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Heavy-Vehicle Driver Injury Severity Analysis by Time of Week:

A Mixed Logit Approach Using HSIS Crash Data

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The Federal Highway Administration (FHWA) is pleased to announce the Highway Safety Information Systems (HSIS) Excellence in Highway Safety Data Awards Program, a competition designed to encourage university students to use HSIS data to investigate a topic that advances highway safety and to develop a paper to document the original research, as well as introduce potential future highway safety professionals to good quality safety data, the application of appropriate research methods to derive recommendations, and the practice of using data to make decisions.

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In the United States, heavy-vehicles (a truck with a gross vehicle weight rating of greater than 10,000 pounds) moved 73.1 percent of all freight by value, 71.3 percent by weight, and 42.0 percent by ton-miles.[1] As these values are expected to increase through 2040, safety regarding heavy-vehicles will be a concern for transportation engineers, transportation planners, safety agencies, federal agencies, and state agencies.[2] For instance, there was a 20 percent increase in the number of fatal crashes involving heavy-vehicles from 2009 to 2013, from 2009 to 2014 there was a 55 percent increase in the number of injury crashes involving heavy-vehicles, and from 2013 to 2014 there was a 31 percent increase in the number of no injury (property-damage-only) crashes involving heavy-vehicles.[3]

Given the importance of heavy-vehicles to the economy, and the highlighted safety concerns, the study of heavy-vehicle crashes is critical to mitigate loss of life and societal costs. With this premise in mind, several previous works have addressed heavy-vehicle crashes with a specific focus on injury severity.[4-11] Although these works have disaggregated crash data by rural, urban, time-of-day, age, gender, etc., the relationship between crash factors, crash severity, and time of the week are not clearly understood. For example, in Minnesota, only 9 percent of heavy-vehicle crashes occurred on weekends in 2015 while greater than 90 percent occurred during weekdays.[12] Still, considering such statistics, the study of heavy-vehicle injury severity factors by time-of-week is scarce.

Taking this into consideration, the present study seeks to identify heavy-vehicle driver injury severity contributing factors by time-of-week in Minnesota (weekday crashes and weekend crashes) through a mixed logit modeling framework that accounts for the unobserved factors commonly present in crash data (this is typically referred to as unobserved heterogeneity). In addition, a parameter transferability test will be conducted to determine if such crashes need to be considered independently for safety analyses. The parameter transferability test will test the null hypothesis that parameter estimates by time-of-week are not statistically different (i.e., weekdays and weekends should be modeled holistically). Therefore, this work aims to determine if the null hypothesis is rejected (i.e., injury severity models by time-of-week need to be considered independently) while identifying injury severity contributing factors by time-of-week.

The remainder of this manuscript is organized as follows: the data employed in this paper is discussed, the modeling framework is explained in detail, and then the modeling estimation results are summarized and synthesized. Finally, the paper is concluded by addressing the key findings, discussing the limitations of the current study, and providing avenues future research.

Data

Data used for analysis consisted of heavy-vehicle crashes that occurred in Minnesota from 2004 to 2014. Each crash file (accident, vehicle, and occupant) were merged. The accident file and vehicle file were merged based on the variable "caseno," then that file was merged once more based on the variables "caseno" and "vehno." The final merge was to incorporate data regarding the roadway, and this was completed using county IDs and milepost markers (see reference 13 for a full explanation of how this was done).[13] Upon merging all files, the final step consisted of filtering the data to represent only the drivers of heavy-vehicles by weekday and weekend crashes.

The Highway Safety Information System (HSIS) data classifies injury severity into five distinct categories: (1) K, fatal injury; (2) A, incapacitating injury; (3) B, non-incapacitating injury; (4) C, evident/possible injury; and, (5) N, no injury. Previous work has shown that due to a small number of severe injury crashes (K and A), injury severities can be joined to create three severities: (1) severe injury (K and A); (2) minor injury (B and C); and, no injury (N).[11,14] Therefore, the current study utilizes the above-mentioned severity groups for analysis.

Several indicator variables were created for each disaggregated dataset of weekday crashes and weekend crashes. Of the created indicator variables, 24 were found to be significant contributing factors for weekday crashes and 17 were found to be significant contributing factors for weekend crashes. Summary statistics and variable definitions are shown in Table 1 and Table 2.

Table 1. Descriptive Statistics and Variable Definitions for Weekday Crashes

Variable	Mean	Standard Deviation
No Injury		
Time of Day (1 if Between 10:00 a.m. and 4:00 p.m., 0 Otherwise)	0.46	0.50
Location (1 if Four-Legged Intersection, 0 Otherwise)	0.22	0.41
Traffic Control Device (1 if Traffic Signal, 0 Otherwise)	0.20	0.40
Surface Condition (1 if Ice, 0 Otherwise)	0.14	0.35
Age (1 if 31 to 40 Years, 0 Otherwise)	0.21	0.40
Contributing Factor (1 if Failure to Yield Right-of-Way, 0 Otherwise)	0.05	0.22
Minor Injury		
Contributing Factor (1 if Illegal or Unsafe Speed, 0 Otherwise)	0.05	0.21
Heavy Vehicle Type (1 if Truck-Tractor With Semitrailer, 0 Otherwise)	0.50	0.50
Age (1 if 21 to 30 Years, 0 Otherwise)	0.16	0.37
Surface Condition (1 if Snow, 0 Otherwise)	0.08	0.27
Lighting (1 if Daylight, 0 Otherwise)	0.81	0.39
Posted Speed Limit (1 if 60 mi/hr, 0 Otherwise)	0.10	0.31
Severe Injury		
Posted Speed Limit (1 if 65 mi/hr, 0 Otherwise)	0.07	0.26
Vehicles Involved (1 if Greater Than 2 Vehicles, 0 Otherwise)	0.08	0.28
Time of Day (1 if Between 5:00 a.m. and 9:59 a.m., 0 Otherwise)	0.29	0.45
Accident Type (1 if Collision With Parked Vehicle, 0 Otherwise)	0.05	0.22
Traffic Control Device (1 if Stop Sign, 0 Otherwise)	0.12	0.33
Lighting (1 if Dark and No Street Lights, 0 Otherwise)	0.06	0.23
Surface Condition (1 if Dry, 0 Otherwise)	0.64	0.48
Road Characteristic (1 if Straight and Level, 0 Otherwise)	0.71	0.46
Gender (1 if Male, 0 Otherwise)	0.94	0.23
Age (1 if Greater Than 60 Years, 0 Otherwise)	0.13	0.34
Heavy Vehicle Type (1 if 2-Axle, 6-Tire Truck, 0 Otherwise)	0.21	0.41
Contributing Factor (1 if Improper or Unsafe Lane Use, 0 Otherwise)	0.05	0.22

Table 2. Descriptive Statistics and Variable Definitions for Weekend Crashes

Variable	Mean	Standard Deviation
No Injury		
Accident Type (1 if Overturn/Rollover, 0 Otherwise)	0.07	0.25
Location (1 if Four-Legged Intersection, 0 Otherwise)	0.18	0.38
Lighting (1 if Daylight, 0 Otherwise)	0.68	0.47
Weather (1 if Snow, 0 Otherwise)	0.14	0.35
Minor Injury		
Posted Speed Limit (1 if 70 mi/hr, 0 Otherwise)	0.16	0.37
Accident Type (1 if Collision With Parked Vehicle, 0 Otherwise)	0.09	0.29
Location (1 if Intersection-Related, 0 Otherwise)	0.06	0.24
Surface Condition (1 if Dry, 0 Otherwise)	0.52	0.50
Heavy Vehicle Type (1 if Truck-Tractor With Semitrailer, 0 Otherwise)	0.48	0.50
Severe Injury		
Posted Speed Limit (1 if 55 mi/hr, 0 Otherwise)	0.25	0.43
Vehicles Involved (1 if Greater Than 2 Vehicles, 0 Otherwise)	0.08	0.27
Accident Type (1 if Collision With a Vehicle in Transport, 0 Otherwise)	0.62	0.48
Traffic Control Device (1 if Traffic Signal, 0 Otherwise)	0.15	0.36
Lighting (1 if Dark With Street Lights On, 0 Otherwise)	0.16	0.36
Weather (1 if Clear, 0 Otherwise)	0.50	0.50
Surface Condition (1 if Wet, 0 Otherwise)	0.11	0.31
Restraint Used (1 if Lap and Shoulder Belt, 0 Otherwise)	0.80	0.40

Modeling Framework

Mixed Logit

Among the popular methods in modeling crash injury severity, unordered (multinomial logit, nested logit, or mixed logit) and ordered (ordered logit or probit) discrete outcome models are the most frequently used methods.[14] Both methods have their benefits and limitations, therefore the employment of the methods is contingent on the availability and characteristics of the crash data.[15] The mixed logit method has been widely utilized and has been shown to be the preferred method for injury severity analyses.[14–19,20,21] Specifically, the mixed logit model can accommodate individual unobserved heterogeneity by allowing parameters to vary across observations, which results in more reliable parameter estimates and corresponding inferences.[14,22,23] Therefore, the mixed logit modeling framework is utilized for the current study.

The modeling framework begins with a linear-in-parameters function, one for each injury severity considered [23]:

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

where S_{in} is injury severity i (no injury, minor injury, and severe injury) for heavy-vehicle crash n; β_i is a vector of estimable parameters; X_{in} is a vector of covariates (e.g., crash, driver, vehicle, and roadway characteristics) used to determine injury severity i for heavy-vehicle crash n; and, ε_{in} is a disturbance term that attempts to capture the unobserved factors in the crash data. Taking Eq. (1), the standard multinomial logit formulation is represented as [23,24]:

$$P_n(i) = \frac{e^{[\beta_i X_{in}]}}{\sum_{\forall I} e^{(\beta_i X_{in})}} \tag{2}$$

where $P_n(i)$ is the outcome probability of heavy-vehicle crash n resulting in injury severity i and all other terms have been defined previously. Referring to Eq. (1), ε_{in} is unable to capture all of the unobserved factors. For instance, crash data is often missing every variable that contributes to an injury severity (this is typically a result of specific data not being on data collection forms used by police or for self-reporting) and can have variation within existing variables. To illustrate, driver physiology is likely to effect severity outcomes, yet is not represented in age or gender variables. Further, seatbelts save lives, but can cause injuries while doing so (see [25] for a full discussion of unobserved heterogeneity and its importance in transportation safety analyses). Therefore, to account for these unobserved factors, the standard multinomial logit is extended to a mixed logit form (a model using a mixing distribution) [23]:

$$P_n(i \mid \phi) = \int_x \frac{e^{[\beta_i X_{in}]}}{\sum_{\forall I} e^{(\beta_i X_{in})}} f(\beta \mid \phi)\, d\beta \tag{3}$$

where $P_n(i \mid \phi)$ is the weighted outcome probability of heavy-vehicle crash n resulting in injury severity i with the weight being determined by $f(\beta \mid \phi)$. $f(\beta \mid \phi)$ is the density function of β with distributional parameter ϕ, where the distribution of β is defined by the analyst. The distribution of β is generally specified to be normal, but several distributions are tested for statistical significance (e.g., log-normal, uniform, etc.). In particular, the density function $f(\beta \mid \phi)$ is what allows parameters to vary across observations—β can now account for observation-specific variations in $P_n(i)$ based on the effect of X.[23]

Marginal effects are now computed to determine the effect of explanatory variable X on the outcome probability $P_n(i)$ of injury severity i. For this work, this represents a one-unit change in $X_{nk(i)}$ on the probability for crash n to result in injury severity i. More specifically, a marginal effect for $X_{nk(i)}$ is the difference in probabilities when $X_{nk(i)}$ changes from zero to one while all other $X_{nk(i)}$ remain constant [26]:

$$M^{P_n(i)}_{X_{nk(i)}} = P_n(i)\left[X_{nk(i)} = 1\right] - P_n(i)\,[X_{nk(i)} = 0] \tag{4}$$

Significance and Parameter Transferability

A log-likelihood ratio test is conducted to evaluate the significance of the log-likelihood values. In this case, the log-likelihood ratio test determines if the mixed logit model log-likelihood (model with estimated random parameters) is of more statistical significance than the model with fixed parameters [23]:

$$x^2 = -2\left[LL(\beta_{Fixed}) - LL(\beta_{Random})\right] \tag{5}$$

where $LL(\beta_{Fixed})$ is the log-likelihood at convergence of the model with fixed parameters; $LL(\beta_{Random})$ is the log-likelihood at convergence of the model with random parameters; and, x^2 is a chi-square distributed statistic with degrees of freedom equal to the number of estimated random parameters.

In terms of parameter transferability, a more complex log-likelihood ratio test is conducted [23]:

$$x^2 = -2\left[LL\left(\beta_{MX_{1MX_2}}\right) - LL\left(\beta_{MX_1}\right)\right] \tag{6}$$

where $LL\left(\beta_{MX_1}\right)$ is the log-likelihood at convergence of model MX_1 and $LL\left(\beta_{MX_{1MX_2}}\right)$ is the log-likelihood at convergence of model MX_1 using model MX_2 data. That is to say, beta (β) estimates and constant estimates are provided for the best fit mixed logit model for weekday crashes, this is model MX_1. Then, the beta (β) values from MX_1 are fixed based on the their estimated values and the constants from are given start values based on their estimated values. Now, the model for weekday crashes is fit using the data from weekend crashes, this is model MX_2 with corresponding log-likelihood $LL\left(\beta_{MX_{1MX_2}}\right)$. The degrees of freedom for x^2 is equal to the number of estimated parameters in MX_2.

Model Estimation Results

Using Eq. (5), it was determined that the log-likelihood values of the models with random parameters are of more significance than the models with fixed parameters. Specifically, with a chi-square statistic of 32.77 and 4 degrees of freedom, the log-likelihood value for the weekday injury severity model is of more significance with well over 99 percent confidence. Likewise, with a chi-square statistic of 7.87 and 2 degrees of freedom, the log-likelihood value for weekend crashes is of more significance with over 98 percent confidence. For best fit model specifications and marginal effects of the weekday and weekend crash models, see Table 3 and Table 4. To ease the discussion, the weekday and weekend injury severity

Table 3. Best Fit Mixed Logit Estimations for Weekday Crashes

Variable	Coefficient	*t*-statistic	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
No Injury					
Constant	5.09	13.09			
Time of Day (1 if Between 10:00 a.m. and 4:00 p.m., 0 Otherwise)	-0.11	-1.98	-0.0063	0.005	0.0013
Location (1 if Four-Legged Intersection, 0 Otherwise)	-0.47	-6.03	-0.0138	0.0110	0.0028
Traffic Control Device (1 if Traffic Signal, 0 Otherwise)	0.45	5.47	0.0105	-0.0088	-0.0017
Surface Condition (1 if Ice, 0 Otherwise)	0.48	5.84	0.0071	-0.0063	-0.0008
Age (1 if 31 to 40 Years, 0 Otherwise)	-0.08	-1.31	-0.002	0.0016	0.0003
Contributing Factor (1 if Failure to Yield Right-of-Way, 0 Otherwise)	-0.52	-5.27	-0.0039	0.0030	0.0009
Minor Injury*					
Constant	3.90	9.96			
Contributing Factor (1 if Illegal or Unsafe Speed, 0 Otherwise)	0.67	4.88	-0.2023	0.1955	0.0068
Heavy Vehicle Type (1 if Truck-Tractor With Semitrailer, 0 Otherwise)	-1.33	-2.50	-0.0212	0.0221	-0.0009
(Standard Deviation of Normally Distributed Parameter)	*(2.96)*	*(3.59)*			
Age (1 if 21 to 30 Years, 0 Otherwise)	0.24	3.18	-0.0042	0.0044	-0.0001
Surface Condition (1 if Snow, 0 Otherwise)	-0.66	-5.66	0.0045	-0.0046	0.0001
Lighting (1 if Daylight, 0 Otherwise)	-0.71	-3.02	-0.0055	0.0055	-0.0001
(Standard Deviation of Normally Distributed Parameter)	*(1.62)*	*(3.72)*			
Posted Speed Limit (1 if 60 mi/hr, 0 Otherwise)	0.20	2.17	-0.0021	0.0022	-0.0001
Severe Injury*					
Posted Speed Limit (1 if 65 mi/hr, 0 Otherwise)	0.50	3.29	-0.0011	-0.0002	0.0013
Vehicles Involved (1 if Greater Than 2 Vehicles, 0 Otherwise)	0.83	6.18	-0.0027	-0.0005	0.0032
Time of Day (1 if Between 5:00 a.m. and 9:59 a.m., 0 Otherwise)	-0.31	-2.70	0.0015	0.0002	-0.0018
Accident Type (1 if Collision With Parked Vehicle, 0 Otherwise)	-1.63	-3.64	0.0003	0.0001	-0.0004
Traffic Control Device (1 if Stop Sign, 0 Otherwise)	0.29	2.39	-0.0012	-0.0002	0.0014
Lighting (1 if Dark and No Street Lights, 0 Otherwise)	-5.23	-1.26	-0.0026	-0.0008	0.0034
(Standard Deviation of Normally Distributed Parameter)	*(5.60)*	*(2.01)*			
Surface Condition (1 if Dry, 0 Otherwise)	0.51	4.62	-0.0084	-0.0014	0.0099
Road Characteristic (1 if Straight and Level, 0 Otherwise)	-0.26	-2.70	0.0039	0.0006	-0.0045
Gender (1 if Male, 0 Otherwise)	1.53	4.15	-0.0328	-0.0055	0.0383
Age (1 if Greater Than 60 Years, 0 Otherwise)	-0.11	-0.16	-0.0039	-0.0007	0.0045
(Standard Deviation of Normally Distributed Parameter)	*(1.30)*	*(1.89)*			
Heavy Vehicle Type (1 if 2-Axle, 6-Tire Truck, 0 Otherwise)	-0.40	-3.26	0.0013	0.0003	-0.0016
Contributing Factor (1 if Improper or Unsafe Lane Use, 0 Otherwise)	-1.71	-4.12	0.0004	0.0001	-0.0005
Model Statistics					
Number of Observations	20,777				
Restricted Log-Likelihood	-22,825.87				
Log-Likelihood at Convergence	-13,176.79				
McFadden Pseudo R^2	0.42				

**Minor Injury (non-incapacitating injuries and possible/event injuries); Severe Injury (incapacitating injuries and fatalities)*

Table 4. Best Fit Mixed Logit Estimations for Weekend Crashes

Variable	Coefficient	*t*-statistic	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
No Injury					
Constant	3.84	10.94			
Accident Type (1 if Overturn/Rollover, 0 Otherwise)	-0.87	-3.67	-0.0095	0.0072	0.0024
Location (1 if Four-Legged Intersection, 0 Otherwise)	-0.34	-2.16	-0.0095	0.0078	0.0017
Lighting (1 if Daylight, 0 Otherwise)	0.30	2.17	0.0271	-0.0204	-0.0068
Weather (1 if Snow, 0 Otherwise)	-0.37	-1.87	-0.0069	0.0055	0.0014
Minor Injury*					
Constant	2.17	6.21			
Posted Speed Limit (1 if 70 mi/hr, 0 Otherwise)	-0.36	-0.44	-0.012	-0.0012	0.0132
(Standard Deviation of Normally Distributed Parameter)	*(2.93)*	*(1.72)*			
Accident Type (1 if Collision With Parked Vehicle, 0 Otherwise)	-1.22	-3.89	0.006	-0.0062	0.0001
Location (1 if Intersection-Related, 0 Otherwise)	-0.51	-1.60	0.0026	-0.0027	0.0001
Surface Condition (1 if Dry, 0 Otherwise)	0.46	2.91	-0.026	0.0275	-0.0016
Heavy Vehicle Type (1 if Truck-Tractor With Semitrailer, 0 Otherwise)	-1.02	-1.18	-0.0275	0.029	-0.0016
(Standard Deviation of Normally Distributed Parameter)	*(2.95)*	*(2.19)*			
Severe Injury*					
Posted Speed Limit (1 if 55 mi/hr, 0 Otherwise)	1.32	5.91	-0.0215	-0.0043	0.0258
Vehicles Involved (1 if Greater Than 2 Vehicles, 0 Otherwise)	0.66	2.02	-0.0028	-0.0004	0.0032
Accident Type (1 if Collision With a Vehicle in Transport, 0 Otherwise)	0.94	3.56	-0.0206	-0.0036	0.0242
Traffic Control Device (1 if Traffic Signal, 0 Otherwise)	-1.36	-2.55	0.0018	0.0004	-0.0022
Lighting (1 if Dark With Street Lights On, 0 Otherwise)	-1.06	-2.40	0.0021	0.0004	-0.0025
Weather (1 if Clear, 0 Otherwise)	0.59	2.41	-0.0104	-0.002	0.0124
Surface Condition (1 if Wet, 0 Otherwise)	0.64	1.93	-0.0027	-0.0004	0.0031
Restraint Used (1 if Lap and Shoulder Belt, 0 Otherwise)	-0.64	-2.52			
Model Statistics					
Number of Observations	2,441				
Restricted Log-Likelihood	-2,681.71				
Log-Likelihood at Convergence	-1,519.36				
McFadden Pseudo R^2	0.43				

*Minor Injury (non-incapacitating injuries and possible/evident injuries); Severe Injury (incapacitating injuries and fatalities)

models will be discussed separately, followed by a comparison of the two models and results from the parameter transferability test.

Discussion

Weekday Injury Severity Model

Referring to Table 3, a total of 24 variables were found to be statistically significant contributing factors. Of the 24 variables, four were found to have statistically significant estimated random parameters based on the significance of the standard deviation. Although several distributions were tested, only the normal distribution was found to be statistically significant. The first random parameter was the estimated parameter for truck-tractors with a semitrailer in the minor injury severity function. With a mean of -1.33 and standard deviation of 2.96, the normal distribution curve indicates that for 32.7 percent of heavy-vehicles the estimated parameter mean is greater than zero and less than zero for 67.3 percent. In other words, 32.7 percent of truck-tractors with a semitrailer are more likely to sustain a minor injury and 67.3 percent are less likely. The non-homogenous nature may be attributed to the safety devices in the cabin of the heavy-vehicle or the experience of the driver. For instance, many heavy-vehicles are not equipped with airbags, therefore the likelihood of sustaining a minor injury for a proportion of heavy-vehicles may be expected. This is also seen through the marginal effects, as marginal effects show a 0.022 higher probability of sustaining a minor injury.

The second random parameter was the estimated parameter for heavy-vehicle crashes that occurred during daylight in the minor injury severity function. With a mean of -0.71 and standard deviation of 1.62, the estimated parameter mean is greater than zero for 33.1 percent of heavy-vehicles and less than zero for 66.9 percent. Although visibility is greater under daylight conditions, it may entice a proportion of drivers to make risky maneuvers that increase their likelihood of sustaining a minor injury if a crash occurs. On the other hand, daylight can provide adequate visibility for a proportion of drivers to avoid more serious crashes (e.g., an experienced driver may be able to avoid a more severe crash if there is adequate visibility, but this is not represented in the crash data). Daylight was also found to have a heterogeneous effect on injury severity in previous work.[27,28] In terms of the impact of such crashes, marginal effects indicate a 0.006 increase in minor injury probability if a crash occurs during daylight.

The third random parameter was the estimated parameter for heavy-vehicle crashes that occurred during dark conditions with no street lights in the severe injury severity function. A mean of -5.23 and standard deviation of 5.60 indicate that 17.5 percent of heavy-vehicles are more likely to sustain a severe injury if a crash occurs in the dark with no street lights, while 82.5 percent of heavy-vehicles are less likely. A possible explanation for the varying effects of this factor may be attributed to a driver's visual acuity in the dark, such as drivers that are required to wear prescription glasses when driving at night. Kim et al. (2010) also found this lighting condition to be heterogeneous across observations for severe injury outcomes. In addition, this factor was found to be one of the more impactful factors in regard to severe injuries being that marginal effects show a 0.003 increase in probability of sustaining a severe injury.

The fourth, and final, random parameter for weekday crashes was the estimated parameter for drivers more than 60 years of age in the severe injury severity function. With a mean of -0.11 and standard deviation of 1.30, the normal distribution curve indicates that 46.6 percent of heavy-vehicle drivers over the age of 60 are more likely to sustain a severe injury and 53.4 percent are less likely. The non-homogenous nature of this factor may be attributed to driver experience or driver physiology. For instance, older drivers are likely to have a substantial amount of experience and may be able to mitigate the severity of crashes. However, at the same time, the physiology of elderly drivers could result in more severe injuries if a crash occurs (e.g., differences in bone mass, physical fitness, etc.) when compared to younger drivers.

Factors with the largest impact on no injury, minor injury, and severe injury outcomes include crashes that occurred at traffic signals, crashes where illegal or unsafe speed was a contributing factor, and crashes in which the drivers were male, respectively. In regard to no injury, crashes that occurred at traffic signals have a 0.011 increase in no injury probability according to marginal effects. A possible explanation for this finding may be attributed to the speeds at which crashes occur at traffic signals (i.e., low speeds are apt to result in less severe injuries). As for crashes where illegal or unsafe safe speed was a contributing factor, marginal effects show a 0.196 higher probability of sustaining a minor injury. This finding is intuitive, as higher speed impacts generally lead to more severe injuries. Lastly, marginal effects indicate that crashes where the driver was male have a 0.038 higher probability of resulting in a severe injury. This finding is in-line with previous work and generally attributed to males being overrepresented in incapacitating and fatal injuries.[18,30]

Weekend Injury Severity Model

Referring to Table 4, a total of 17 variables were found to be statistically significant contributing injury severity factors. Of the 17 variables, just two had randomly estimated parameters based on the statistical significance of the standard deviation. The first random parameter was the estimated parameter for crashes that occurred where the posted speed limit was equal to 70 miles per hour in the minor injury severity function. With a mean of -0.36 and standard deviation of 2.93, the normal distribution curve implies that 45.1 percent of heavy-vehicle crashes that occurred where the posted speed limit was equal to 70 miles per hour are more likely to sustain a minor injury, whereas 54.9 percent are less likely. The varying effect across observations might be attributed to congestion. That is, a proportion of the crashes may have occurred during congested conditions where speeds are much lower, while other crashes happened under free flow conditions. The heterogeneous effects may also be a result of road surface conditions, age, and gender, where high speed limits impact injury severity outcomes of each group differently.[28]

Tantamount to the weekday injury severity model, the second random parameter for the weekend injury severity model was the estimated parameter for truck-tractors with a semitrailer in the minor injury severity function. A mean of -1.02 and standard deviation of 2.95 suggest that 36.5 percent of truck-tractors with a semitrailer are more likely to sustain a minor injury, yet 63.5 percent are less likely. In addition to being heterogeneous, this was the largest impact variable on minor injury outcomes. Based on marginal effects, there is a 0.029 increase in probability of sustaining a minor injury. Truck-tractors with trailers have shown to increase the likelihood of sustaining injuries in former studies, but unlike the current study, found that the indicator was homogenous across crash observations.[4,6,31] As discussed previously, the varying effects may be attributed to the vehicles' safety devices and experience of the driver.

In regard to high impact factors, crashes that occurred during daylight and posted speed limits equal to 55 miles per hour have the largest impact on no injury and severe injury outcomes, respectively. For crashes that occurred during daylight, there is a 0.027 increase in no injury probability according to marginal effects. As formerly discussed, this may be attributed to increased visibility that allows drivers to avoid potential hazards and mitigate crash severity (e.g., vehicles crossing the median into on-coming traffic, vehicles running through intersections, animals crossing the road, etc.). For crashes that occurred along roadway segments with a posted speed limit equal to 55 miles per hour, marginal effects show a 0.026 higher probability of sustaining a severe injury. Again, as described earlier, higher speeds are likely to result in more severe crashes and is illustrated here through marginal effects.

Parameter Transferability

From Eq. (6), it was determined that parameter estimates are statistically different from weekdays to weekends. That is to say, the null hypothesis that weekday and weekend crashes need to modeled holistically was rejected; these crashes need to be analyzed separately. Table 5 shows that heavy-vehicle injury severity analyses for weekday and weekend crashes need to done independently with well over 99 percent confidence.

In addition to the parameter transferability test, the difference in factors that affect injury outcomes by time of week further illustrate the need to analyze such crashes separately. If a contributing factor was shared between the two models, it was significant for a different severity. For example, collisions with a parked vehicle was significant in the minor injury severity function for weekend crashes, but significant in the severe injury severity function for weekday crashes. The same is true for crashes that occurred during daylight, in which there was significance in the no injury severity function for weekend crashes and significance in the minor injury severity function for weekday crashes. The only factor to be significant in the same severity function was truck-tractors with a semitrailer, and was also found to be heterogeneous in both injury severity models. Overall, the injury severity contributing factors are significantly different by time-of-week.

Table 5. Chi-Square Statistics and Degrees of Freedom for Parameter Transferability Test

MX_1	MX_2	
	Weekday	**Weekend**
Weekday	0	22,768 (22)
Weekend	146,445 (16)	0

Summary and Recommendations

The current study investigated heavy-vehicle driver injury severity by time-of-week in an attempt to fill the noticeable gap in literature regarding heavy-vehicle injury severity studies. To accomplish this, a mixed logit modeling framework was applied to account for the unobserved heterogeneity often present in crash data and to prevent biased and inaccurate inferences. Further, a parameter transferability test was conducted to determine if heavy-vehicle injury severity analyses need to be done by time-of-week.

In addition to the difference in contributing factors between severity models, the parameter transferability test resulted in a rejection of the null hypothesis that weekend and weekday crashes need to be modeled holistically with a high level of confidence (i.e., heavy-vehicle crashes by time-of-week need to considered separately for safety analyses). For instance, specific times of day were found to impact injury severity on weekdays, but no times were found to impact severity on weekends. This may prompt Minnesota to further research regarding off-hour delivery times during weekdays. Stop signs increase the likelihood of severe injuries on weekdays, therefore an economically viable solution to reduce severity could be to effectively place stop signs along freight routes that are prone to high weekday volumes. Likewise, surface conditions impact injury severity conditional on time-of-week. Dry surface conditions increase the likelihood of a severe injury during the week and increase the likelihood of a minor injury during the weekend, while wet surfaces increase the likelihood of a severe injury on weekends. A possible solution may include implementing work-zone-type signage in high risk areas, or a flashing yellow light that changes from weekdays to weekends to caution drivers. Lastly, different speed limits were found to increase severe injury likelihood by weekdays and weekends. Therefore, warning sings in terms of speed, or heavy-vehicle speed studies, can be implemented to mitigate the severity of heavy-vehicle crashes by time-of-week.

The authors further suggest that crash data continue to be disaggregated to produce safety analyses, results, and corresponding recommendations with more precision depending on need. This may include crashes by lighting condition, heavy-vehicle type, or weather. In doing so, federal and state agencies can better direct their funding and resources in terms of transportation safety. In addition, the "heterogeneity" method and parameter transferability test presented in this work can have promising results if implemented by state and federal agencies. For instance, in general, current methods consist of crash frequency analyses that do not account for data heterogeneity and data is not disaggregated to better understand why specific crashes occur and their contributing factors.

In summary, heavy-vehicle crashes by time-of-week need to be considered separately for future safety analyses (e.g., frequency studies, crash rate studies, etc.). In addition, the use of "raw" crash data is recommended to confirm the results presented in this study. In other words, the data used for this study is extensively filtered before it reaches researchers and does not include the variety of variables that state-specific crash data has (e.g., Texas, Washington State).

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