (1 if wet)	Wet	0.02	0.33	0	1
	Icy (1 if icy)	Icy	0.08	0.27	0	1
Weather Conditions	Rain (1 if rain)	Rain	0.08	0.27	0	1
	Snow (1 if snowing)	Snow	0.02	0.14	0	1
Crash Characteristics	Three or more vehicles (1 if three or more involved)	Yes	0.27	0.44	0	1
	Two vehicles (1 if two involved)	Yes	0.36	0.48	0	1
	Work zone presence (1 if work zone present)	Yes	0.08	0.27	0	1
	Presence of heavy vehicle	Yes	0.06	0.23	0	1
	Night and dark conditions with lighting	Dark	0.28	0.45	0	1

Table 3
Summary statistics for categorical variables.

Category	Variable	Level	Before ATM Deployment		After ATM Deployment	
			Frequency	Percent	Frequency	Percent
Response Variable	Injury Severity	Severe + Moderate	845	18.15	590	23.38
		Minor	677	17.88	120	4.76
		No injury	3134	67.31	1813	71.86
Roadway Characteristics	Presence of Guard Rail	Yes	125	2.68	78	3.09
		No	4531	97.32	2445	96.91
	Average Annual Daily Traffic (veh/day)	< 40,000	342	7.35	133	5.27
		40000 − 70000	805	17.29	490	19.42
		> 70,000	3509	75.37	1900	75.31
	Presence of Horizontal Curve	Yes	470	10.09	417	16.53
		No	4186	89.91	2106	83.47
Temporal Effects	AM Peak EB (1 if between 5:30 − 11:00)	Yes	907	19.48	567	22.47
	Midday (1 if between 11:00 − 14:00)	Yes	554	11.90	304	12.05
	PM Peak WB (1 if between 14:00 − 18:00)	Yes	1647	35.37	827	32.78
Crash Type	Angle (1 if angle)	Yes	322	6.92	166	6.58
		No	4334	93.08	2357	93.42
	Rear end (1 if rear end)	Yes	1248	26.80	653	25.88
		No	3408	73.20	1870	74.12
	Sideswipe (1 if sideswipe)	Yes	398	8.55	249	9.87
		No	4258	91.45	2274	90.13
	Animal Involvement (1 if animal involved)	Animal related	515	11.06	226	8.96
		No animal	4141	88.94	2297	91.04
Pavement Condition	Wet (1 if wet)	Wet	107	2.30	38	1.51
		Not wet	4549	97.70	2485	98.49
	Icy (1 if icy)	Icy	401	8.61	183	7.25
		Not icy	4255	91.39	2340	92.75
Weather Conditions	Rain (1 if rain)	Rain	401	8.61	183	7.25
		No rain	4255	91.39	2340	92.75
	Snow (1 if snowing)	Snow	113	2.43	40	1.59
		No snow	4543	97.57	2483	98.41
Crash Characteristics	Three or more vehicles (1 if three or more involved)	Yes	1273	27.34	640	25.37
		No	3383	72.66	1883	74.63
	Two vehicles (1 if two involved)	Yes	1742	37.41	860	34.08
		No	2914	62.59	1663	65.91
	Work zone presence (1 if work zone present)	Yes	550	11.81	25	0.99
		No	4106	88.19	2498	99.01
	Representing presence of heavy vehicle	Yes	236	5.07	159	6.30
		No	4420	94.93	2364	93.70
	Representing night and dark conditions with lighting	Dark	1296	27.84	721	28.58
		Not Dark	3360	72.16	1802	71.42

5. Methodology

Since all factors influencing injury severity may not be collected, unobserved factors may result in variation of association between independent variables and crash severity known as unobserved heterogeneity (Mannering et al., 2016). While several modeling approaches exist (Abdel-Aty, 2003; Ye and Lord, 2014), this study utilized mixed logit models in a Bayesian framework to provide efficient estimation and take unobserved heterogeneity into account.

The injury severity outcome of crashes serves as the dependent variable. Since the data only had 3 fatalities and relatively few serious injury crashes, fatalities were discarded and serious and moderate injury categories were combined together to achieve significant parameter estimates. The severities were coded into three outcomes: (1) (AB crashes) that involved severe and moderate injuries, (2) (C crashes) involving minor and apparent injuries, and (3) (O crashes) involving no injuries. The independent variables included details about ATM presence, crash and vehicle related factors, environmental conditions, and geometry. Following the approach in Milton (Milton et al., 2008), the three injury severities are estimated using Eq. 1, where Y is the function of crash characteristics (Ben-Akiva and Lerman, 1985; Washington et al., 2011).

$$Y_{ij} = \beta_i X_{ij} + \varepsilon_{ij} \tag{1}$$

Where X_{ij} is the variable including night, day or AADT, β is the coefficient of the variable and ε_{ij} accounts for unobserved impacts including driver and crash characteristics. Assuming ε_{ij} as a generalized extreme value (McFadden, 1981), the multinomial logit is provided by Eq. 2:

$$P_n(i) = \frac{\exp(\beta_i X_{ij})}{\sum_I \exp(\beta_i X_{ij})} \tag{2}$$

Where the probability of a crash severity outcome of a crash j with the set of all possible injury severity categories i resulting in severity outcome is given by $P_n(i)$. This is generalized by allowing the parameters to vary across roadway segments (variations in β). This is done by introducing a mixing distribution providing the injury severity outcome in equation 3 as follows:

$$P_n(i) = \frac{\exp(\beta_i X_{ij})}{\sum_I \exp(\beta_i X_{ij})} f\beta|\varnothing) d\beta \tag{3}$$

Where the parameters of the density function are given by $\varnothing$ and the density function is given by $f\beta|\varnothing)$. β is determined using the density function $f\beta|\varnothing)$, taking unobserved heterogeneity (Milton et al., 2008) into account. The authors considered different distributions for random parameters, and a normal distribution $\beta_{ij\sim Normal(\beta_{j},\sigma^2)}$ resulted in the best fit (Ahmed et al., 2018; Xie et al., 2018). Further, the marginal elasticities were also estimated to better interpret the results. These reveal change in propensity of severity for the intermediate categories. The change is specified as a unit difference for dummy variables starting from base of zero and ending at 1. Likewise, the change for continuous variables is specified as one standard deviation change from the mean. The data were formatted and cleaned using SAS and R and modeling was conducted in R Studio. Variables with a correlation coefficient greater than 0.91 were deemed to be highly correlated variables (Khattak et al., 2017; Washington et al., 2011) and were discarded. Most selected variables had a correlation coefficient below 0.80, which is consistent with past studies (Khattak et al., 2017; Washington et al., 2011). Further, Variance Inflation Factor (VIF) was also tested to check potential multicollinearity effects. The selected variables had a VIF below 2, revealing no potential multicollinearity. According to the literature (Chatterjee and Hadi, 2015; Greene, 2008) a VIF above 10 shows high multicollinearity, while a VIF less than 5 is commonly used as a threshold for variable selection.

5.1. Full Bayesian framework

A full Bayesian framework was utilized to determine fixed and random parameters of mixed logit models. The parameters are considered random in the Bayesian framework while the belief about parameter behavior is updated using the data. This has many advantages over frequentist approach, which treats parameters as fixed. For instance the temporal and spatial variations are accounted for, unobserved heterogeneity, and hierarchies within models are taken into account (Khattak et al., 2019a). Since all factors that may influence the injury severity resulting from ATM deployment may not be observed, resulting in unobserved heterogeneity. The authors thus, employed Bayesian framework to fully account for unobserved heterogeneity.

Bayesian inference utilized prior beliefs from historical data to derive posterior probabilities and estimate credibility intervals (Khattak et al., 2019b). The specification of the prior distribution of the parameters is essential. This study used flat priors for fixed parameters. For random parameters, informative priors ($\beta_{ij} \sim Normal(1,\ 100^2)$) and ($\sigma_{ij}^2 \sim Normal(0,\ \mathrm{J})$) were used based on the set of historical data samples, which is consistent with the literature (Ahmed et al., 2018; Dong et al., 2016; Qin et al., 2005; Xie et al., 2018). The informative priors were derived for standard deviation of the random parameters σ, the variable J specifies the upper limit for the uniform density. The limits were carefully crafted starting at a lower value and increasing in small increments until convergence failed or Bayesian Information criterion did not improve. This approach has been successfully implemented elsewhere (Asparouhov and Muthén, 2017; Boggs et al., 2020; Gelman et al., 2013).

The posterior distribution was derived using the Markov chain Monte-Carlo (MCMC) Gibbs sampler technique to quantify the estimates for β_{ij} and σ_{ij}^2. For this purpose, repeated samples were utilized until the generated samples of the posterior distribution converged to the target posteriors. The convergence was tested using a subsample of draws and later discarded as a burn-in sample. Specifically, 100,000 total draws were initiated with 50,000 used as burn-in. The Brooks-Gelman-Rubin statistic (Spiegelhalter et al., 2002) revealed a value less than 1, indicating convergence.

The significance of parameters was analyzed using 95 % Bayesian Credible Interval (95 % BCI) (Ahmed et al., 2018). Finally, the model performance and fit were evaluated using the Deviance Information Criteria (DIC). According to Spiegelhalter et al. (2002), the DIC is a Bayesian generalization of the Akaike information Criteria. The model complexity and fit are checked by this criterion. The DIC is defined in Eq. 4:

$$DIC = D_{bar} + D_{bar} - D_{hat} \tag{4}$$

The posterior mean of the deviance is given by D_{bar}, while replacing D_{bar} in D provides D_{hat}. When the difference in DIC between two models is greater than 10, then the model with higher DIC is discarded. As a general rule, differences between 5 and 10 may be considered substantial (Spiegelhalter et al., 2003).

6. Results

The results for the best fitting injury severity models are presented here. The calibration and validation were performed with an 80/20 data split. Random sampling was conducted but consistency of data points across different categories was assured by sampling 80 % and 20 % of data points from each individual category. The effect of the covariates on severities is presented with their marginal effects. Separate models were created based on whether or not the ATM section had HSR present so that the impact of that specific ATM component on severities can be identified. The Bayesian models outperformed their counterpart models, however the results for only Bayesian models are provided for the sake of brevity.

Table 4
Bayesian Models and Marginal Effects for ATM without HSR.

Variable	Fixed Parameters Logit		Mixed Logit		Marginal Effects for Mixed Logit		
	Coef	95 Percent Credible Intervals	Coef	95 Percent Credible Intervals	Severe + moderate	Minor	No injury
Presence of ATM without HSR (1 if present) [NI]	0.23	(0.142, 0.641)*	0.17	(0.068, 0.321)*	−0.1240	−0.0833	0.2073
Horizontal Curve (1 if curve is present) [NI]	−0.25	(-1.021, 0.043)**	−0.34	(-0.852, -0.131)*	0.0132	0.0110	−0.0242
Presence of Work Zone [NI]	–	–	−0.60	(-0.731, -0.426)*	0.0372	0.0238	−0.0610
Rear end crashes (1 if rear end) [NI]	0.13	(0.013, 0.457)*	0.27	(0.063, 0.394)*	−0.0258	−0.0147	0.0405
Sideswipe crashes (1 if sideswipe) [SM]	−0.43	(-0.831, -0.146)*	−1.32	(-1.453, -0.526)*	−0.1044	0.0477	0.0567
Speed limit [SM]	0.03	(0.015, 0.564)*	0.15	(0.034, 0.282)*	0.0159	0.0177	−0.0336
AADT (1 if AADT is > 100,000) [NI]	−0.18	(-0.643, -0.154)*	−0.17	(-0.343, -0.032)*	0.0542	0.0186	−0.0728
AM peak (1 if AM peak) [MI]	0.13	(0.031, 0.563)*	0.29	(0.113, 0.594)*	0.0143	0.0077	−0.0220
Mid-day (1 if Mid-day) [MI]	0.77	(0.237, 0.954)**	0.63	(0.273, 0.884)*	0.0727	0.0171	−0.0898
PM Peak (1 if PM peak) [MI]	–	–	0.33	(0.134, 0.573)*	0.1132	0.0620	−0.1752
3 or more vehicles involved (1 if 3 or more vehicles) [NI]	−0.40	(-0.730, -0.341)*	−0.24	(-0.443, -0.103)*	−0.0594	0.1270	−0.0676
Animal involvement (1 if animals are involved) [MI]	0.15	(0.021, 0.543)*	0.21	(0.037, 0.341)*	0.0159	0.0177	−0.0336
Unobserved effects (Standard deviation)							
ATM	–	–	0.434	(0.320, 0.524)*	–	–	–
Rear End	–	–	0.363	(0.223, 0.454)*	–	–	–
Speed limit	–	–	0.510	(0.343, 0.651)*	–	–	–
AADT	–	–	0.521	(0.425,0.641)*	–	–	–
Summary Statistics							
Deviance Information Criteria	2547		2486		NA	NA	NA

Variables defined for SM = Severe plus moderate, MI = minor injury, NI = no injury.
* Significant at 95 % confidence level.
** Significant at 90 % Confidence level.

6.1. Models for ATM without HSR

The severity model results and marginal effects for ATM segments without HSR are presented in Table 4. It should be noted that the results do not model the probability or frequency of crashes rather shows the increase or decrease in probability of injury severity outcomes, given the crash has occurred. Table 4 shows that ATM that does not include HSR reduces the probability of injury category outcomes compared to conditions without ATM. The marginal effects show that severe + moderate injury outcome propensity reduced by 12.4 % and minor injury outcomes propensity reduced by 8.3 %, respectively. This may be attributed to improved traffic flow conditions resulting from real time information provided by ATM and advance warning of congestion. These results show consistency with crash frequency studies (Dutta et al., 2019). Presence of curves was observed to reveal a higher likelihood of severe + moderate injury outcomes by 1.32 % and minor injury outcomes by 1.10 %. Work zone presence also increased the likelihood of severe category outcomes by 3.72 % (severe + moderate injury) while an increase of 2.38 % was observed in minor injury outcomes. Increasing base posted speed limits produced higher likelihood of severe injury outcomes by 1.50 %.

Crash characteristics were also observed to significantly affect injury severities. The probability for severe injury outcomes sustained by drivers decreased in rear end collisions. The severe category injury outcomes decreased by 2.58 % (severe + moderate injury) and 1.47 % (minor injury) without HSR. Sideswipe crashes were also observed to lead to a reduction in severe injuries given the crash had occurred. Increases of 1.59 % (severe + moderate injury outcomes) and 1.79 % (minor injury outcomes) in likelihood were observed with involvement of animals in the crash. The involvement of higher number of vehicles led to higher probability of minor injuries by 12.70 % and lower probability of severe and no injury outcomes by 6.76 % and 5.94 % given that the crashes have occurred.

Volume also played a role in crash severity. AADTs above 100,000 veh/day increased the probability of injury outcomes by 5.42 % (severe + moderate outcomes) and 1.86 % (minor injury outcomes). Since traffic conditions are variable by time of day, temporal variation was also tested to observe if any difference occurred by time of day. Marginal effects revealed that injury outcomes were more likely to occur by 1.43 % (severe + moderate) and 0.77 % (minor injury) during the AM peak, 7.27 % (severe + moderate) and 1.71 % (minor injury) during midday, and 11.32 % (severe + moderate) and 6.20 % (minor injury) in the peak PM period. These findings are attributable to congestion and variability in traffic that occurred during the peak travel times on the corridor.

6.2. Models for ATM with HSR

Table 5 shows the severity model for ATM segments with dynamic HSR, along with corresponding marginal effects. It should be noted that these results only reveal the probability of injury severity outcomes given the crash has occurred and does not reveal the probability of a crash to occur or crash frequency. The model shows that the likelihood of injury severity outcomes reduces with the presence of ATM with dynamic HSR compared to the before condition. Marginal effects reveal likelihood changes of -15.9 % (moderate + severe injury outcomes), -10.10 % (minor injury outcomes), and +26.0 % (no injury outcomes). These indicate that the probability of injury severity outcomes under ATM deployment decrease, with a corresponding increase in propensity for property damage during crashes. The reduction is higher compared to ATM deployment without HSR, which shows that including HSR can further reduce severe injury outcomes during crashes. This incremental benefit is likely attributable to the additional capacity afforded by the use of the dynamic HSR. These results are consistent with prior crash frequency studies (Dutta et al., 2019).

Several roadway characteristics also had an impact on severities. Curves increase the probability of injury outcomes given the crashes have occurred. Marginal effects reveal a relative increase of 3.57 % (severe + moderate injury outcomes) and 4.17 % (minor injury outcomes) in injury crashes, respectively, for curves with HSR as compared to a respective increase of 1.32 % and 1.11 % for curves with no HSR. The likelihood of severe and no injury outcomes reduced with the presence of work zones, while guardrails presence led to lower propensity for minor and no injury outcomes given the crashes had

Table 5
Bayesian models and marginal effects for ATM with HSR.

Variable	Fixed Parameters Logit		Mixed Logit		Marginal Effects of Mixed Logit		
	Coef	95 Percent Credible Intervals	Coef	95 Percent Credible Intervals	Severe + Moderate	Minor	No injury
Presence of ATM (1 if present) [NI]	0.10	(0.064, 0.241)*	0.20	(0.101, 0.463)*	−0.1590	−0.1010	0.2600
Presence of Horizontal Curve (1 if curve present) [NI]	−0.31	(-3.461, -.214)*	−0.54	(-0.831, -0.302)*	0.0357	0.0417	−0.0774
Presence of Guard Rail (1 if guard rail present) [SM]	0.14	(0.013, 1.431) *	0.29	(0.173, 0.559) *	0.1295	−0.0972	−0.0323
Presence of Work Zone [SM]	–	–	−0.74	(-1.243, -0.464)*	−0.0201	0.0377	−0.0176
Angle Crash (1 if angle) [SM]	−.0.18	(-0.520, -0.143)*	0.26	(0.054, 0.531)*	0.0279	−0.0553	0.0274
Rear End Crash (1 if rear end) [NI]	0.23	(0.131, 0.542)*	0.34	(0.210, 1.352)*	−0.0210	−0.0527	0.0737
Speed Limit [MI]	−0.34	(-0.414, -0.231)*	−0.25	(-1.230, -0.461)*	0.0105	−0.0047	−0.0058
AADT (1 if AADT is > 100,000) [NI]	−0.06	(-0.432, -0.021)*	−0.22	(-1.214, -0.037)*	0.0979	0.0180	−0.1159
AM peak (1 if AM Peak) [SM]	−0.31	(-0.958, -0.057) *	−0.83	(-1.346, -0.231)*	−0.0582	0.0217	−0.0365
Mid-day (1 if Mid-day) [SM]	−0.45	(-1.543, -0.127)*	−1.13	(-1.943, -0.531)*	−0.0142	0.0101	−0.0041
PM Peak (1 if PM Peak) [SM]	−0.26	(-0.821, -0.143)*	−0.47	(-0.731, -0.154)*	−0.0387	0.0021	−0.0366
Number of Lanes [MI]	–	–	−0.72	(-.861, -0.214)*	0.1155	−0.1852	−0.0697
3 or More Vehicles Involved (1 if 3 or more vehicles) [NI]	−0.32	(-0.416, 0.013)**	−0.07	(-0.181, -0.031)*	0.0827	0.0367	−0.1194
Heavy Vehicle (1 if heavy vehicle involved) [NI]	−0.17	(-0.214, 0.024)**	−0.16	(-0.214, -0.063)*	0.0709	0.0910	−0.1619
Unobserved effects (Standard deviation/scale parameters)							
ATM	–	–	0.436	(0.410, 0.579)*	–	–	–
Rear end	–	–	0.532	(0.457, 0.610)*	–	–	–
Speed limit	–	–	0.512	(0.436, 0.593)*	–	–	–
AADT	–	–	0.589	(0.476, 0.651)*	–	–	–
Summary Statistics							
Deviance Information Criterion (DIC)	3661.5		3561.3		NA	NA	NA

Variables defined for SM = Severe plus moderate, MI = minor injury, NI = no injury.
* Significant at 95 % confidence level.
** Significant at 90 % Confidence level.

occurred. These are intuitive findings in the sense that curves are expected to increase the severity of injuries during crashes since they may increase roadway departure crashes. The shoulder use for travel may interact with curvature in this case to increase severity since there is less recovery room available. Guardrails produced a 12.95 % increase and work zones produced a 2.01 % decrease in severe plus moderate injury outcomes. This guardrail effect is counterintuitive since guardrails are expected to reduce the severity of injuries during crashes. This may be attributed to the fact that the guardrail effect is being analyzed independent of the crash type. Although guardrails may mitigate the severity of injuries during crashes resulting from running off the road, striking the guardrail may be more severe than a regular rear end crash or other crash type. The work zone finding is interesting and may possibly be attributed to congestion and reduced speeds created by the work zone. Increasing the base posted speed limit revealed higher likelihoods for severe injury outcomes by 1.05 % while a decrease of 0.47 % and 0.58 % in minor and no injury outcomes. This show consistency with (Haleem and Abdel-Aty, 2010; Milton et al., 2008).

AADT was observed to have a negligible impact, although time of day effects were significant. The effects of time of day revealed a decrease of 5.82 %, 1.42 %, and 3.87 % in severe plus moderate injury outcomes for AM, Midday and PM peak with a corresponding increase of 2.17 %, 1.01 %, and 0.21 % for minor injury outcomes. This is likely indicative of lower speed operation during congestion during the peak periods.

Crash characteristics including type of crash, vehicles involved, and involvement of heavy vehicles also impacted crash severity. More severe injury outcomes were observed for angle collisions, while occupants are less likely to sustain more severe injury outcomes for rear end collisions. These are intuitive findings showing consistency with (Jonsson et al., 2013; Khattak, 2001; Qi et al., 2013).

The involvement of 3 or more vehicles in a crash showed higher likelihoods for injury severity outcomes by 8.27 % (severe + moderate injury) and 3.67 % (minor injury). The presence of heavy vehicles revealed higher likelihoods for injury severity outcomes by 7.09 % for severe and moderate injuries and 9.10 % for minor injuries.

6.3. Model validation and temporal transferability

The study validated the models for their performance on a separate validation dataset (20 % of data points) that was not used for initial model development to assess forecast accuracy. Although it's not possible to achieve a 100 % prediction accuracy (Chen et al., 2016; Fountas and Anastasopoulos, 2017; James et al., 2017), the Bayesian models performed well on the validation data. Mean absolute deviation, mean squared error, and root mean squared error were used to assess the forecast accuracy. The average difference in the observed and predicted outcomes is used to calculate the relative difference for each observation individually by estimating average error magnitude. For instance, the injury severity outcomes for each individual observation of training and validation dataset were estimated. Then the relative difference with the observed outcome was estimated and forecast accuracy was estimated by summation of differences across observations and division over total observations. The forecast accuracy reveals the classification accuracy of the outcomes as opposed to the true predictions. Good prediction with accurate forecasts is revealed by smaller values close to zero. Table 6 provides the forecast accuracy for best fit models with both training and validation datasets.

Furthermore, the temporal transferability of the models was also tested according to the specification in (Washington et al., 2011) shown in Table 7. For this purpose, separate models were estimated for the ATM sections deployed within individual years of the group of two years and then models for combined years within the groups using the 80 % calibration datasets. The likelihood ratio test was conducted as:

$$(\chi^2 = -2\ [\mathrm{LL}(\beta_{comb}) - \mathrm{LL}(\beta_{year\ A}) - \mathrm{LL}(\beta_{year\ B}) \tag{5}$$

Where LL (β_{comb}) represents combined likelihood for best-fit model, LL ($\beta_{year\ A}$) is the loglikelihood of first year within the combination while the log-likelihood for second year within the combination is given by LL ($\beta_{year\ B}$). The models were estimated using same specifications of covariates. The difference between the degrees of freedom (DOF) of combined and individual models provides the overall DOF. The results

Table 6
Forecast accuracy.

Measure of Effectiveness	Training Data		Validation Data	
	ATM with HSR	ATM without HSR	ATM with HSR	ATM without HSR
Mean absolute deviation $MAD = \frac{\sum_{i=1}^{n} \lvert \varepsilon_i \rvert}{n}$	0.269	0.271	0.298	0.302
Mean squared error $MSE = \frac{\sum_{i=1}^{n} \varepsilon_i^2}{n}$	0.276	0.279	0.301	0.304
Root mean squared error $RMSE = \sqrt{\frac{\sum_{i=1}^{n} \varepsilon_i^2}{n}}$	0.522	0.524	0.557	0.560

$\varepsilon_i = Observed\ Outcome - Predicted\ Outcome;\ n = Number\ of\ Observations.$

specify the temporal stability of the models and show that the estimated covariates are widely transferable across years.

7. Conclusions and limitations

This study analyzed the ATM system's effect on crash severity using basic freeway segments. The study calibrated and validated injury severity models for ATM with and without dynamic HSR. The study revealed that propensity of severe injury crashes decreases with ATM deployment. More specifically, ATM with and without HSR revealed less severe injury outcomes, given the crashes had occurred. Furthermore, injury severity increased with additional contributory factors of roadway and crash characteristics as opposed to crashes without injuries. The model was observed to be spatially transferable and produced MAD of 0.301 and 0.304, revealing better performance with validation data. There results could be beneficial to agencies seeking to invest in ATM systems and for improving freeway crash risk at critical locations.

The I-66 ATM is unique in the sense that EB AM peak and the WB PM peak in the before period had a static time of day HSR. This changed to dynamic operation in the after period. This can be expected to impact the results since commuters in the corridor had experience with the HSR operation prior to ATM deployment. Although the period when static HSR was in operation was removed from both the before and after period for the analysis, there could be residual impacts on other hours of the day. The VSLs present were also advisory, not regulatory, speed limits, which may impact compliance level and ultimately have an impact on operations and safety. Automated enforcement was also not present in the corridor, so severity impacts could change if it were present to enforce the VSLs. The study did not consider individual crash type and frequency models since the study aimed at investigation of the impact ATM had on severity of freeway segment crashes. However, previous studies have analyzed the crash frequency effects through crash modification factors for ATM and could be more useful in the long run for crash frequency estimation.

There are several avenues for future research. The crash severity results from this study can be compared with individual models representing frequency of crashes and crash types. The insights about the effects of ATM systems on crash severities can be enhanced with data from additional deployments across different states. ATM systems are unique and these deployments are rare across the country, with limited high-quality data, which makes the current study one of the first to analyze the severity impact of ATM systems. The current study will serve as a base for future studies to draw a comparison against performance of ATM systems as more data becomes available. Further, a comparison between econometric models and machine learning algorithms can be conducted and used to estimate models with high prediction accuracy. Finally, the ATMs impact on freeway crash severities was examined in this research. However, future research could focus on examining similar severity impacts on freeway interchange influence areas. The speed of vehicles involved in a crash is an important factor that could influence the crash severity. However, the only speed estimates available are those provided on the police report, which are either estimated by the drivers involved or the responding officer after

Table 7
Temporal transferability of models.

Model[a] Groups	Temporal Transferability test	Observations[b]	Log-Likelihood
Year Group 1	Year 2011 Model	647	−531.06
	Year 2012 Model	629	−528.71
	Combined Model	1276	−1065.20
	Likelihood ratio χ^2		−2(-1065.20 + 531.06 + 528.71) = 10.86
	χ^2 crit(0.01)		27.68
Year Group 2	Year 2013 Model	849	−768.63
	Year 2014 Model	795	−704.21
	Combined Model	1644	−1478.30
	Likelihood ratio χ^2		−2(-1478.30 + 768.63 + 764.63) = 10.92
	χ^2 crit(0.01)		27.68
Year Group 3	Year 2015 (Jan-Aug) Model	748	−711.13
	Year 2016 Model	897	−784.03
	Combined Model	1645	−1501.43
	Likelihood ratio χ^2		−2(1501.43 + 711.13 + 784.03) = 12.54
	χ^2 crit(0.01)		27.68
Year Group 4	Year 2017 Model	940	−824.21
	Year 2018 (Jan-Feb) Model	149	−101.33
	Combined Model	1089	−931.04
	Likelihood ratio χ^2		−2(-931.04 + 824.21 + 101.33) = 11
	χ^2 crit(0.01)		24.72

[a] 80 % data was used.
[b] All models within each group were estimated using same specification of covariates.

the crash. Given the potential inaccuracies in this data, speed estimates were not used. Future studies could collect these real-time at-fault speeds (Khattak et al., 2018a) using connected vehicle data, which could provide useful insights into the impact of this variable on crash severity prior to involvement in a crash event.

Author statement

Study Conceptualization: Zulqarnain Khattak; Data Collection: Zulqarnain Khattak and Michael Fontaine; Methodology and Analysis: Zulqarnain Khattak; Draft Manuscript Preparation and Revision: Zulqarnain Khattak and Michael Fontaine.

Conflict of interest

The authors declare no conflict of interest.

Acknowledgment

This manuscript has been authored by UT-Battelle, LLC, under Contract No. DE-AC05-00OR22725 with the US Department of Energy. The United States Government retains a nonexclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes.

References

AASHTO, 2010. Highway Safety Manual, Washington D.C [WWW Document]. American Association of State Highway and Transportation Officials.
Abdel-Aty, M., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J. Safety Res. 34 (5), 597–603. https://doi.org/10.1016/j.jsr.2003.05.009.
Abegaz, T., Berhane, Y., Worku, A., Assrat, A., Assefa, A., 2014. Effects of excessive speeding and falling asleep while driving on crash injury severity in Ethiopia: a generalized ordered logit model analysis. Accid. Anal. Prev. 71. https://doi.org/10.1016/j.aap.2014.05.003.
Ahmed, M.M., Franke, R., Ksaibati, K., Shinstine, D.S., 2018. Effects of truck traffic on crash injury severity on rural highways in Wyoming using Bayesian binary logit models. Accid. Anal. Prev. 117, 106–113.
Anarkooli, A.J., Hosseinpour, M., Kardar, A., 2017. Investigation of factors affecting the injury severity of single-vehicle rollover crashes: A random-effects generalized ordered probit model. Accid. Anal. Prev. 106. https://doi.org/10.1016/j.aap.2017.07.008.
Aron, M., Seidowsky, R., Cohen, S., 2013. Safety impact of using the hard shoulder during congested traffic. The case of a managed lane operation on a French urban motorway. Transp. Res. Part C Emerg. Technol. 28, 168–180. https://doi.org/10.1016/j.trc.2010.12.006.
Asparouhov, T., Muthén, B., 2017. Prior-posterior predictive p-values. MPlus Web Notes.
Ben-Akiva, M., Lerman, S.R., 1985. Discrete Choice Analysis. MIT Press.
Bham, G.H., Long, S., Baik, H., Ryan, T., Gentry, L., Lall, K., Arezoumandi, M., Liu, D., Li, T., Schaeffer, B., 2010. Evaluation of Variable Speed Limits on I-270/I-255 in St. Louis. Missouri Department of Transportation, Missouri.
Boggs, A.M., Wali, B., Khattak, A.J., 2020. Exploratory analysis of automated vehicle crashes in California : a text analytics & hierarchical Bayesian heterogeneity-based approach. Accid. Anal. Prev. 135 (October 2019), 105354. https://doi.org/10.1016/j.aap.2019.105354.
Boateng, R.A., Fontaine, M.D., Khattak, Z.H., 2019. Driver Response to Variable Speed Limits on I66 in Northern Virginia. J. Transp. Engineering. https://doi.org/10.1061/JTEPBS.0000236. Part A: Systems 145 6.
Chatterjee, S., Hadi, A.S., 2015. Regression Analysis by Example, 5th ed. .
Chen, C., Zhang, G., Yang, J., Milton, J.C., Dely, A., 2016. An explanatory analysis of driver injury severity in rear-end crashes using a decision table / Naïve Bayes (DTNB) hybrid classifier. Accid. Anal. Prev. 90, 95–107. https://doi.org/10.1016/j.aap.2016.02.002.
Cheng, Z., Lu, J., Li, Y., 2018. Freeway crash risks evaluation by variable speed limit strategy using real- world traffic flow data. Accid. Anal. Prev. 119 (June), 176–187. https://doi.org/10.1016/j.aap.2018.07.009.
Chun, P., Fontaine, M.D., 2016. Evaluation of the Impact of the I-66 Active Traffic Management System. Virginia Department of Transportation. http://www.virginiadot.org/vtrc/main/online_reports/pdf/17-r5pdf.
De Pauw, E., Daniels, S., Franckx, L., Mayeres, I., 2017. Safety effects of dynamic speed limits on motorways. Accid. Anal. Prev. 114, 83–89.
Dong, C., Clarke, D.B., Nambisan, S.S., Huang, B., 2016. Analyzing injury crashes using random-parameter bivariate regression models. Transportmetrica A: Transp. Sci 12, 794–810.
Dutta, N., Fontaine, M.D., Boateng, R.A., Campbell, M., 2018. Evaluation of the Impact of the I-66 Active Traffic Management System: Phase II. Virginia Transportation Research Council, VDOT.
Dutta, N., Boateng, R.A., Fontaine, M.D., 2019. Safety and operational effects of the interstate 66 active traffic management system. J. Transp. Eng. Part A Syst. 145, 3. https://doi.org/10.1061/JTEPBS.0000220.
Elvik, R., 2002. The importance of confounding in observational before-and-after studies of road safety measures. Accid. Anal. Prev. 34, 631–635.
Fan, W., Hale, E., 2014. Analysis of Severity of Vehicle Crashes at Highway-rail Grade Crossings:multinomial Logit Modeling. Transportation Research Board 93rd Annual Meeting.
FHWA, 2016. Reliability of Safety Management Methods. US Department of Transportation.
Fountas, G., Anastasopoulos, P.C., 2017. A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. Anal. Methods Accid. Res. 15, 1–16. https://doi.org/10.1016/j.amar.2017.03.002.
Gelman, A., Stern, H.S., Carlin, J.B., Dunson, D.B., Vehtari, A., Rubin, D.B., 2013. Bayesian Data Analysis. Chapman and Hall CRC.
Greene, W., 2008. Econometric Analysis. Pearson Prentice Hall, Upper Saddle River, New Jersey.
Haleem, K., Abdel-Aty, M., 2010. Examining traffic crash injury severity at unsignalized intersections. J. Safety Res. 41 (4), 347–357. https://doi.org/10.1016/j.jsr.2010.04.006.
Haleem, K., Alluri, P., Gan, A., 2015. Analyzing pedestrian crash injury severity at signalized and non-signalized locations. Accid. Anal. Prev. 81, 14–23. https://doi.org/10.1016/j.aap.2015.04.025.
Holdridge, J.M., Shankar, V.N., Ulfarsson, G.F., 2005. The crash severity impacts of fixed roadside objects. J. Safety Res. 36.
Hourdos, J., Zitzow, S., 2014. Investigation of the Impact of I-94 ATM Systems on the Safety of I-94 Commons High Crash Areas. Minnesota Department of Transportation.
Hu, W., Donnell, E.T., 2010. Median barrier crash severity: some new insights. Accid. Anal. Prev. 42 (6), 1697–1704. https://doi.org/10.1016/j.aap.2010.04.009.
Iteris, 2011. I -66 Active Traffic Management System ConOps. Virginia Department of Transportation.
Jalayer, M., Shabanpour, R., Rouholamin, M.P., Golshani, N., Zhou, H., 2018. Wrong-way driving crashes: a random-parameters ordered probit analysis of injury severity. Accid. Anal. Prev. 117.
James, G., Witten, D., Hastie, T., Tibshirani, R., 2017. An Introduction to Statistical Learning. Springer, Newyork, NY.
Jonsson, B., Tingvall, C., Krafft, M., Bjornstig, U., 2013. The risk of whiplash-induced medical impairment in rear-end impacts for males and females in driver seat compared to front passenger seat. Iatss Res. 37 (1), 8–11. https://doi.org/10.1016/j.iatssr.2013.04.001.
Khattak, A.J., 2001. Injury severity in multivehicle rear-end crashes. Transp. Res. Rec., J. Transp. Res. Board 1746. https://doi.org/10.3141/1746-08.
Khattak, Z.H., Magalotti, M.J., Miller, J.S., Fontaine, M.D., 2017. Using New mode choice model nesting structures to address emerging policy questions: a case study of the Pittsburgh Central Business District. Sustainability. https://doi.org/10.3390/su9112120.
Khattak, Z.H., Fontaine, M.D., Boateng, R.A., 2018a. Evaluating the impact of adaptive signal control technology on driver stress and behavior using real-world experimental data. Transp. Res. Part F 58, 133–144. https://doi.org/10.1016/j.trf.2018.06.006.
Khattak, Z.H., Park, H., Hong, S., Boateng, R., Smith, B.L., 2018b. Investigating cybersecurity issues in active traffic management systems. Transp. Res. Rec., J. Transp. Res. Board. https://doi.org/10.1177/0361198118787636.
Khattak, Z., Magalotti, M., Fontaine, M., 2019a. Operational performance evaluation of adaptive traffic control systems: a Bayesian modeling approach using real-world GPS and private sector PROBE data. J. Intell. Transp. Syst. Technol. Plan. Oper. https://doi.org/10.1080/15472450.2019.1614445.
Khattak, Z.H., Fontaine, M.D., Smith, B.L., Ma, J., 2019b. Crash severity effects of adaptive signal control technology: an empirical assessment with insights from Pennsylvania and Virginia. Accid. Anal. Prev. 154, 151–162. https://doi.org/10.1016/j.aap.2019.01.008.
Khattak, Z.H., Smith, B.L., Park, H., Fontaine, M.D., 2020. Cooperative lane control application for fully connected and automated vehicles at multilane freeways. Transp. Res. 111, 294–317. https://doi.org/10.1016/j.trc.2019.11.007.
Kochanek, K., Murphy, S.L., Xu, J., Tejada-Vera, B., 2014. Deaths: Final Data for 2014. National Vital Statistics Reports: From the Centers for Disease Control and Prevention, National Center for Health Statistics 64. National Vital Statistics System, pp. 1–122.
Kockelman, K.M., Kweon, Y.-J., 2002. Driver injury severity: an application of ordered probit models. Accid. Anal. Prev. 34.
Kuhn, Beverly, Balke, K., Wood, N., 2017. Active Traffic Management (ATM) Implementation and Operations Guide. Office of Transportation Management, Federal Highway Administration.
Liu, J., Khattak, A.J., Richards, S.H., Nambisan, S., 2015. What are the differences in driver injury outcomes at highway-rail grade crossings? Untangling the role of pre-crash behaviors. Accid. Anal. Prev. 85, 157–169. https://doi.org/10.1016/j.aap.2015.09.004.
Mannering, F.L., Bhat, C., 2014. Analytic methods in accident research: methodological frontier and future directions. Anal. Methods Accid. Res.
Mannering, F.L., Shankar, V., Bhat, C.R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Anal. Methods Accid. Res.
McFadden, D., 1981. Econometric models of probabilistic choice. In: Manski, D., McFadden (Eds.), A Structural Analysis of Discrete Data With Econometric Applications. The MIT Press, Cambridge, MA.
Mehta, G., Lou, Y., 2013. Modeling school bus seat belt usage: nested and mixed logit

approaches. Accid. Anal. Prev. 51, 56–67. https://doi.org/10.1016/j.aap.2012.10.008.

Milton, J.C., Shankar, V.N., Mannering, F.L., 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accid. Anal. Prev. 40 (1), 260–266. https://doi.org/10.1016/j.aap.2007.06.006.

Nataliya, V.M., Mannering, F.L., 2009. Markov switching multinomial logit model: an application to accident-injury severities. Accid. Anal. Prev. 41. https://doi.org/10.1016/j.aap.2009.04.006.

Obeng, K., 2011. Gender differences in injury severity risks in crashes at signalized intersections. Accid. Anal. Prev. 43 (4), 1521–1531. https://doi.org/10.1016/j.aap.2011.03.004.

Pu, Z., Li, Z., Zhu, W., Cui, Z., Wang, Y., 2017. Evaluating safety effects of variable speed limit system using empirical bayesian Before-after analysis. In: Proceedings of the 96th Annual Meeting of the Transportation Research Board. Washington, D.C.

Qi, Y., Srinivasan, R., Teng, H., Baker, R., Qi, Y.I., Srinivasan, R., Teng, H., Baker, R., 2013. Analysis of the Frequency and Severity of Rear-End Crashes in Work Zones Analysis of the Frequency and Severity of Rear-End Crashes in Work Zones 9588. https://doi.org/10.1080/15389588.2012.675109.

Qin, X., Ivan, J.N., Ravishanker, N., Liu, J., 2005. Hierarchical Bayesian estimation of safety performance functions for two-lane highways using Markov chain Monte Carlo modeling. J. Transp. Eng. 131, 345–351.

Quddus, M.A., Noland, R.B., Chin, H.C., 2002. An analysis of motorcycle injury and vehicle damage severity using ordered probit models. J. Safety Res. 33.

Savolainen, P.T., Mannering, F.L., Lord, D., Quddus, M.A., 2011. The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. Accid. Anal. Prev. 43.

Sparmann, J., 2006. Freeway operation in Germany: experiences in hessen. In: Proc., 1st Int. Symp. on Freeway and Tollway Operations. Athens, Greece.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., van der Linde, A., 2002. Bayesian measures of model complexity and fit (with discussion). J. R. Stat. Soc. Ser. B 64, 583–639.

Spiegelhalter, D., Thomas, A., Best, B., Lunn, D., 2003. Winbugs User Manual. Medical Research Council Biostatistics Unit. Medical Research Council Biostatistics Unit, Cambridge.

USDOT, 2017. Traffic Signals [WWW Document]. Brief Issue on Safe Roads. URL https://safety.fhwa.dot.gov/intersection/other_topics/fhwasa09027/resources/Intersection Safety Issue Brief 5.pdf (accessed 8.23.17). .

Washington, S.P., Karlaftis, M.G., Mannering, F.L., 2011. Statistical and Econometric Methods for Transportation Data Analysis. CRC Press Taylor adn Francis Grouphttps://doi.org/10.1198/tech.2004.s238.

Wu, Z., Sharma, A., Mannering, F.L., Wang, S., 2013. Safety impacts of signal-warning flashers and speed control at high-speed signalized intersections. Accid. Anal. Prev. 54, 90–98. https://doi.org/10.1016/j.aap.2013.01.016.

Xie, M., Cheng, W., Gill, G.S., Zhou, J., Jia, X., 2018. Investigation of Hit-and-run Crash Occurrence and Severity Using Real-time Loop Detector Data and Hierarchical Bayesian Binary Logit Model With Random Effects 9588. https://doi.org/10.1080/15389588.2017.1371302.

Ye, F., Lord, D., 2014. Comparing three commonly used crash severity models on sample size requirements: multinomial logit, ordered probit and mixed logit models. Anal. Methods Accid. Res. 1, 72–85. https://doi.org/10.1016/j.amar.2013.03.001.

Zeng, Q., Gu, W., Zhang, X., Wen, H., Lee, J., Hao, W., 2019. Analyzing freeway crash severity using a Bayesian spatial generalized ordered logit model with conditional autoregressive priors. Accid. Anal. Prev. 127. https://doi.org/10.1016/j.aap.2019.02.029.

Zhao, S., Khattak, A., 2015. Motor vehicle drivers' injuries in train-motor vehicle crashes. Accid. Anal. Prev. 74, 162–168. https://doi.org/10.1016/j.aap.2014.10.022.