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Understanding the effects of vehicle platoons on crash type and severity

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ABSTRACT

Crash type is an informative indicator to infer driving behaviors and conditions that cause a crash. For example, rear-end and side-swipe crashes are typically caused by improper vehicle interaction such as sudden lane-changing or speed control while hit-object crashes are likely the result of a single driver's mistake. This study investigated the impact of vehicles travelling as a group (platoon) and its configuration (i.e., types of vehicles consisting of the platoon) on crash type and severity since the vehicles could affect each other when travelling in close proximity. This study applied Generalized Structure Equation Modeling (GSEM) to capture the complex relationships among the various crash factors such as traffic condition, driver characteristics, environmental conditions, and vehicle interaction to the crash attributes including type and severity.

This study collected over 3 million individual vehicle data from 39 traffic count sites in California to estimate the vehicle interactions and driving behaviors. The microscopic traffic data are matched to 1417 crash reports. Results showed that vehicles traveling in platoons are associated with more rear-end and side-swipe crashes. Speed difference in the platoon had a positive effect on hit-object crashes if the platoon comprises vehicles of homogeneous type – either trucks or non-trucks. In addition, human factors such as age and gender were identified as significant influential factors in all type of crashes, however truck involvement particularly played an important role amongst side-swipe crashes. Crash severity was negatively affected by total flow, and rear-end crashes were more likely to be severe compared with hit-object crashes. Based on findings, this study suggests practical operational strategies to reduce traffic instability associated with platooned vehicle patterns. Understanding the high-risk factors for different crash types and severities would provide valuable insights for decision-makers and transportation engineers to develop targeted intervention strategies in consideration of road users and traffic conditions such as fleet mix and speed.

1. Introduction

Trucks typically keep lower speed and longer clearance from a leading vehicle due to limited acceleration and deceleration capabilities. Trucks' desired gap to the leading vehicle and lower speed would result in lane changes or speed controls of the following vehicles. For example, when a non-truck (i.e., passenger vehicle) follows a truck, the non-truck is likely to change its lane to overtake the truck or decelerate to adopt the slower speed of the truck (Dimitriou et al., 2018). These interactions are more common when traffic volume is high and close to capacity because an acceleration or a deceleration maneuver has to occur over a short period of time (Sarvi, 2013). Moreover, psychological impacts influence vehicle interacting behaviors. Non-truck drivers tend to feel uncomfortable behind a truck due to their obscured vision from the large physical dimension of the leading truck (Zhao and Lee, 2018). Peeta et al. (2005) investigated a car-truck interaction and found that non-truck drivers feel discomfort near trucks especially when they travel within 2-second time gap to the truck. This psychological impact may trigger car drivers to change lanes or speeds adjacent to trucks.

This study aims to investigate the how vehicle interactions affect crash type and severity by understanding the platooned vehicle patterns. Previous studies (Golob and Regan, 2004; Lee et al., 2002; Stuster, 1999; Björnstig et al., 2008) indicated that vehicle interaction increases when a non-truck follows a truck or a truck follows a non-truck (refers to as a heterogeneous vehicle platoon in this study), compared to a vehicle group comprising with the same type of vehicles (e.g., when a truck

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follows a truck or a non-truck follows a non-truck; refers to as a homogenous platoon) or vehicles do not travel as a platoon. In addition, if the number of vehicles that form a platoon is increased, traffic flow becomes unstable due to increased vehicle interactions within and between the vehicle platoons. To understand the impacts of vehicle platoons on crash risks, this study develops vehicles platoon measures by characterizing the group by the type and speed of vehicles. This study also considers environmental and human factors as other crash determinants because vehicle platoons may show varying driving behaviors in a different weather or driving condition.

Crash factors determined by vehicle platoon characteristics or environmental and human factors may directly affect the crash severity and crash type. However crash severity also relates to crash types, which structures an indirect relationship between crash factors and severity because a crash type is interrelated with both crash severity and crash factors. Kim et al. (1995) highlighted the importance of understanding the contributing factors on crash types and severity through complex relationships present among all variables. Capturing such indirect impacts among the crash variables are important to reduce a biased estimation in a crash prediction and analysis model (Mokhtarian and Cao, 2008). In this study, General Structural Equation Modeling (GSEM) analyzes the relationships among the endogenous variables of crash type, severity, and truck involvement, and the relationships between endogenous and the exogenous variables such as human, environmental, and traffic factors.

The rest of the paper is organized as follows. The next section introduces previous studies of crash factors and modeling approaches. Next, the paper describes data and methodology, followed by results and discussion. In addition, the paper provides operational strategies and policy recommendations that could minimize crash risks based on the model findings. Lastly, this paper provides a conclusion with a summary of key findings and directions for future study.

2. Literature review

2.1. Vehicle interactions and crash likelihood

Vehicle interactions in the vicinity of trucks are one of the most important crash factors (Peeta; et al., 2005), and quantifying such behaviors is of significance in safety analysis. The presence of a truck was shown to increase crash risks (Office of Motor Carrier Research, 1999) because of the speed differences typically observed between trucks and non-trucks (Golob and Regan, 2004), and abrupt maneuvers of non-truck drivers near trucks (Stuster, 1999). Björnstig et al. (2008) pointed out that roadway became more dangerous when more passenger cars shared the road with trucks. Ahmed et al. (2018) showed that the likelihood of a severe crash was 4.5 times higher when the crash involved a truck on interstate highways.

Intuitively, crash risks can be minimized by maintaining adequate space between vehicles because it can reduce abrupt vehicle interactions (Abdel-Aty and Abdelwahab, 2004). In other words, if a following vehicle travels with a large gap to a leading vehicle, the leading vehicle's driving or physical characteristics would have a diminished effect on the following vehicle since the follower has sufficient time and space gap to react to the leader safely. Conversely, if the follower travels too close to the leading vehicle, the following vehicle may be more easily affected by even a minor driving maneuver of the leading vehicle, which could elevate crash risk.

Recently, the impacts of vehicle interactions on crash likelihood have been investigated at the microscopic level by capturing driving behaviors of individual vehicles. Hyun et al. (2018) showed that different car-following cases had varying impacts on crash risks by traffic condition. Under heavy traffic conditions, a non-truck following a truck likely caused a risky condition while a truck following a non-truck significantly affected crash risk under a light traffic condition. Dimitriou et al. (2018) also found that vehicle interactions represented by traffic flow and speed variation positively affect rear-end crash potentials in an urban network.

Although the vehicle interactions were found to be significant crash factors, little is known about how different types of risky behaviors influenced by vehicle interactions relate to crash types and severity. Crash type is an informative indicator of risky driving actions that leads to a crash. Rear-end crashes, which occur when a vehicle crashes into its leading vehicle, are typically caused by failing to keep a sufficiently safe distance to the leading vehicle when a sudden speed change occurs. A side-swipe, which occurs when sides of two vehicles collide, is likely to be caused by lane-changing events. A hit-object crash is usually caused by driver errors such as distraction, inattention, and falling asleep (Shi and Abdel-Aty, 2015). Therefore, compared to hit-object crashes, rear-ends and side-swipes are more likely caused by vehicle interactions and the resulting driving behaviors.

2.2. Other crash factors

Crash type is also known to be affected by various factors including road geometry, traffic condition, and driver characteristics such as age and gender (Christoforou et al., 2011). An improper driving maneuver that causes a crash may be additionally influenced by environmental or traffic conditions in various ways. According to the Large Truck Crash Causation Study (LTCCS) (2007), 87 percent of crashes occurred due to driver-related factors, followed by 10 percent that were vehicle-related and the remaining 3 percent due to environmental related factors. The main driver-related factors included intentional driver decisions (e.g., driving too fast), distraction, and non-performance (e.g., falling asleep) (Craft, 2007). In addition, extensive research was conducted to identify the influential factors from weather, lighting, road surface, or drivers' socioeconomic characteristics to a crash likelihood and severity. Specifically, the severity of crash involved with a truck significantly increased with icy and snowy conditions (Ahmed et al., 2012; Lep et al., 2011). Age and gender were identified as the most important demographic crash factors. The study from Ryan et al. (1998) showed that younger drivers (under age 25 years) were more involved in crashes compared with drives aged 70 and over. Notwithstanding, age was also associated with the types of driving behaviors and movements that cause crashes – younger drivers more likely to cause rear-end crashes while older drivers tend to cause side-swipe crashes (Ryan et al., 1998).

2.3. Crash modeling using structural equation modeling (SEM)

A variety of statistical modeling approaches such as Generalized Linear Models (GLM) (e.g., probit, logit), and machine learning algorithms (e.g., artificial neural network, classification tree) were previously employed to understand the factors influencing crash types and severity (Savolainen et al., 2011*)*; however, such methodological techniques were limited to capturing simultaneous relationships and endogeneity among the variables. Structural Equation Modeling (SEM) has been widely applied to previous studies to address complex and recursive relationships between variables, Najaf et al. (2018) showed how urban form affected traffic safety, particularly through transportation networks as a mediator variable. Wang and Qin (2014) measured crash severity of single-vehicle crashes using SEM and found that vehicle speed and collision force could increase severity. Kim et al. (2011) found that the human factor was the most influential on crash severity compared to vehicle and road factors. SEM constructs the multiple interrelated equations (endogenous relationships) to reflect the multi-directions of causality (Mokhtarian and Cao, 2008). However, standard SEM assumes that a response variable is normally and non-continuously distributed (Grace et al., 2012). A Generalized Structural Equation Model (GSEM) overcomes this limitation by allowing the model to possess both continuous and discrete variables grouped together in the same latent construct (Agresti, 2003; Rabe-Hesketh et al., 2004). GSEM is known to combine the power and flexibility of both SEM and GLM.

3. Data

3.1. Traffic data

Individual vehicle-level data is critical to define traffic-related variables, especially to estimate vehicle platoon characteristics described in this paper. Traffic data represent flow or vehicle stream conditions prior to a crash as a precursor of the crash representing flow disruptions or instable vehicle interactions. This study used inductive loop detectors (ILD) to collect a large set of anonymous vehicle event data. ILDs are one of the most commonly used data sources in crash analysis because of its prevalence in the US and its ability to provide temporally continuous data (Tok et al., 2017; Hyun et al., 2017). Data from various temporal and spatial spans would be beneficial in the crash analysis to capture diverse environmental and traffic conditions. In this study, traffic data comprised 3,162,288 individual vehicle detections obtained from 39 ILD sites in California, collected from January 2016 to April 2018 (see Fig. 1).

Impact areas of ILD sites are defined as 1-mile segments located up and downstream from the detector as suggested from the previous study (Abdel-Aty and Abdelwahab, 2004). Therefore, the traffic data obtained by an ILD is assumed to represent an overall segment of 2 miles. The study uses the crashes that occur within the 2-mile segment of the ILDs and traffic data collected by each ILD represents the overall traffic conditions of the segment. Traffic data was integrated with crash records based on the crash location using a GIS program. ILD sites installed on-ramp and intersections were not included in this study to avoid any exogenous factors affecting abrupt traffic changes over the 2-mile segment.

ILD only provides limited vehicle information such as timestamp, defined as the time a vehicle is detected by the system, and duration, defined as the total time that a vehicle stays on the detector. Additional modeling was employed based on the timestamp and duration data from the ILDs to estimate detailed attributes of traffic such as vehicle type and speed. Further details are discussed in the Metric Development section.

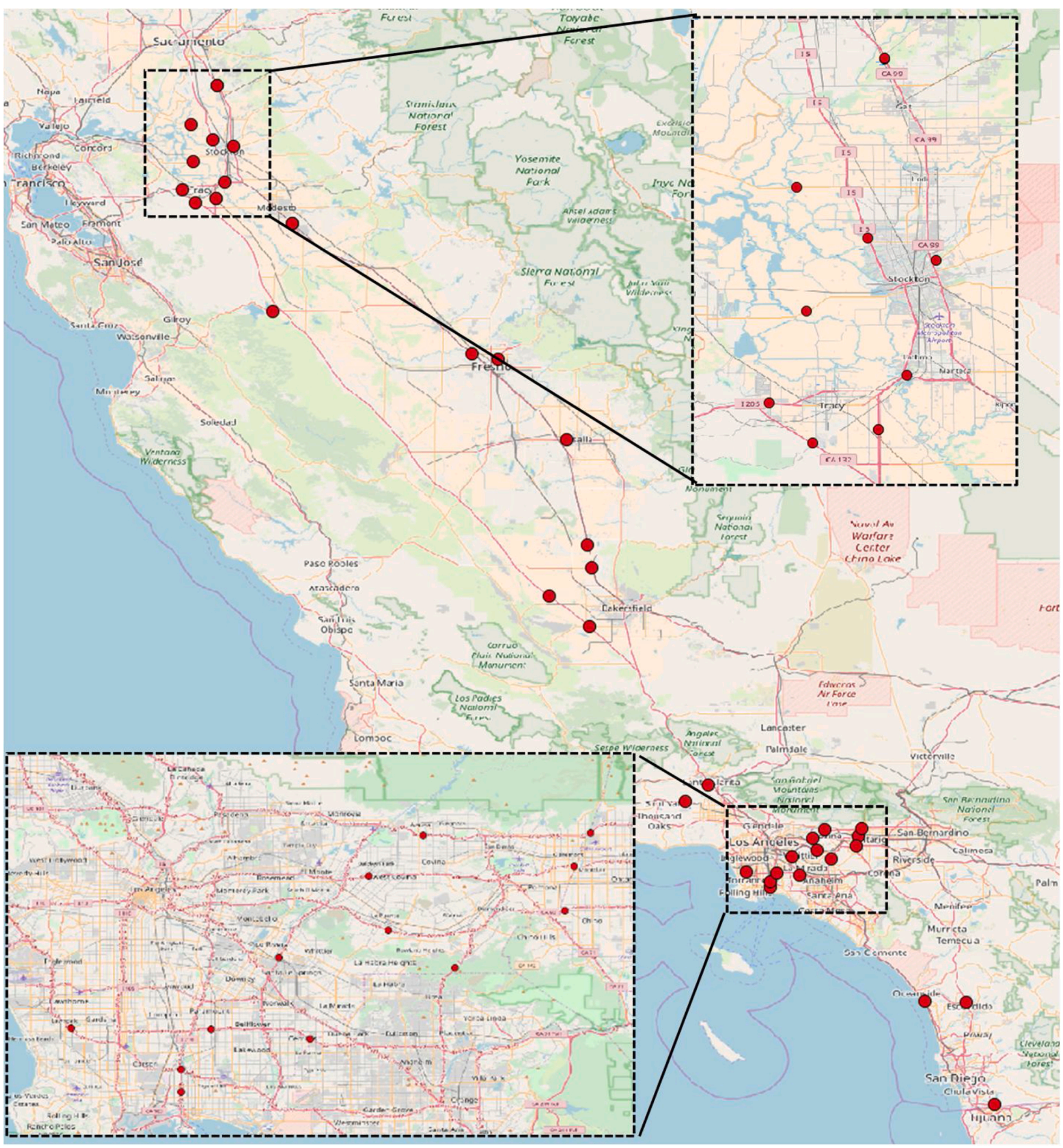


Fig. 1. Study Area.

3.2. Crash data

The Statewide Integrated Traffic Records Systems (SWITRS) is the repository for crash data in California collected by the California Highway Patrol and police reports. This study acquired comprehensive information on crashes including crash severity, location, driver conditions, and environmental details from SWITRS. The coordinates and time of the crash from the SWITRS database were used to match with traffic data. It should be noted that human and environmental factors were crash specific as they were recorded at the crash site. However, traffic data were collected prior to the crashes. This is because vehicle flow characteristics inferred by the platooned vehicles measures should represent the traffic conditions prior to a crash as a precursor of the crash.

A total of 1417 crashes collected between January 2016 and April 2018 from various geographic areas (i.e., urban, sub-urban, and rural regions) were matched to the identified ILDs. Of these 1417 crashes, 823 were rear-end, 300 were side-swipe, 206 were hit-object, and the remaining 88 were categorized as others. Fig. 2 presents the crash types by (a) truck involvement, (b) road condition, and (c) alcohol involvement. Interestingly, 50 percent of truck-involved crashes were side-swipe while 60 percent of non-truck involved crashes were rear-end. However, more hit-object crashes were observed when the road condition was wet and when drivers were under the influence of alcohol.

Fig. 3 illustrates the injury types by (a) truck involvement, (b) road condition, and (c) crash type. A total of 407 crashes (29 percent of total crashes) caused injury (which refers to as a severe crash in this study). More injuries were observed from rear-end compared to side-swipe and hit-object crashes. Interestingly, truck-involved crashes showed less severity than non-truck related crashes, which might be because the crashes were more likely side-swipes.

4. Method

4.1. Metrics development

4.1.1. Vehicle type identification and speed estimation

Vehicle type was identified from traffic event data obtained by ILDs. Since conventional loop detectors do not have a capability of identifying vehicle types, a binary vehicle identification algorithm developed by Hyun et al. (2018) was applied to categorize vehicles into two categories – non-truck and truck — where truck are defined as vehicles belonging to FHWA axle classes 8 and above (tractor-trailer units). Since trucks are typically longer than non-trucks, they generally produce longer duration measurements compared with non-trucks. A Gaussian mixture model was applied to analyze the different ranges of duration by vehicle type and estimated a cut-off duration value between non-trucks and trucks. Notwithstanding, all vehicles would also generate longer duration measures during the congested conditions, therefore the threshold of duration should be updated in relatively short time periods to accommodate dynamic changes in traffic condition. The developed algorithm updates the threshold every 15 min, which allows varying traffic conditions to be accurately reflected in the model. Hyun et al. (2018) used real world ground truth traffic data representing a total of 323 15-minutes periods to validate the model and showed that the developed algorithm attained over 95 percent accuracy in classifying trucks and non-trucks.

With known vehicle lengths, individual vehicle speeds can be calculated using a vehicle's duration with the following equation:

$$\text{speed (ft/s)} = \frac{3600}{5200} * \frac{(vehicle\ length + detector\ length)}{duration}$$

However, the vehicle length was not observed when a single-loop detector was used. Previous studies suggested applying generalized vehicle lengths, 61–70 feet for trucks and 18–20 feet for passenger vehicles (Coifman and SeoungBum, 2009; Kwon et al., 2003). This study adopted 65 feet for trucks and 19 feet for non-trucks (Hyun et al., 2018).

4.1.2. Vehicle platoon metrics

A vehicle platoon, in general, is defined as vehicles travelling together according to Highway Capacity Manual (Bonneson, 2010). McLean (1989) defined that vehicles are considered to form a group when their time headway is less than a critical headway; however varying headway was suggested as a critical threshold, ranging from 2 to 8 s in previous studies. Al-Kaisy and Durbin (2011) suggested that vehicle interaction was shown within 5–7 seconds of headway between successive vehicles, while Kumar and Rao (1998) assumed 2 s time headways in their experiment. In a steady car-following state on a two-lane road, Dey and Chandra (2009) analyzed time headway in a mixed traffic condition, and the maximum headway was shown between

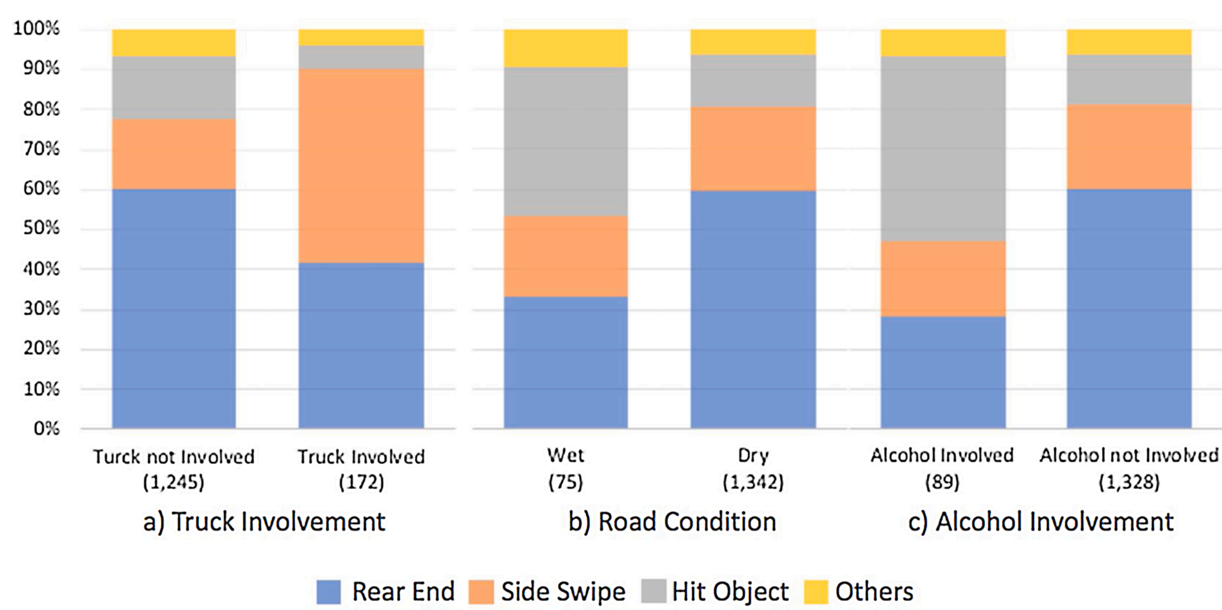


Fig. 2. Crash type.
Note: the number in parenthesis shows the total observations in each category

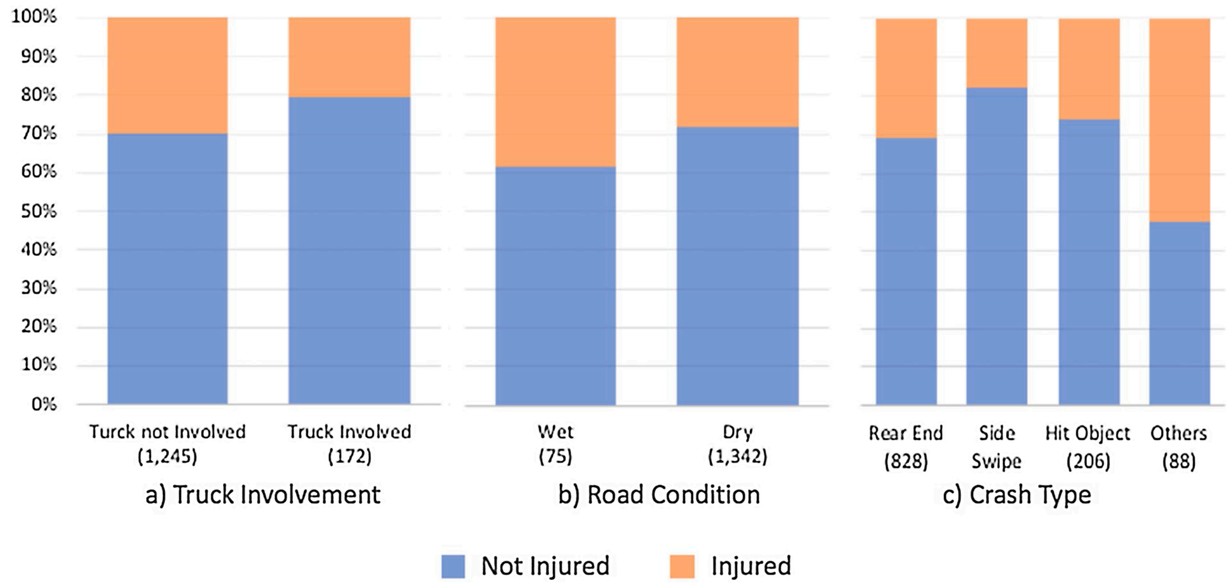


Fig. 3. Injury type.
Note: the number in parenthesis shows the total observations in each category.

3.30–4.08 seconds regardless of vehicle types. Although the vehicle interaction in a platoon may depend on traffic condition and mix of vehicles present, Sadeghhosseini and Benekohal (1997) showed that vehicles may be considered to be part of a platoon when time headway was less than 4 s. Ramezani et al. (2010) also confirmed that the maximum threshold was shown as 3.97 s from field data observation. This study adopted 4 s as a threshold to define a platoon in consistency with previous studies. This study identified two types of vehicle platoons – homogenous and heterogeneous – where a homogenous platoon was composed of the same vehicle types – either solely non-trucks or trucks – traveling within 4-second headways as shown in Fig. 4. Conversely, a combination of non-trucks and trucks travelling within 4-second headways was defined as a heterogeneous platoon. The speed difference within the group was also estimated by platoon type. It should be noted that all traffic variables used in this study were estimated from traffic data aggregated over the time window interval (i.e., 5 min).

4.1.3. *Other factors*

Along with vehicle platoon attributes, metrics representing traffic conditions such as total volume and overall average traffic speed were estimated and added to modeling. Environmental and human factors were extracted from SWTIRS reports and used as independent variables as shown in Table 1. Road surface, weather, and light conditions were used to characterize the environmental state during crash occurrences, and gender, age and sobriety of driver represented the human factors.

4.2. *Generalized structural equation modeling (GSEM)*

To understand the complex relationships among the crash factors, types, and crash severity, this study employed GSEM to handle complex relationships among variables within a flexible framework (Golob, 2003; Mitra and Saphores, 2019). GSEM captures simultaneous relationships among variables, and parametrizes endogenous relationships for categorical variables (Savolainen et al., 2011; Golob, 2003).

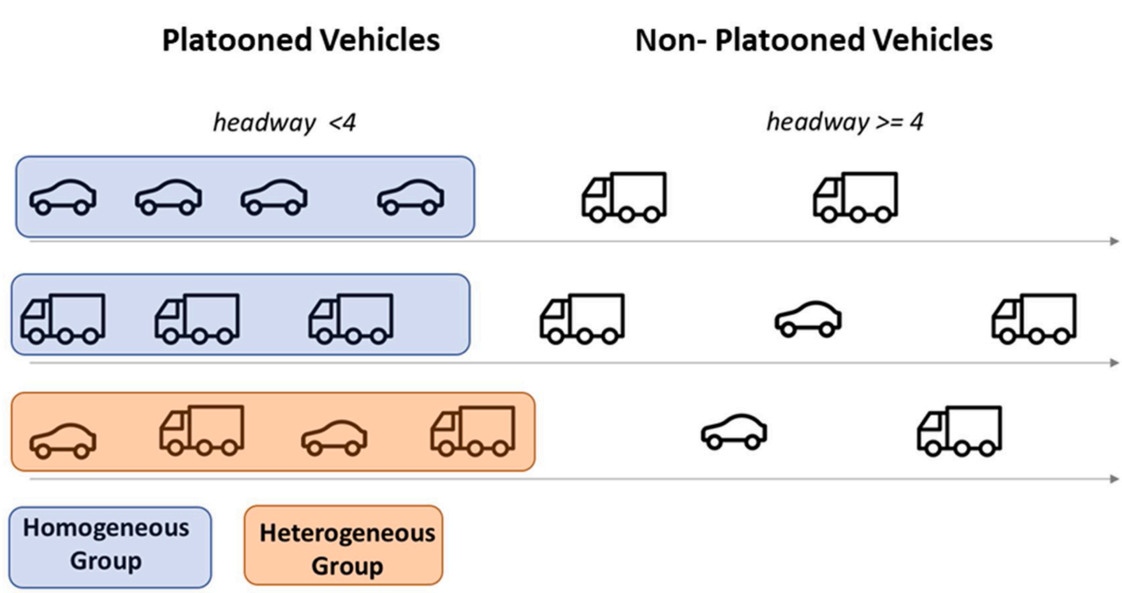


Fig. 4. An Illustration of vehicle platoons.

Table 1
Descriptions of variables.

Category	Variables	Description
Crash description	Crash severity	The injury severity resulting from the collision – Injured or not
	Crash type	Type of collision – Rear-end, Side-swipe, Hit-object, and other
	Truck Involvement	Whether the collision involved a truck
General traffic	Total volume	Total number of vehicles
	Speed average	Average speed of all vehicles
Platooned vehicles	Proportion of vehicle consisting homogenous platoon	Number of vehicles in homogenous vehicle platoon divided by the total number of vehicles in a 5 min window
	Speed difference of homogenous platoon	Average vehicle speed difference of homogenous vehicle platoon
	Proportion of vehicle consisting heterogeneous platoon	Number of vehicles in heterogeneous vehicle platoons divided by the total number of vehicles
	Speed difference of heterogeneous platoon	Average vehicle speed difference of heterogeneous vehicle platoon
Environmental factor	Weather	Clear or not (including cloudy, rain and snow)
	Road surface	Dry or Wet
	Lighting	Daylight or not
Human factor	Driver's age	The age of the driver at the time of the collision
	Driver's gender	The gender of the driver
	Driver's Sobriety	Had not been drinking or Had been drinking

GSEM has been commonly used to construct and assess models with unobservable latent variables since a GSEM structure links latent and its measurement variables. However, more importantly, GSEM is an advantageous approach for addressing direct and indirect effects among variables where the indirect effect captures the interactions between the variables that are related through a mediate variable (Sliva et al., 2012; Van Acker et al., 2014; Mitra and Saphores, 2017). This study focused on identifying relationships among the endogenous variables as well as both direct and indirect effects between exogenous and endogenous variables through the GSEM structure.

Fig. 5 shows the conceptual model of the study. In this structure, endogenous variables (truck involvement, crash type, and crash severity) are influenced by exogenous variables (driver characteristics, environmental factors, overall traffic and vehicle platooning characteristics) either directly or indirectly through other endogenous variables (Kline, 2015). GSEM decomposes the mediating effect of truck involvement and crash type on crash severity by estimating direct, indirect, and total effects of endogenous and exogenous variables. The total effects represent the sum of direct and indirect effects (Long et al., 2006; Long et al., 2006; Jeong et al., 2017). For example, crash severity is directly affected by the exogenous variables such as vehicle platoons and environmental factors and the endogenous variable of the crash type. Since the crash type is also directly impacted by the same exogenous variables, the exogenous variables directly and indirectly affect the severity through the crash type. Truck involvement is influenced by driver characteristics, environmental factors, overall traffic condition and vehicle platoon characteristics. Truck involvement and other exogenous variables then jointly affect the crash type. Finally, crash severity is determined by the crash type, truck involvement, and other exogenous variables. A simultaneous equation system (Golob, 2003) of GSEM is as follows:

$$\Pr(Y_i = 1|\widehat{S}_i) = \frac{\exp(\widehat{S}_i)}{1 + \exp(\widehat{S}_i)} \tag{1}$$

where the system Eqs. (2a)-2(c) represents the causal paths shown on

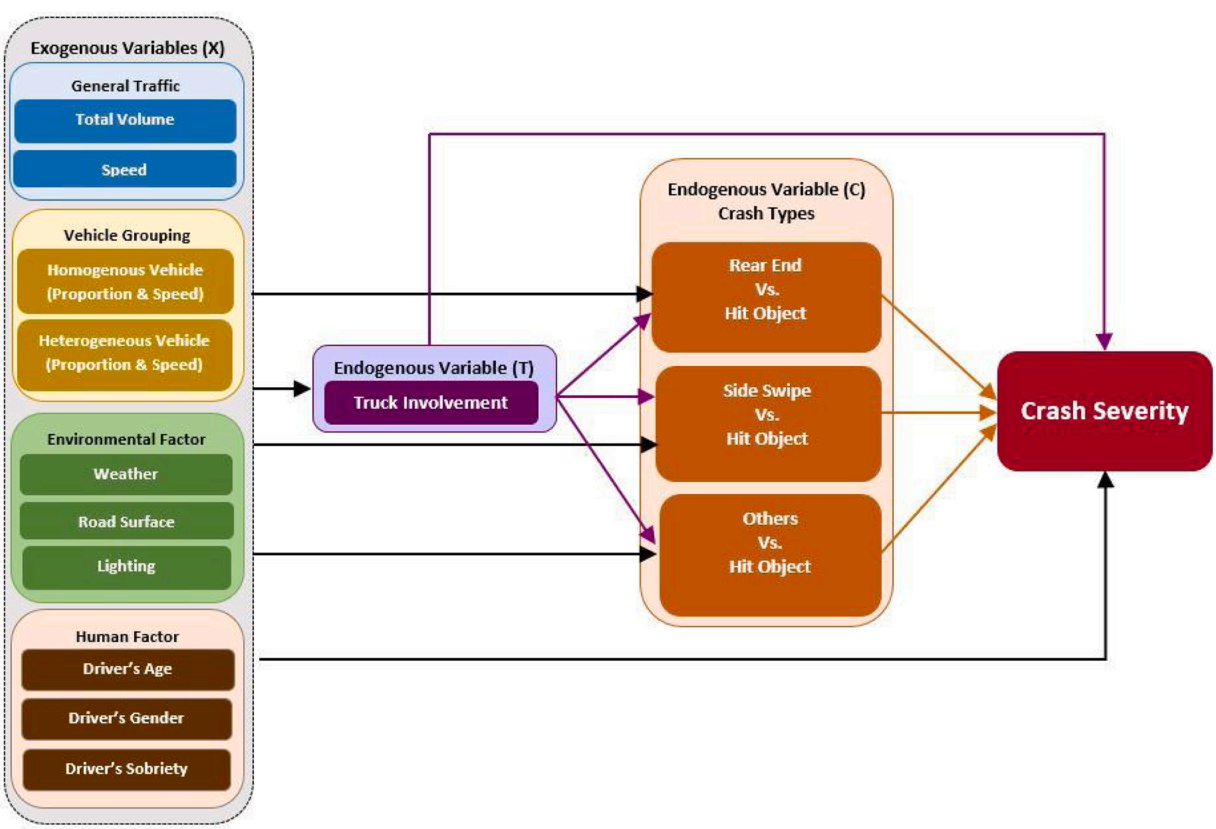


Fig. 5. Conceptual Model.

Fig. 5.

$$\begin{cases} T = \alpha_1 + X_1\Gamma_1 + \varepsilon_1 \\ C = \alpha_2 + \beta_{22}T + X_2\Gamma_2 + \varepsilon_2 \\ S = \alpha_3 + \beta_{31}C + \beta_{32}T + X_3 3 + \varepsilon_3 \end{cases} \quad (2a\text{–}2c)$$

where, Y_i is binary which equals 1 if the crash i causes injury, and 0 otherwise; **T** is an n×1 vector of latent variables (for logit model) that represents the potential of truck involvement in a collision; C is an n×1 vector of latent variables (for multinomial logit model) that represents different crash type (baseline: hit-object); S is an n×1 vector of latent variables (for logit model) that represents each crash's potential to be severe; $\widehat{S}$ is its estimated vector from equation 2(c); ; $\mathbf{X_i}$ are exogenous variables including driver characteristics, environmental factors, overall traffic and platooned vehicles characteristics; $\beta_{22,}$ β_{31} and β_{32} are coefficients of endogenous variables; Γ_1 and Γ_2 are coefficients of exogenous variables $\mathbf{X_i}$; $\alpha_{1,}$ α_2, α_3 are intercepts; $\varepsilon_{1,}$ $\varepsilon_{2,}$ $\varepsilon_{3,}$ are error terms. The variables **T**, **C**, and **S** in the equations 2(a)-2(c) are endogenous variables. It is a well-identified recursive model since all causal paths are unidirectional (see Fig. 5).

The likelihood for the specified model is derived under the assumption that each response variable is independent and identically distributed across the estimation sample. The response variables are also assumed to be independent of each other. These assumptions are conditional on the latent variables and observed exogenous variables. Following Rabe-Hesketh (2004), the marginal likelihood for the response vector y_i, can be written as

$$\mathscr{L}(\theta) = \int_{D_{(\eta)}} f(\boldsymbol{y}_i|\eta,\ \boldsymbol{x}_i, \boldsymbol{\theta})\phi(\eta|\boldsymbol{x}_i\ ; \boldsymbol{\theta})\partial\eta \quad (3)$$

Where $\boldsymbol{y}_i$ be the vector of observed endogenous response variables, $\boldsymbol{x}$ be the vector of observed exogenous variables, and η are latent variables; $D_{(\eta)}$ is the domain of integration; $\boldsymbol{\theta}$ is a vector of the unique model parameters.

Since it is a multi-level model, the likelihood is computed at the cluster level, so the conditional density is also a product of the observation-level density contributions with a given cluster

$$f(\boldsymbol{y}|\boldsymbol{x}, \eta, \boldsymbol{\theta}) = \prod_{i=1}^{n}\prod_{j=1}^{t} f(\boldsymbol{y}_{ij}|\boldsymbol{x}_j, \eta, \boldsymbol{\theta}) \quad (4)$$

Where t is the number of individuals within the cluster. This extends to more levels (in this case 3) by expanding the products down to the observations nested within the hierarchical groups.

To estimate model parameters, GSEM minimizes the difference between the sample covariance and the predicted model covariance (Long et al., 2006). Following Bollen (1989, p.80–88), the model-replicated covariance matrix $\sum(\theta)$ can be written:

$$\sum(\theta) = \begin{bmatrix} (\mathrm{I}-\mathrm{B})^{-1}(\Gamma\Phi\Gamma' + \Psi)\left[(\mathrm{I}-\mathrm{B})^{-1}\right]' & (\mathrm{I}-\mathrm{B})^{-1}\Gamma\Phi \\ \Phi\Gamma'(\mathrm{I}-\mathrm{B})^{-1} & \Phi \end{bmatrix} \quad (5)$$

where: $\mathrm{B} = \begin{pmatrix} \beta_{11}\mathrm{I_n} & \beta_{12}\mathrm{I_n} & \beta_{13}\mathrm{I_n} \\ \mathrm{K_n} & \beta_{22}\mathrm{I_n} & \mathrm{K_n} \\ \mathrm{K_n} & \mathrm{K_n} & \mathrm{K_n} \end{pmatrix}$ $\mathrm{B} = \begin{pmatrix} \beta_{11}\mathrm{I_n} & \beta_{12}\mathrm{I_n} & \beta_{13}\mathrm{I_n} \\ \mathrm{K_n} & \beta_{22}\mathrm{I_n} & \mathrm{K_n} \\ \mathrm{K_n} & \mathrm{K_n} & \mathrm{K_n} \end{pmatrix}$ and $\Gamma = \begin{pmatrix} \delta_{11}\mathrm{I}_n & \cdots & \delta_{1p}\mathrm{I}_n \\ \delta_{21}\mathrm{I}_n & \cdots & \delta_{2p}\mathrm{I}_n \\ \delta_{31}\mathrm{I}_n & \cdots & \delta_{3p}\mathrm{I}_n \end{pmatrix}$.

In the Eq. (5), Φ is the covariance matrix of exogenous variables in X; Ψ is the covariance matrix of error terms $\boldsymbol{\varepsilon_j}$, with j$\varepsilon${1, 2, 3}; and $\mathrm{k_n}$ and $\mathrm{I_n}$ are respectively the n × n zero and identity matrices. Here, the $\boldsymbol{\varepsilon_j}$ s are uncorrelated, all causal paths are directed to $\boldsymbol{y}$, **B** is upper triangular, and Ψ is diagonal, so the model is identifiable recursively (Bollen, 1989).

In this study, a quasi-maximum likelihood with Stata's implementation of the Huber-White sandwich estimator (Bollen, 1989) was applied to estimate coefficients. This method relaxes the assumption that errors are identically and normally distributed. It is a special case of the Generalized Method of Moments estimator, which is consistent and asymptotically normal (Bollen, 1989). In addition, the time window to aggregate traffic conditions and platoon characteristics prior to the crash occurrence was determined to be five minutes. This was determined after testing with increased time windows of 10 min and 15 min with the developed model.

5. Results and discussion

A total of 1417 crash records and corresponding traffic data were analyzed in this study. Table 2 shows the summary statistics for crash and traffic variables aggregated by the pre-determined five-minute time window. Crash severity and truck involvement are binary variables where 1 indicates a crash resulting in injury and a truck-involved crash, respectively. Among the total crashes, 29 percent and 12 percent of crashes resulted in injury and were truck-involved crashes, respectively. The mean of total volume for the five-minute time window was 170 vehicles with a mean speed of 47.15 mph. On average, 27 percent of vehicles were found in a homogenous platoon (26.6 percent), which is much higher than that of a heterogeneous platoon (6.2 percent). Homogenous platoons showed a lower speed difference when compared with the heterogenous platoons.

In this study, the GSEM model was estimated using Stata 14. This study used Count R^2 to evaluate the goodness-of-fit of a model with a binary or categorical dependent variable (Long et al., 2006), resulting in a satisfactory fit with 71.8 percent Count R^2. A calculation of variance inflation factors (VIF) for the explanatory variables shows that multicollinearity is not present as the largest VIF is less than five.

The following section discusses the direct and total effect results of three models: truck involvement model (Equation 2a), crash type model (Equation 2b), and crash severity model (Equation 2c) as shown in Tables 3 through 5. Although insignificant direct effects were constrained to be zero, they may still interact with other variables to produce total effects. Tables 3 through 5 also provide marginal effects (for binary variables) and elasticity (for continuous variables) of direct effects.

Table 2
Model variables and summary statistics.

Category	Variables	Mean	Std. Dev.	Min	Max
Crash description	Crash severity (1=injured)	0.29	0.45	0	1.00
Crash description	Truck Involvement (1=truck-involved)	0.12	0.33	0	1.00
General traffic	Total volume (Vol, unit = veh)	169.88	85.77	2	741.00
General traffic	Speed average (Speed, unit = mph)	47.15	11.03	20.01	179.77
Platooned vehicles	Proportion of vehicle consisting homogenous platoon	26.62	26.60	0	92.68
Platooned vehicles	Speed difference of homogenous platoon	5.05	4.69	0	35.64
Platooned vehicles	Proportion of vehicle consisting heterogeneous platoon	6.15	4.72	0	23.30
Platooned vehicles	Speed difference of heterogeneous platoon	8.29	6.41	0	36.99
Environmental factor	Weather (0: clear)	0.02	0.16	0	1.00
Environmental factor	Road surface (0: dry)	0.05	0.23	0	1.00
Environmental factor	Lighting (0: day light)	0.27	0.44	0	1.00
Human factor	Driver's age	40	14.62	16	88.00
Human factor	Driver's gender (1: Male)	0.59	0.49	0	1.00
Human factor	Driver's Sobriety (1: Sober)	0.09	0.28	0	1.00

Table 3
Estimation results for the truck involvement model (Equation 2a).

Variables	Direct Effects (Γ_3) (Coef.)	Marginal Effects/ Elasticity
Driver Characteristics		
Gender: Binary: 1 if Male	1.503***	0.123***
Age	0.014***	0.492***
Alcohol Involved: Binary:1 =Yes	−2.282**	−0.111***
Environment		
Binary: 1= If weather is bad	–	–
Binary: 1 = If road surface is wet	–	–
Binary: 1 = If dark	–	–
Overall Traffic		
Total Volume	–	–
Speed	–	–
Platooned vehicles Characteristics		
Homogenous platoon (%)	–	–
Homogenous platoon speed (mph)	–	–
Heterogeneous platoon (%)	0.025***	0.022***
Heterogeneous platoon speed (mph)	−0.053**	−0.614***

Notes: $N = 1360$. * Significance at 10 %. ** Significance at 5 %. *** Significance at 1 %.

5.1. Truck involvement model (Eq. 2a)

The direct and marginal effects/elasticity between the truck-involved crash and endogenous variables are shown in Table 3. While human factors (being male and older drivers) were positively associated with truck involved crashes, alcohol showed a negative influence on the truck involved crashes. Environmental and overall traffic conditions did not show statistically significant relationships to truck-involved crashes. Smaller speed differences between a truck (or a car) and the following car (or the following truck) appear to increase a likelihood of a crash. Truck-involved crashes were associated with driving factors such as improper lane change, unsafe driving behaviors performed during lane change even if following vehicles were travelling at a similar speed to leading vehicles.

5.2. Crash type model (Eq. 2b)

This study considered four types of crashes (as shown in Fig. 5) – rear-end, side-swipe, hit-object, and others – with hit-object crashes used as the baseline. Therefore, all estimation results shown in Table 4 were the effects of the associated crash type compared to hit-object crashes. Truck involvement was identified as a significant influential factor only for side-swipe crashes. With consideration that side-swipe crashes are commonly caused by improper lane changes, the presence of trucks could raise the risk of unsafe overtaking and consequently increase likelihoods of side-swipe crashes. Human factors also played important roles in all types of crashes; the elderly were more likely to be involved in rear-end, side-swipe, and others crashes compared with hit-object crashes. Richardson et al. (1996) also found that older drivers had a higher likelihood to be involved with side-swipe and rear-end crashes while younger drivers were associated with a much higher frequency of rollovers. The higher frequencies of side-swipe crashes associated with older adults could be attributed their diminishing driving perception skills with age. In addition, alcohol involvement was more highly associated with single-vehicle crashes (such as hit-object) than multi-vehicle crashes including rear-end, side-swipe, and others. Shyhalla (2014) showed that alcohol involvement is a more significant predictor of risky driving behaviors such as speeding and being distracted while driving compared to gender and age variables. Wet surfaces were shown to increase hit-object crashes. Speed was also found as an important influence on increased hit-object crashes. Total volume was not associated with either rear-end or side-swipe crashes (at the significance level 5 %), but increased hit-object crashes compared to other crashes (e.g., head-on or rollover types).

Vehicle platoon measures were found to have significant impacts on crash types. If vehicles form a platoon, a likelihood of rear-end and side-swipe increased compared to hit-object regardless of the vehicle type mix within the platoon. This confirmed that vehicle interactions are more likely to yield rear-end and side-swipe crashes. Interestingly, the total effects of side-swipe were greater than the direct effects with an

Table 4
Estimation results for the crash type model (Eq. 2b).

Variables	Rear-end Vs Hit-object		Side-swipe vs Hit-object		Others Vs Hit-object	
	Direct Effects	*Total Effects*	*Direct Effects*	*Total Effects*	*Direct Effects*	*Total Effects*
Truck Involvement (β_{22})						
Binary: 1= Truck Involvement	0.300		1.851***		0.262	
Driver Characteristics (Γ_2)						
Gender: Binary: 1 if Male	–	0.451	–	2.783***	–	0.393
Age	0.031***	0.036***	0.037***	0.063***	0.025***	0.029***
Alcohol Involved: Binary:1 =Yes	−2.562***	−3.247***	−1.593***	−3.247***	−1.233***	−1.829
Environment (Γ_2)						
Binary: 1= If weather is bad	0.607		−0.003		1.730**	
Binary: 1 = If road surface is wet	−1.927***		−1.291***		−1.705***	
Binary: 1 = If dark	−0.202		0.359		−0.652*	
Overall Traffic (Γ_2)						
Total Volume	−0.077		−0.119*		−0.343***	
Speed	−0.059***		−0.032**		−0.071***	
Platooned vehicles (Γ_2)						
Homogenous platoon (%)	0.029***		0.043***		0.023***	
Homogenous platoon speed (mph)	–		–		–	
Heterogeneous platoon (%)	0.056***	0.064***	0.048***	0.094***	−0.029	−0.023
Heterogeneous platoon speed (mph)	−0.030**	−0.046*	−0.031	−0.129***	−0.013	−0.027

Notes: $N = 1360$. * Significance at 10 %. ** Significance at 5 %. *** Significance at 1 %.

increase of heterogeneous platoons. This indicates that heterogeneous platoons cause traffic instability that results in a higher chance of truck-involved side-swipe crashes. Speed difference in a homogenous platoon is not significant although the platoon increases the likelihood of rear-end and side-swipe. Therefore, the presence of platoons in itself rather than vehicle speed differences within a platoon are more highly associated with rear-end and side-swipe than hit-object crashes.

Table 5 shows the marginal effects or elasticity of the crash type model. Marginal effects of binary variables showed the change in probability when the predictor or independent binary variable changes from 0 to 1. For continuous variables, elasticity represents the percentage change in probability over percentage change in the independent variables. For example, when a crash involved a truck, the probability of the crash being categorized as a hit-object decreased by 6.9 percent and rear-end by 22.7 percent, but increased by 31.8 percent for sideswipe. When a driver is not sober, the probability of hit-object crash increased by 31.4 percent.

5.3. Crash severity model (Eq. 2c)

The final analysis addressed the model coefficients associated with crash severity as shown in Table 6. Overall, crash types played significant roles in crash severity. The results are in line with the findings from Richardson et al. (1996) who revealed that head-on and rollovers (other types of crashes in this study) caused more severe crashes. Both direct, marginal, and total effects were estimated based on hit-object as reference cases (see Fig. 5). Rear-end and other type crashes were likely to be severe while there was no significant crash severity tendency among side-swipes. This provides some insight to the reason truck-involved crashes are not always severe since side-swipes were the most common type of crash associated with trucks. Vehicles platoon measures did now show significant total effects on the crash severity although they affected the crash type which has a direct impact on severity. Overall traffic conditions represented by total volume and speed were found to negatively affect crash severity, which is corroborated by the results from previous studies (Greene, 2003; Quddus et al., 2009; Martin, 2002). High traffic flow likely resulted in less severe crashes because of typically lower associated speeds when vehicles collide. Alcohol involvement caused risky driver behavior resulting in more rear-end or side-swipe crashes, however, no direct or indirect associations with the severity were found. Two possible reasons are suggested. First, alcohol involvement is shown to relate to less severe crashes such as side-swipe and rear-end crashes compared to hit-object or other types. Second, alcohol involvement is often underreported in a policy report, which results in underestimating the effect of alcohol in statistical analyses (Guo et al., 2007). Only 4 percent of crashes were alcohol involved ones, which is much smaller proportion compared to previous studies (Ahmed et al., 2018).

Table 5
Marginal effects or elasticity of the crash type model (Eq. 2b).

	Pr (Hit-object)	*Pr (Rear-end)*	*Pr (Side-swipe)*	*Pr (Others)*
Truck Involvement				
Binary: 1= Truck Involvement	−0.069***	−0.227***	0.318***	−0.022
Driver Characteristics				
Age	−1.143***	0.118	0.326**	−0.128
Alcohol Involved: Binary:1 =Yes	0.314***	−0.341***	0.012	0.015
Environment				
Binary: 1= If weather is bad	−0.056	0.026	−0.084	0.114
Binary: 1 = If road surface is wet	0.233***	−0.231***	0.019	−0.022
Binary: 1 = If dark	0.011	−0.069**	0.089***	−0.031**
Overall Traffic				
Total Volume	0.444**	0.061	−0.151	−1.257***
Speed	2.073***	−0.661***	0.578*	−1.241**
Platooned vehicles				
Homogenous platoon (%)	−0.027***	0.002	0.016***	−0.004
Heterogeneous platoon (%)	−0.041***	0.015***	0.006	−0.071***
Heterogeneous platoon speed (mph)	0.333**	−0.063	−0.067	0.165

Notes: $N = 1360$. * Significance at 10 %. ** Significance at 5 %. *** Significance at 1 %.

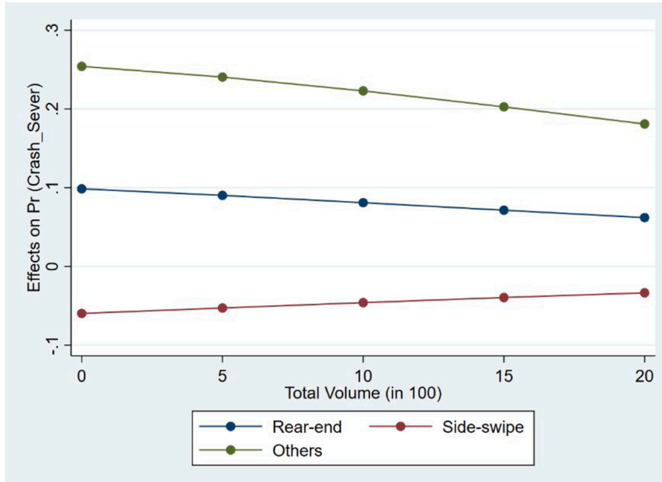
Table 6
Estimation results for the severity model (Eq. 2c).

Variables	Direct Effects Coef.	Total Effects Coef.	Marginal Effects/ Elasticity
Crash Type (Base: Hit -object) (β_{31})			
Rear-end	0.459**	0.459**	0.090**
Side-swipe	−0.328	−0.328	−0.053
Others	1.099***	1.099***	0.239***
Truck Involvement (β_{32})			
Binary: 1= Truck Involvement	–	−0.183	
Driver Characteristics (Γ_3)			
Gender: Binary: 1 if Male	–	−0.275	
Age	–	0.028	
Alcohol Involved: Binary:1 =Yes	–	−1.589	
Environment (Γ_3)			
Binary: 1= If weather is bad	–	2.181***	
Binary: 1 = If road surface is wet	0.618**	−1.716	0.133**
Binary: 1 = If dark	–	−0.927*	
Overall Traffic (Γ_3)	–		
Total Volume in hundreds	−0.045*	−0.418**	−0.162*
Speed	–	−0.094***	
Platooned vehicles (Γ_3)			
Homogenous platoon (%)	–	0.025	
Homogenous platoon speed (mph)	–	–	
Heterogeneous platoon (%)	−0.17**	−0.044	−0.012**
Heterogeneous platoon speed (mph)	–	−0.008	

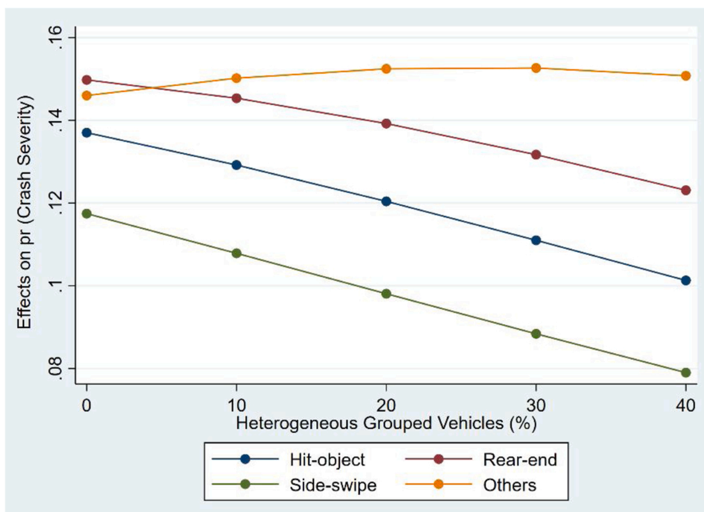
Notes: $N = 1360$. a: The total effects are calculated based on Hit as a baseline in the.
Crash Type Model. * Significance at 10 %. ** Significance at 5 %. *** Significance at 1 %.

Results also found significant differences between direct and total effects for environmental factors. For example, wet road surfaces positively affected crash severity only in the direct relation while lighting conditions had a negative total effect on crash severity. This could be confirmed by the crash type analysis that inferred that poor visibility conditions were associated with more hit-object crashes, which tend to have lower severity than rear-end crashes.

From the marginal effects, this study estimated a 9 percent increase in likelihood of a severe crash in rear-end compared to hit-object crashes. In addition, crashes were 13 percent more likely to be severe under wet conditions (compared to dry conditions). Fig. 6a shows the marginal effect of crash types for different traffic volumes. The changes in marginal effect increased as the volume increases for side-swipe where as it decreases for rear-end crash type. Fig. 6b shows the marginal effect of wet road surface on severity for different crash types as well as for different percentage share of heterogenous traffic. The



a: Average marginal effects of Crash types (baseline: Hit-object) at different traffic volumes



b: Average marginal effects of wet road surface on severity for different crash types at different percentage of heterogeneous traffic

Fig. 6. a. Average marginal effects of Crash types (baseline: Hit-object) at different traffic volumes. b. Average marginal effects of wet road surface on severity for different crash types at different percentage of heterogeneous traffic.

marginal effects of wet road surface on severity decreased for all crash types as the percentage share of heterogenous platoon increases with a slight deflection for 'other' crash type at the lower percentage share of mix traffic.

6. Recommendation and intervention

This paper investigated the impacts of platooned vehicle characteristics on crash risks using GSEM. Vehicle interactions appear to increase unsafe vehicle maneuvers such as abrupt lane change or braking. Based on the modeling outcomes, this section recommends interventions that could reduce crash risks and unsafe vehicle interactions particularly for platooned vehicles. As Smiley and Rudin-Brown (2020) pointed out, safety countermeasures introduced to literature and current practices do not always yield positive outcomes since drivers' characteristics (e.g., overconfidence or less perceived risks) or driving environment may vary by geographical locations or driving scenarios, which may possibly offset the positive intentions of countermeasures. In this section, we considered potential operational and technological strategies that may help drivers maintain safe driving behaviors, increase awareness, and reduce unsafe interactions with other vehicles. We referenced current safety practices and literature to expand the discussion to provide practical recommendations and operational strategies.

6.1. Proactive traffic operation to increase traffic stability within and between vehicle platoons

Multi-vehicle crashes are likely caused by drivers' misjudgment when vehicles interact with other vehicles, especially when they change their lanes or control driving speed. Our model showed that rear-end and other types (e.g., head-on) crashes positively associate with platooned vehicles measures. We further looked into factors associated with platooned vehicles that increase the likelihood of multi-vehicle crashes, and found that the presence of platooned vehicles itself increases a likelihood of multi-vehicle crashes regardless of the vehicle type in the platoon. A heterogeneous vehicle platoon likely increases truck involved crashes since crash likelihood increases when non-truck drivers perform unsafe lane change to overtake a leading truck under heavy traffic conditions (Hyun et al., 2017). Traffic instability caused by vehicle interactions within platoons is also an important crash determinant, particularly for the roadway sections with near capacity. As a proactive crash prevention strategy to reduce instability across the roadway, variable speed limit can be considered to major freight truck corridors or high traffic roadway sections. Lee et al. (2003) found that speed variance could reduce by employing different sectional speeds. This lower speed variance between the roadway sections would reduce the total instability of traffic. Drivers tend to reduce their highest speed when variable speed limit is enforced (Rämä, 1999) and maintain adequate headway (Smulders, 1990). Abdel-Aty et al. (2007) also confirmed the positive impacts of variable speed limit to reduce the crash risks in moderate to high speed roadway conditions. The safety benefit of variable speed limit is therefore to make traffic stream perform homogenously in terms of speed and time headway among the vehicles. This intervention could be considered for roadway sections with high vehicle interactions since vehicle platoons of heavy traffic conditions likely increase the instability within the platoon and between the platoons.

6.2. *In-vehicle warning technology to elevate driver awareness*

The relationship between platooned vehicles and multi-vehicle crashes emphasizes the importance of drivers' attentiveness to surrounding vehicles to reduce crash risks. We suggest a potential strategy that increases driver awareness and attentiveness such as advanced in-vehicle information system or collision warning system. These technologies already exist, however they can play an important role to provide additional information on traffic conditions or call active attention to nearby vehicles. Bao et al. (2012) investigated truck drivers' safety and evaluated the feasibility of in-vehicle warning system to improve drivers' reaction time and headway maintenance. The warning system increased 0.28-second average headway in heavy traffic, and this helped them maintain a safe distance from the leading vehicle with increase in their attentiveness of surroundings, which in turn reduced the likelihood of rear-end crashes. As this study found the strong positive relationships between multi-vehicle crashes (rear-end and sideswipe) and severity, such technology could also reduce severe crashes. The warning system could also alert the drivers of roadway surface conditions. Since the model outcome shows the increased level of hit-object crashes in dark conditions, drivers can be notified of any disruptive conditions such as the presence of work zones that are in their vicinity.

7. Conclusion

Crash factors are grouped into four main categories according to the Highway Safety Improvement Program (Highway Safety Improvement Program (FHWA), 2020): human, vehicle, environmental, and roadway factors. In general, human factors were considered the most important characteristics, but all factors were inter-related and contribute to crashes (Aarts and Van Schagen, 2006). This study examined how different factors related to vehicle interactions affect crash types and severity. Since different crash types (e.g., rear-end, side-swipe, and hit-object) can result from inappropriate lane changing and abrupt deceleration, understanding the relationships among crash factors and crash type is of importance to safety improvement.

This study assumed that the vehicle interaction is present when the leading and following vehicles travel within a platoon. The vehicle platoon was further categorized into two different types to better capture different driving behaviors that may be affected by vehicle mix within the platoon. A homogenous vehicle platoon was defined where only one type of vehicles (either truck or non-truck only) formed the platoon while a heterogeneous platoon comprised a mix of both truck(s) and non-truck(s). The proportion of vehicles comprising each platoon and their average speed difference within platoons were estimated to represent the vehicle interactions. This study applied GSEM with logit structures to investigate the complex relationships among the variables while controlling for endogeneity issues. The model results for crash severity found significant differences between the direct effects and the total effects, suggesting the importance of indirect effects of exogenous variables on crash severity mediating through the endogenous variables (truck involvement and crash type).

The results showed that vehicle interactions are associated with the occurrence of rear-end and side-swipe crashes. However, the speed difference between vehicles within heterogeneous platoons has a positive effect on hit-object crashes. Age was found to positively affect rear-end and side-swipe while alcohol involvement strongly influenced hit-object crashes. High traffic flow near capacity likely resulted in less severe crashes. The findings of this study can be used to identify high-risk factors for various crash types. As the types of crashes relate not only to severity of crashes but also magnitude of impacts to overall traffic, knowledge on the key factors that increase the risk of a particular type of crash under given environmental and traffic conditions will provide specific enhancement of road infrastructure or operational interventions to reduce the number and impact of crashes. Based on the findings, the study introduced several intervention strategies that can potentially reduce human errors in driving. In-vehicle technology or proactive operational strategies that harmonize platoon speeds and following distance seem promising to reduce crash risks because these interventions allow drivers to prepare for potential hazardous conditions ahead of time.

A future study may include road geometry factors to further predict crash risks and severity at hot spot locations by estimating potential risky driving behaviors. Emerging technologies such as sensing and communication systems would enable researchers analyze real-time travel behaviors and vehicle interactions to understand the road and traffic conditions in real time and adjust traffic management strategies accordingly.

Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

CRediT authorship contribution statement

Kyung (Kate) Hyun: Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft. **Suman Kumar Mitra:** Methodology, Writing - original draft, Writing - review & editing. **Kyungsoo Jeong:** Data curation, Writing - original draft, Writing - review & editing. **Andre Tok:** Writing - review & editing.

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