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Uncovering Deep Structure of Determinants in Large Truck Fatal Crashes

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Abstract
The number of fatalities and severe injuries in large truck-related crashes has significantly increased since 2009. According to the safety experts, the recent increase in large truck-related crashes can be explained by the significant growth in freight tonnage all over the U.S. over the past few years. This notable freight-haul growth has allowed continuous day–night movement of freight on roads and highways, exposing the trucks to a greater number of potential crashes or near-crash scenarios. There are many ongoing research efforts that aim to identify the different factors that influence large truck crashes; however, further research with innovative approaches is still needed to better understand the relationship between crash-related factors. In this study, the project team applied taxicab correspondence analysis (TCA), a data-mining method known for dimension reduction, to large truck fatal crash data to investigate the complex interaction between multiple factors under a two-dimensional map. For this study, 6 years (2010–2015) of large truck fatal crash data from the Fatality Analysis Reporting System (FARS) were used. The study found five clusters of attributes that show patterns of association between different crash attributes such as two-lane undivided roadways, intersection types, posted speed limit, crash types, number of vehicles, driver impairment, and weather. The findings of this study will help the safety professionals, trucking industry, and policymakers to make decisions for safer road design, and improvement in truck driver training, and education.

Large trucks account for over 80% of freight tonnage. Large truck crashes interrupt traffic flow and cause tremendous economic loss; however, the number of deaths and the severity of injuries sustained in these crashes are certainly the most acute and dire effects. The number of fatal crashes involving large trucks or buses has increased by 29% since 2009 (*1*). According to the National Highway Traffic Safety Administration (NHTSA), there were 4,951 fatalities involving large trucks in the year 2018 (increased by 5.8% from 2016); this amount accounted for 13.5% of all fatalities in that year. Furthermore, the risk associated with large trucks in relation to exposure accounts for 9% of the overall vehicle miles traveled and 4% among all registered vehicles in 2018 (*1*). According to national crash statistics, large truck-related crashes have increased significantly in recent years. This has drawn the attention of safety researchers, but more focus should be directed toward the issue to improve overall truck safety and to mitigate the impacts of these crashes on the U.S. economy and human lives. A more robust statistical approach was needed to understand the mechanisms and factors of roadway crashes involving large trucks.

A large truck is defined as a "medium or heavy truck having a gross vehicle weight rating (GVWR) of more than 10,000 lb, excluding busses and recreational vehicles (RVs)" (*1*). Because of their considerable weight and size, crashes involving large trucks are more likely to result in a fatality or severe injury (*2, 3*). Therefore, a specialized investigation of crash causation with fatality and injury severity analysis is necessary to identify the mechanisms involved in these crashes and to provide effective countermeasures. There are many ongoing research efforts, both conventional and innovative, that aim at

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determining the factors that influence large truck crash occurrences to develop more effective safety treatments. However, the number of large truck-related crashes is still very high, as shown by recent crash statistics. Thus, there is a need for research efforts with additional resources and newer approaches and techniques.

Correspondence analysis (CA) is a multivariate statistical method that summarizes the essential aspects of a data set by projecting the complex nature of multivariate data into a two- or three-dimensional space. In the recent years, Taxicab correspondence analysis (TCA) has been emerged as a robust variant of CA. This approach can smoothly handle complex multivariate data sets and can generate meaningful results even with the data set containing significant missing values. In recent years, much of research attention has been shifted toward determining the factors that significantly affect crash occurrences. This study used large truck-related crash data from 2010 to 2015 from the Fatality Analysis Reporting System (FARS). The application of TCA on this data set is appropriate because of the method's suitability in addressing the research problem related to these data.

Literature Review

A few recent research studies have conducted innovative statistical analyses to investigate traffic crashes involving large trucks. One of the earliest research efforts in documenting and investigating crash causation and crash risk factors associated with large trucks was carried out jointly by the U.S. Department of Transportation's (DOT) Federal Motor Carrier Safety Administration (FMCSA) and NHTSA in the early 2000s (*4*). This study, named the Large Truck Crash Causation Study (LTCCS), used crash data from 17 states from 2001 to 2003 and aimed to identify key factors of large truck crashes. Although the database created under this project contains descriptive data like other national traffic safety databases (e.g., FARS), the LTCCS also considered pre-crash factors leading to a crash occurrence such as driver fatigue, distraction, weather, and roadway conditions. Before the LTCCS database was created, crash count and severity analyses involving large trucks were conducted using conventional police report and hospital data (*5*).

Lemp et al. conducted an extensive large truck-related crash severity analysis using standard and heteroskedastic ordered probit models with the LTCCS, General Estimates System (GES), and Vehicle Inventory and Use Survey data sets (*6*). The focus of this study was to analyze the effect of vehicle, driver/occupant, and environmental characteristics on the severity of injuries sustained during large truck-related crashes. In another study, Hickman et al. compared the LTCCS data with naturalistic driving data and argued that this comparison is necessary to bridge the information gap between high-severity crash occurrences in the LTCCS data set with non-crash related vehicular conflicts (*7*). Koupaenejad investigated the factors contributing to the severity of crashes occurring between passenger cars and large trucks by using multinomial logit (MNL) and ordered probit models (*8*).

The factors influencing crash severity in hazardous material (HAZMAT) carrying large truck-related crashes utilizing ordered probit models with random and set parameters were investigated by Uddin and Huynh (*9*). In this study, the most substantial factors that influence the crash severity of HAZMAT truck crashes were found to be drivers' sex and age, time of day, lighting condition, terrain, and crash type. In addition, Islam and Hernandez included random parameter ordered probit models to approximate the possibility of five injury severity outcomes (*10*). In another study, Islam and Hernandez utilized random parameter tobit regression examining the large truck-involved fatal crash rates (instead of frequencies) in per million truck-miles traveled and ton-miles of freight as continuous censored variables (*11*). This study quantified fatality rates with factors related to the crash mechanism, temporal and spatial characteristics, road and environmental attributes, vehicle configuration, and driver and passenger attributes, which were found to be statistically significant. Some unobserved effects were found as a result from the intricate interaction between driver, roadway, traffic, and environmental factors that affect the injury severity of crashes. Qin et al. utilized partial proportional odds (PPO), MNL, and mixed logistic models in large truck-related crash severity analysis (*12*). Drivers' age and seatbelt laws were found to not be statistically significant factors in influencing the severity of large-truck related crashes. In addition, Zheng et al. used the gradient-boosting data-mining technique to perform a crash severity analysis (*13*). Eleven variables were found which accounted for over 80% of the total severe crashes in the data set acquired from FMCSA in Colorado and North Dakota from 2010 to 2016. In comparison to other roadway or traffic-related factors, Kotikalapudi and Dissanayake found that driver-related factors had more of an effect on crash injury occurrences endured during large truck-related crashes (*14*).

Besides these severity analyses, the current literature consists of studies that investigate count data to examine and estimate the total number of crash occurrences and crash frequency. Amarasingha and Dissanayake evaluated the association of geometric properties and traffic with large truck-related crashes using Poisson and negative binomial (NB) regression models for access-controlled highways, like freeways (*15, 16*).

Similarly, Dong et al. performed a study in which the authors considered NB and zero-inflated NB (ZINB) models and identified seven factors that were statistically significant in causing truck-related crashes, the majority of which were consistent with the earlier studies (*17*). Offei et al. reviewed the association between crash rates involving large trucks and truck percentages using regression models (*18*).

Apart from the common modeling techniques, other statistical and innovative machine learning methods have been used to examine the injury severity and crash frequency of large truck-related crashes. Some of these examples consist of the classification tree model (*19*), hierarchical Bayesian random intercept model (*20*), skewed logistic model (*21*), and a risk analysis model dependent on collision diagram (*22*). Even though most of these studies concentrated on highway crashes, Qin et al. analyzed the factors contributing to the severity and frequency of truck-related crashes at freeway diverging section with the use of NB and MNL models (*23*). They found different genetic elements associated with median/shoulder width, deceleration areas, numbers of lanes, curvature, grade, speed limit, truck percentage, and annual average daily traffic (AADT) to be key factors in large truck-related crashes at freeway sections. However, Taylor et al. conducted a similar study but found that geometric attributes of roadways (e.g., number of lanes, shoulder and median widths) and specific crash types were not significant factors influencing the severity and frequency of freight truck-related crashes (*24*). Ullman and Iragavarapu investigated fatal work-zone crashes involving large trucks using odds ratio and found that these crashes are over-represented in the fatal work-zone crash statistics when analyzed in relation to the time of day and roadway functional classes (*25*).

Although most of the studies found in the literature investigated factors that contribute to large truck-related crashes, a few other studies only looked at the effect of specific factors such as lighting condition (*2*), time of day (*26*), geometric elements such as horizontal curvatures (*27*), roadway separation (*28*), and crash types—for example rear-end crashes (*29*), rollover crashes (*30*), run-off-road crashes (*31*), angle crashes (*21*), and driver age group (*32*)—on crash occurrence or injury severity. Trimble et al. conducted a GES analysis on rear-end crashes involving large trucks to determine the causation of this type of crash and to improve rear-signaling under a national project by NHTSA (*29*). Table 1 represents the key variables used by previous studies.

CA has become more popular in the field of transportation safety research (*34–44*). In the presence of rarely occurring variable categories, TCA produces visuals that are clearer and more easily interpreted than those produced by multiple correspondence analysis (MCA). The present study aims to investigate the trends of key contributing factors for large truck crashes via the application of TCA to 6 years (2010–2015) of FARS data. This new method gives this study unique value because it can easily handle the complex nature of large truck-related crash data and provide intuitive and significant results.

Methodology

Taxicab Correspondence Analysis

In a series of studies, Choulakian introduced the TCA method (*45–47*). This study describes the key concepts of TCA, which is mostly based on Choulakian's studies (*45–47*).

Unlike CA, which is based on Euclidean distance, TCA uses the Manhattan, City Block, or Taxicab distance as the key distance measure. Let, $X, Y, and\, \boldsymbol{v}$ be such that $X = (x_1, x_2, \ldots.., x_n)$ and $Y = (y_1, y_2, \ldots.., y_n)$ are the two components of a vector $\boldsymbol{v} = (v_1, v_2, \ldots.., v_n)$ in a two-dimensional space. The distances can be described as:

$$\begin{aligned} &\text{Euclidean Distance} = \text{ED}(X, Y)\\ &= \sqrt{\sum\nolimits_{i=1}^{n} (x_i - y_i)^2}\\ &[\text{with } L_2 \text{ Norm} = \|v\|_2 = \sqrt{\sum\nolimits_{i=1}^{n} (v_i)^2}] \end{aligned} \tag{1}$$

$$\begin{aligned} &\text{Taxicab Distance} = \text{TD}(X, Y)\\ &= \sum\nolimits_{i=1}^{n} |x_i - y_i| \; [\text{with } L_1 \text{Norm} = \|v\|_1 = \sum\nolimits_{i=1}^{n} |v_i|] \end{aligned} \tag{2}$$

Singular value decomposition (SVD) is the key concept to understand the logic behind CA and TCA. This concept includes the decomposition of a real matrix A to $M\Lambda^{1/2}N'$, where Λ is the diagonal matrix of the real non-negative eigenvalues of AA', M is the orthogonal matrix of the corresponding eigenvectors, and N is the matrix of eigenvectors of $A'A$ (with constraints $M'M = I \text{ and } N'N = I$). The reconstruction formula of a k -rank matrix can be written as:

$$a_{ij} = \sum_{i=1}^{k} \sqrt{\lambda_\alpha} m_{i\alpha} n_{i\alpha} \tag{3}$$

The SVD solution is developed via a recursive optimization process in the TCA framework. To solve the equivalent optimization problem, one must locate the first vectors m_1 and n_1 which are principal components of A. The solution provides the largest singular value of A. The TCA framework also includes a distance matrix known as L_∞ matrix. The aim is to minimize the rank of T (and consequently of N) without displacing relevant information. To formalize the solution, an appropriate

Table 1. Variables Considered in Large Truck Safety Studies

Variable name		Found in studies
Driver/Occupant characteristics	Action or inaction by drivers (maneuver, braking, acceleration, deceleration)	Department of Transportation (DOT) (*4*), Hickman et al. (*7*); Islam and Hernandez (*10*); Kotikalapudi and Dissanayake (*14*); Chen et al. (*20*); Balakrishnan et al. (*21*); Trimble et al. (*29*); Park and Pierce (*30*); Al-Bdairi et al. (*31*)
	Driver perception and decision errors	DOT (*4*); Hickman et al. (*7*); Kotikalapudi and Dissanayake (*14*); Trimble et al. (*29*); Park and Pierce (*30*)
	Performance errors (sleeping, illness, disability)	DOT (*4*); Hickman et al. (*7*); Kotikalapudi and Dissanayake (*14*)
	Fatigue	DOT (*4*); Hickman et al. (*7*); Al-Bdairi et al. (*31*)
	Speeding	DOT (*4*); Hickman et al. (*7*); Kotikalapudi and Dissanayake (*14*); Dong et al. (*17*); Eustace et al. (*19*); Qin et al. (*23*); Trimble et al. (*29*); Islam and Hernandez (*11*)
	Driver age	Charbotel et al. (*5*); Koupaenejad (*8*); Uddin et al. (*9*); Zheng et al. (*13*); Islam and Hernandez (*10, 11*); Eustace et al. (*19*); Chen et al. (*20*); Balakrishnan et al. (*21*); Taylor et al. (*24*); Islam and Ozkul (*32*)
	Gender	Charbotel et al. (*5*); Koupaenejad (*8*); Uddin et al. (*9*); Islam and Hernandez (*10*); Eustace et al. (*19*); Chen et al. (*20*); Balakrishnan et al. (*21*); Taylor et al. (*24*)
	Driver licensing	Zheng et al. (*13*); Al-Bdairi et al. (*31*); Islam and Hernandez (*11*)
	Number of occupants	Lemp et al. (*6*); Chen et al. (*20*); Islam and Hernandez (*11*)
	Tailgating	Kotikalapudi and Dissanayake (*14*); Trimble et al. (*29*)
	Laws and features (seat belt law, driving under influence [DUI] law, airbags)	Charbotel et al. (*5*); Islam and Hernandez (*10*); Eustace et al. (*19*); Chen et al. (*20*); Balakrishnan et al. (*21*); Taylor et al. (*24*)
Vehicle characteristics	Vehicle types	Charbotel et al. (*5*); Uddin et al. (*9*); Balakrishnan et al. (*21*); Qin et al. (*23*); Taylor et al. (*24*); Yang et al. (*28*)
	Malfunction in braking system (brake failure, loss of control)	DOT (*4*); Hickman et al. (*7*); Kotikalapudi and Dissanayake (*14*); Trimble et al. (*29*); Al-Bdairi et al. (*31*)
	Vehicle design elements (front and rear overhang, width, weight, length, trailing unit)	Lemp et al. (*6*); Koupaenejad (*8*); Zheng et al. (*13*); Kotikalapudi and Dissanayake (*14*); Park and Pierce (*30*); Islam and Hernandez (*11*)
	Number of trucks or other vehicles (truck percentages, traffic volume, vehicles involved in the crash)	Lemp et al. (*6*); Islam and Hernandez (*10*); Offei et al. (*18*); Chen et al. (*20*); Qin et al. (*23*); Wang et al. (*33*); Taylor et al. (*24*); Al-Bdairi et al. (*31*); Yang et al. (*28*)
Environmental, roadway and crash characteristics	Roadway condition (classification, terrain, visibility of markings, surface condition)	DOT (*4*); Charbotel et al. (*5*); Lemp et al. (*6*); Hickman et al. (*7*); Uddin et al. (*9*); Offei et al. (*18*); Eustace et al. (*19*); Chen et al. (*20*); Balakrishnan et al. (*21*); Qin et al. (*23*); Taylor et al. (*24*); Ullman and Iragavarapu (*25*); Park and Pierce (*30*); Al-Bdairi et al. (*31*); Fitzsimmons et al. (*27*); Yang et al. (*28*)
	Adverse weather effect	DOT (*4*); Lemp et al. (*6*); Hickman et al. (*7*); Kotikalapudi and Dissanayake (*14*); Offei et al. (*18*); Eustace et al. (*19*); Taylor et al. (*24*); Fitzsimmons et al. (*27*); Yang et al. (*28*); Islam and Hernandez (*11*)
	Interruptions in traffic flow (intersection, previous crash, work zone, peak hour congestion)	DOT (*4*); Hickman et al. (*7*); Amarasingha and Dissanayake (*15*); Dong et al. (*17*); Eustace et al. (*19*); Ullman and Iragavarapu (*25*); Park and Pierce (*30*)
	Roadway design elements (curvature, grade, width, median)	Islam and Hernandez (*10, 11*); Amarasingha and Dissanayake (*15*); Dong et al. (*17*); Eustace et al. (*19*); Chen et al. (*20*); Qin et al. (*23*); Wang et al. (*33*); Taylor et al. (*24*); Park and Pierce (*30*); Al-Bdairi et al. (*31*); Fitzsimmons et al. (*27*)
	Lighting condition	Al-Bdairi et al. (*2*); Koupaenejad (*8*); Uddin et al. (*9*); Islam and Hernandez (*10*); Eustace et al. (*19*); Chen et al. (*20*); Taylor et al. (*24*); Ullman and Iragavarapu (*25*); Pahukula (*26*); Fitzsimmons et al. (*27*); Yang et al. (*28*)
	Divided/undivided	Koupaenejad (*8*); Qin et al. (*23*); Taylor et al. (*24*); Al-Bdairi et al. (*31*); Yang et al. (*28*)
	Posted speed limit	Eustace et al. (*19*); Balakrishnan et al. (*21*); Qin et al. (*23*); Taylor et al. (*24*); Trimble et al. (*29*); Fitzsimmons et al. (*27*)

(continued)

Table 1. (continued)

Variable name		Found in studies
	Time of day	Charbotel et al. (*5*); Uddin et al. (*9*); Islam and Hernandez (*10, 11*); Zheng et al. (*13*); Eustace et al. (*19*); Balakrishnan et al. (*21*); Ullman and Iragavarapu (*25*); Pahukula (*26*); Fitzsimmons et al. (*27*); Yang et al. (*28*)
	Crash type (head on, t-collision, angle and rear-end crashes, roll over)	Charbotel et al. (*5*); Hickman et al. (*7*); Koupaenejad (*8*); Uddin et al. (*9*); Islam and Hernandez (*10, 11*); Zheng et al. (*13*); Eustace et al. (*19*); Chen et al. (*20*); Balakrishnan et al. (*21*); Taylor et al. (*24*); Al-Bdairi et al. (*31*); Fitzsimmons et al. (*27*); Yang et al. (*28*)
	Miscellaneous (Truck company attributes)	Zheng et al. (*13*)

reduced rank matrix $\hat{T}$ is considered that best approximates T in the sense of the weighted least squares, that minimizes the residuals $\boldsymbol{R}$ that can be expressed as (*41*):

$$\boldsymbol{R} = n \sum_{i=1}^{r} \sum_{j=1}^{l} \frac{(t_{ij} - \hat{t}_{ij})^2}{t_{i.}t_{.j}} = n \operatorname{trace}\left(D_l^{-1/2}(T - \hat{T})' D_r^{-1}(T - \hat{T}) D_l^{-1/2}\right) \tag{4}$$

The TCA approach can be defined as the Taxicab SVD of the data table $D = T - rl'$, considering the profiles of the table, $R = D_r^{-1}D$ for the rows and $L = D_l^{-1}D$ for each of the columns. The solution is recursive at each step by considering the residuals from the previous factors, which differentiates it from CA. After the final transformation has been conducted, it can be written as:

$$n_{ij} = nr_i l_j (1 + \sum_{\alpha=2}^{k} \frac{1}{\lambda_\alpha} b_{i\alpha} c_{j\alpha}) \tag{5}$$

Data Description

A large truck is any medium or heavy truck, excluding buses and motor homes, with a GVWR greater than 10,000 lb. Table 2 displays the description of the vehicles that are considered as large trucks in the FARS database (*48*).

In this study, 6 years (2010–2015) of large truck fatal crash data were obtained from FARS. The crash data file, vehicle data file, and person data file are selected for this study. Preliminary data exploration was conducted at the beginning to examine the significant factors that may contribute to crash occurrence. After the preliminary analysis, this study excluded irrelevant and other redundant variables from the raw data before applying TCA. Figure 1 shows the flow chart of the data preparation task.

There are 14 key variables in the final data set; Table 3 displays the proportional distribution of these variables.

Table 2. Large Truck Codes in the Fatality Analysis Reporting System

Code	Description
60	Step van
61	Single-unit straight truck (10,000 lb < GVWR ≤ 19,500 lb)
62	Single-unit straight truck (19,500 lb < GVWR ≤ 26,000 lb)
63	Single-unit straight truck (GVWR > 26,000 lb)
64	Single-unit straight truck
66	Truck/tractor (cab only, or with any number of trailing units: any weight)
67	Medium/heavy pickup (GVWR > 10,000 lb)

Note: GVWR = gross vehicle weight rating.

Roadway functional class accounts for the roadway classification for each crash occurrence. From the percentage distribution, over 50% of the fatal crashes occurred under a rural environment, which agrees with the study conducted by Chen et al. (*20*). They investigated the key factors affecting large truck-related crashes; they found significant statistical evidence that rural areas are more crash-prone for large trucks. They also found that, based on intersection type, approximately 75% of all crashes occurred on roadway segments. Furthermore, the proportions of attributes in roadway alignment show that approximately 83% of all roadway crashes occur on straight roadway segments. These large representations of crash statistics on roadway segments are in line with the findings by Dong et al. (*17*), in which the authors investigated the effect of geometric design features and found a strong association of longer straight segment lengths to crash occurrences. The proportion distribution of several of the variables are also in line with other studies such as lighting condition (*2*), roadway gradient (*17*), posted speed limit (*19*), time of day (*26*), weather condition (*24*), number of vehicles involved (*6*), and types of

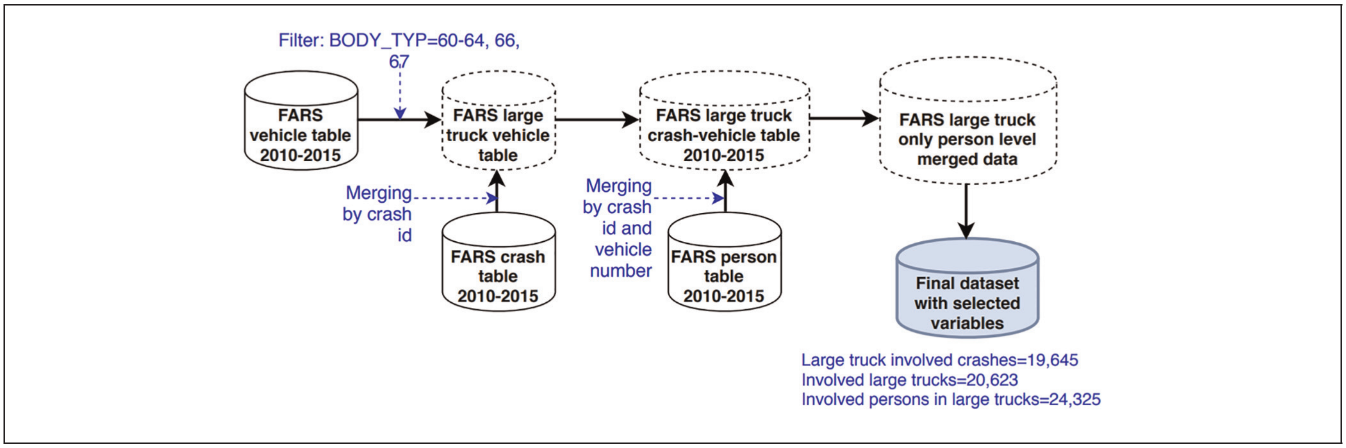

Figure 1. Flowchart of the data preparation.
Note: FARS = Fatality Analysis Reporting System.

collision (*9, 21*). Three person-level variables (previous accident record of the drivers, driver's past license suspension record, and impaired driving) are associated with the driving patterns of the large-truck drivers associated with fatal crashes. However, association with prior crashes has high proportions compared with the other two traits.

Results and Findings

The TCA method compiles the key components of a complex data set by mapping the multivariate data on two-dimensional or three-dimensional displays. Ultimately, the goal is to produce a thorough biplot. The readability and interpretability of the map is highly important in most cases. The biplot displays the key attributes of the selected variables identified by their labels; for example, the selected variable could be roadway type, and rural two-lane roadways with a barrier would be displayed and identified by their labels. In the presence of a large set of attributes, the biplot can become cluttered and the labels might not be easy to read.

An important characteristic of TCA and CA is that columns (or rows) with identical profiles (conditional probabilities) possess the same factor scores. An important benefit of TCA compared with CA is that it directly acts on the correspondence matrix P without calculating a dissimilarity (or similarity) measure between the rows or columns; thus, it remains closer to the original data. Furthermore, TCA performs better in the presence of missing data.

The percentage of variance explained by both axes is around 52% (axis 1 explains 28.16% of the variance, and axis 2 explains 23.75% of variance). The locations of the variable categories indicate their association patterns. Figure 2 shows the complete TCA plot. As the plot is very cluttered with the presence of all attributes on the same plot, four separate plots are recreated (see Figure 3) for better visualization and interpretation. The solid parabolic shapes represent a cluster with a distinct association pattern. The clusters with both obvious and trivial associations are shown by dotted parabolic shapes.

Cluster 1a (Urban Collector or Minor Arterial, Intersection=T-Intersection or 4-Way Intersection, Posted Speed Limit=30–40 mph)

This cluster is visible in the first quadrant of the TCA plot (see Figure 2). Although several studies have invested research efforts in identifying factors corresponding to large truck-related crashes in a rural environment, only a few have investigated crashes in an urban environment. Charbotel et al. explored the differences of crash scenarios in both rural and urban areas in large truck-related crashes and found that the injury severity in truck-involved crashes has been increasing significantly, especially in urban collectors or arterials (*5*). Pahukula et al. found a close association between factors of intersection and posted speed limit as contributing to crashes occurring in urban areas (*26*). Cluster 1b (shown in a dotted parabola in Figure 3*b*) in quadrant 1 shows a cluster of several attributes with trivial associations.

Cluster 2a (Lighting=Dark Lighted or Dark Not Lighted, Roadway=Two-Way Divided Unprotected, Collision=Front to Rear)

The first dominant cluster identified in the second quadrant indicates that the dark, not lighted condition in the two-way unprotected-divided roadway is prone to rear-end crashes involving large trucks (as shown in Figure 2). This cluster is also in the close neighborhood of interstate and high posted speed limit (60 mph and above). The

Table 3. Descriptive Statistics of Key Variables[a]

Attributes	Perc.	Attributes	Perc.
ROAD_FNC (FC)		VSPD_LIM (Posted Speed Limit or PSL)	
Rural interstate	29.7	0–25 mph	2.0
Rural principal arterial	10.0	30–40 mph	10.3
Rural minor arterial	8.4	40–60 mph	49.3
Rural collector	4.1	60–70 mph	29.5
Rural unknown	0.2	>70 mph	8.4
Urban interstate	12.6	Unknown	0.6
Urban principal arterial	8.7	HOUR (Hour)	
Urban minor arterial	3.9	12–6 a.m.	20.3
Urban collector	1.3	7 a.m.–12 p.m.	31.5
Urban local	3.1	1–6 p.m.	31.6
Urban unknown	0.4	7 p.m.–12 a.m.	14.0
Unknown	17.6	Unknown	2.5
TYP_INT (Int.)		WEATHER (Weather)	
Segment	74.9	Clear	70.7
4-way intersection	17.2	Rain	7.4
T-intersection	7.1	Others	21.9
Others	0.9	VE_TOTAL (Inv.)	
VTRAFWAY (Trafficway)		Single	18.6
Two-way undiv.	49.1	Two	60.6
Two-way div. barrier	22.0	Multi	20.8
Two-way div. unprotected	22.6	MAN_COLL (Coll.)	
Others	6.3	Not with other veh.	25.8
VALIGN (Align.)		Angle	30.2
Straight	82.8	Front-to-rear	20.9
Curve left	8.2	Front-to-front	14.4
Curve right	6.1	Sideswipe (oppo.)	3.8
Others	3.0	Sideswipe (same)	3.4
LGT_COND (Light)		Others	1.5
Daylight	62.1	PREV_ACC (Prev_Crash)	
Dark—not lighted	24.0	No	76.1
Dark—lighted	9.3	Yes	23.9
Others	4.7	PREV_SUS (Prev_Sus)	
VPROFILE (V_Profile)		No	88.4
Level	69.9	Yes	11.6
Grade, unknown slope	13.2	DR_DRINK (Dr_Alc)	
Downhill	5.6	No	97.6
Uphill	4.6	Yes	2.5
Others	6.7		

[a]Variable code used in Fatality Analysis Reporting System (FARS) (variable code used in this study).

association of factors discerned in this cluster is in line with multiple studies found in the literature. Al-Bdairi et al. found that speeding while driving in darker conditions can significantly increase the chances of more severe crashes on rural interstate highways (*2*). Trimble et al. investigated the factors contributing to rear-end crashes involving large trucks and concluded that speeding, including acceleration and deceleration in anticipation of drivers' attempted avoidance maneuvers, is a significant factor of crashes (*29*). In a comprehensive study, Koupaenejad found an association between no divided medians and younger male drivers leading to severe crashes on interstate highways (*8*).

Cluster 3a (Impaired Driver, Single Truck or Sideswipe Same Direction, and Single or Multiple Vehicle Involvement)

The attributes in this cluster, as shown in Figure 2, illustrates close agreement with the findings by Chen et al., in which the authors showed that driver impairment in relation to drug or alcohol consumption, and several vehicles involved in the crash are significant factors in severe injury or fatal crashes (*20*). The findings of Al-Bdairi et al. suggest that single-vehicle crashes that involve running off-road under a dark condition with a fixed roadside object can lead to fatality in large truck-related crashes (*2*). Uddin and Huynh's findings show contradiction to these

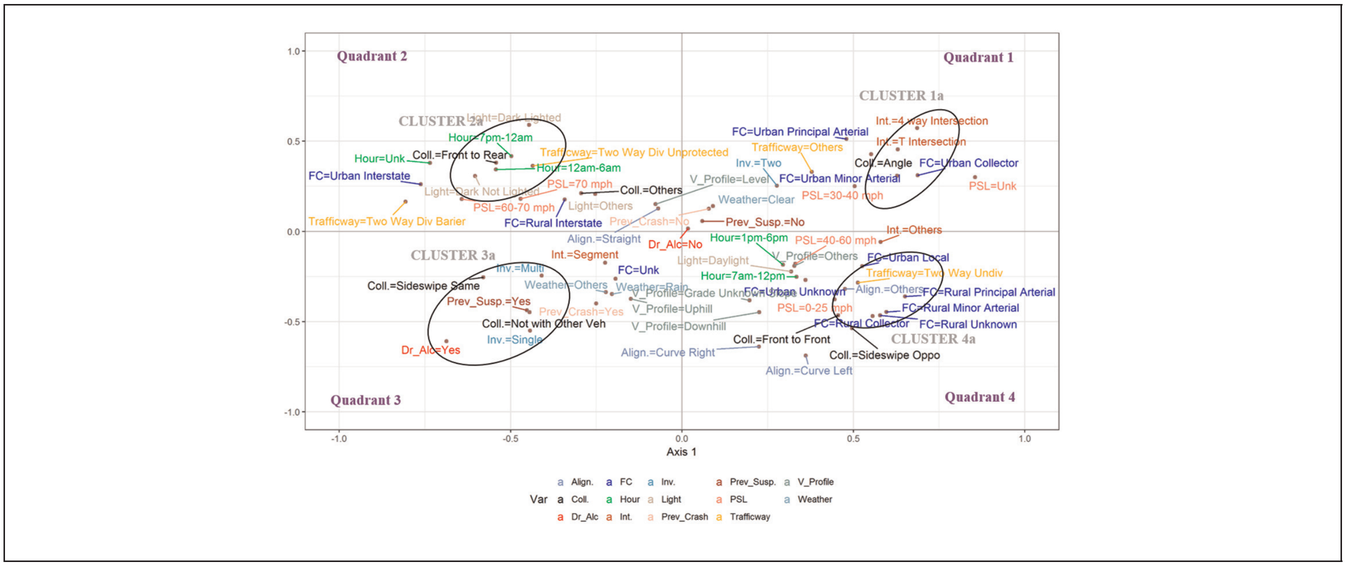

Figure 2. Taxicab correspondence analysis (TCA), plot with two axes and quadrants for distinct association pattern.

studies; the authors claim that actions corresponding to single-vehicle crashes involving large trucks such as sideswipe, run-off-road, and hitting stationary object are associated with a decreased probability of injury severity (*9*). In addition, the likelihood of fatal or severe injury crashes increases for single-vehicle involvement and decreases if there are multiple vehicles involved in the crash (*9, 31*).

Cluster 3b (Segment, Weather=Rain or Others, Uphill, Previous Crash Conducted by the Truck Driver=Yes and Unknown Functional Class)

The association is Cluster 3b, as shown in Figure 3*c*, suggests that adverse weather conditions, such as raining and dust on an uphill gradient, significantly increase the probability of fatal crashes involving large trucks, specifically with drivers having past crash experience. The relationship deciphered in this cluster can be justified by the findings of Dong et al., in which the authors found that an uphill or downhill gradient significantly increases the chance of a severe crash under adverse weather condition (*17*). The association of these geometric and weather conditions with that of the driver's previous crash experience is explainable by the plausible assumption that the drivers with past crash experience may have issues with safe driving behavior. Thus, this factor is well expected to be a significant one in contributing to a fatal crash.

Cluster 4a (Functional Class=Rural Principal or Minor Arterial, Collector and Urban Local, Roadway=Two-Way Undivided, Collision=Sideswipe Opposite, Low-Posted Speed Limit, and Alignment=Others)

As illustrated in Figure 2, the attributes grouped under this cluster agree with the findings listed in Cluster 1a and Cluster 1b, which identified two sets of significant factors related to large truck fatal crashes in rural and urban areas. Although a greater number of factors are found in one single cloud in this cluster, a distinction can be drawn as to which ones are related to the land-use context (rural versus urban). This is supported by a study conducted by Islam and Hernandez (*10*). For example, two-way undivided roadways are more likely to be found in the rural principal or minor arterials, whereas the low-speed limit is likely to be associated with urban collector and local roadways. Cluster 4b is not referencing a strong cluster inference (shown in Figure 3*d*).

The final data set contains 26,275 individual data points representing the personal information of the large truck drivers and occupants (LTDO) involved in crashes. With the TCA method, LTDO locations (on the two-dimensional space in Figure 4) can be divided into 69 distinct clusters. Figure 4 provides an illustration of the distribution of each LTDO (mapping the individuals in the biplot instead of mapping the variable attributes) on both axes. This illustration shows 69 distinctive clusters if one clusters the points vertically based on axis 1 (each cluster represents each vertical line on the x-axis), and there are clusters located on both the positive and negative side of the x-axis. Points that are larger in size represent a greater count of LTDO with the same co-ordinates.

Four general crash prevalence conditions were considered for further analysis. These conditions are LTDO involvement in previous crashes (yes/no), LTDO with a record of previous suspension history (yes/no), intoxication (yes/no) of LTDO, and single truck crash (yes/no). Table 4 lists the importance of the clusters by computing the log odds ratio (LOR) of the crash prevalence

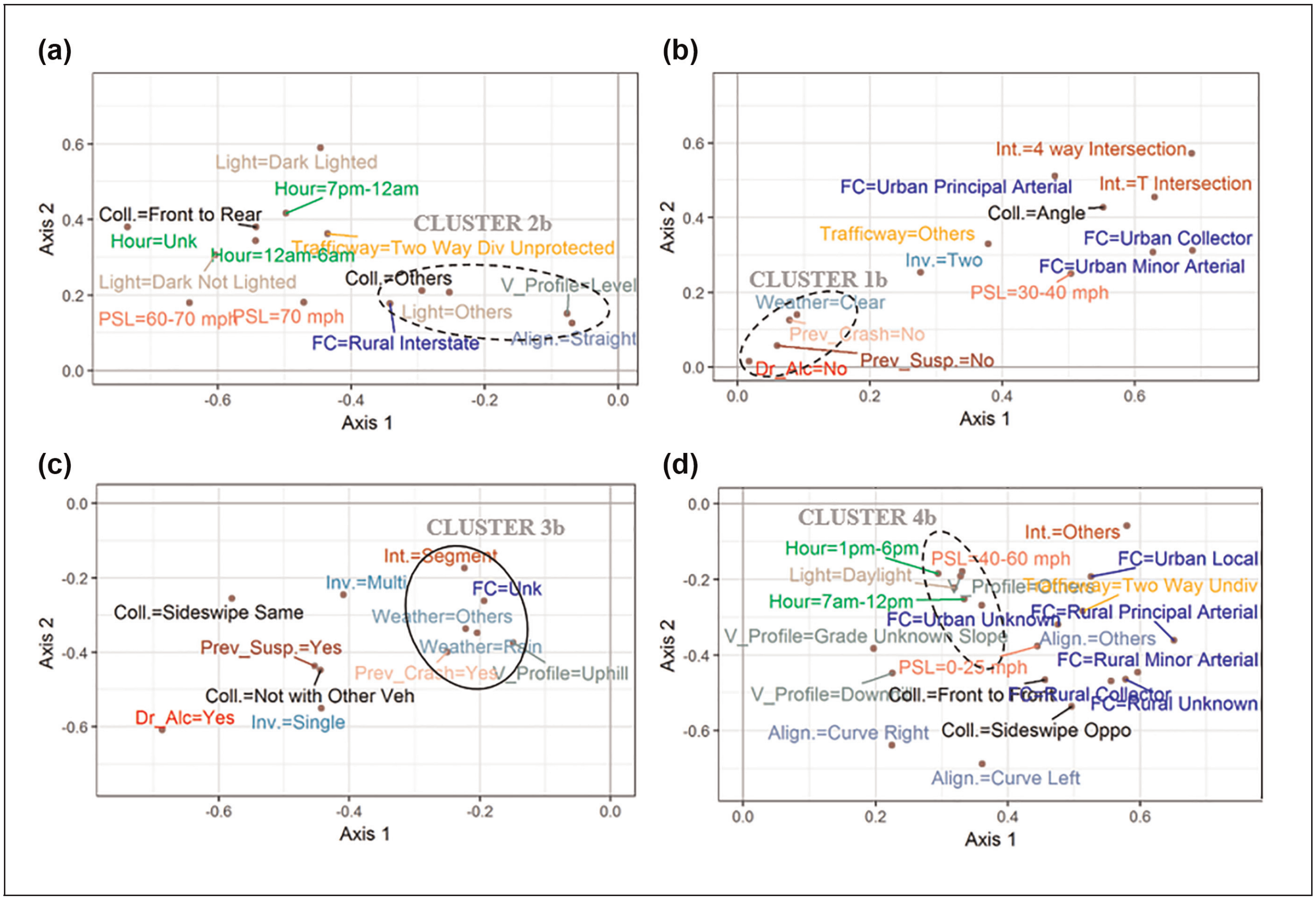

Figure 3. Taxicab correspondence analysis (TCA) plot by quadrants for closer association pattern.

conditions with respect to the marginal distribution. The interpretation of LOR (X = x) is as follows:

- LOR (X = x) = 0.00 indicates that the proportion of category A in cluster x is equal to the proportion of category B in the sample. For example, the LOR value for LTDO in previous crashes (yes versus no) is 0 for Cluster07. Cluster07 is associated with 29 LTDO.
- LOR (X = x) > 0.00 refers that the proportion of category A in cluster x is greater than the proportion of category B in the sample. For example, the LOR value for LTDO in previous crashes (yes versus no) is 1.77 for Cluster04. This cluster has 275 LTDO. The LOR value indicates that this cluster is positively associated with LTDO who have previous crash histories.
- LOR (X = x) < 0.00 refers that the proportion of category A in cluster x is smaller than the proportion of category B in the sample. For example, the LOR value for LTDO in previous crashes is –0.59 for Cluster23. It indicates that this cluster is negatively associated with LTDO who have previous crash histories.

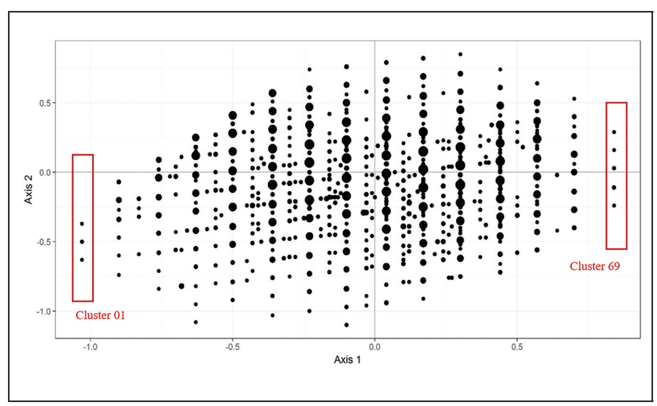

Figure 4. Clusters of large truck-involved people.

Some of the clusters have zero LOR values for all the crash prevalence scenarios. These clusters involved only 0.75% of all LTDOs. Table 4 lists that 13 clusters have LOR values greater than zero for all prevalence groups in the collected data set. These clusters represent 8,339 LTDOs. Out of these 8,339 LTDOs, the people having these prevalence traits are over-represented. Future

Table 4. Log Odds Ratio of Four Crash Prevalence Scenarios

Row labels	Count	Prev_crash (Y_vs_N)	Prev_suspen (Y_vs_N)	Alc (Y_vs_N)	SingleVeh (Y_vs_N)
Cluster01	7	2.07	3.82	3.97	3.27
Cluster02	72	2.67	2.72	1.61	1.42
Cluster03	16	2.26	3.97	1.74	2.58
Cluster04	275	1.77	1.82	1.51	1.59
Cluster05	3	0.00	0.00	0.00	0.00
Cluster06	30	0.47	1.34	2.30	2.49
Cluster07	29	0.00	0.00	5.03	3.64
Cluster08	5	0.00	0.00	0.00	0.00
Cluster09	764	1.14	1.09	0.82	1.01
Cluster10	6	0.00	2.03	0.00	0.00
Cluster11	5	0.00	0.00	0.00	0.00
Cluster12	72	0.47	1.69	0.13	1.93
Cluster13	9	0.00	2.72	0.00	0.00
Cluster14	1623	0.61	0.80	0.60	0.66
Cluster15	4	0.00	0.00	0.00	0.00
Cluster16	9	0.00	2.72	4.38	0.00
Cluster17	86	–0.17	0.70	1.41	1.43
Cluster18	18	0.47	0.42	2.08	2.17
Cluster19	8	1.16	2.03	0.00	1.48
Cluster20	11	0.98	0.00	0.00	1.29
Cluster21	2405	0.30	0.39	0.37	0.35
Cluster22	15	0.75	2.43	2.30	1.88
Cluster23	108	–0.59	–0.25	0.85	1.18
Cluster24	32	–0.31	–0.24	3.43	1.73
Cluster25	5	0.00	0.00	0.00	0.00
Cluster26	9	0.00	0.00	0.00	0.00
Cluster27	3006	0.15	0.20	0.16	0.16
Cluster28	4	0.00	0.00	0.00	0.00
Cluster29	12	0.00	0.00	2.59	0.00
Cluster30	5	0.00	0.00	0.00	0.00
Cluster31	18	0.00	0.00	0.00	0.00
Cluster32	106	–0.72	–0.03	1.80	1.59
Cluster33	5	0.00	0.00	0.00	0.00
Cluster34	36	0.06	0.42	1.29	2.17
Cluster35	8	1.16	0.00	0.00	1.48
Cluster36	12	0.00	0.00	0.00	0.00
Cluster37	3124	–0.05	–0.03	0.06	0.14
Cluster38	37	0.00	0.00	0.00	0.00
Cluster39	116	–0.41	0.20	1.32	1.55
Cluster40	27	–0.09	0.00	1.61	1.70
Cluster41	4	0.00	0.00	0.00	0.00
Cluster42	11	0.00	0.00	0.00	0.00
Cluster43	3186	0.05	–0.10	–0.61	0.02
Cluster44	4	0.00	0.00	0.00	0.00
Cluster45	3	0.00	0.00	0.00	0.00
Cluster46	134	–0.58	–0.12	–0.50	1.69
Cluster47	89	0.68	–1.33	0.00	1.72
Cluster48	8	1.16	0.00	0.00	0.00
Cluster49	6	0.00	0.00	0.00	0.00
Cluster50	3328	–0.05	–0.36	–0.86	–0.38
Cluster51	4	0.00	0.00	0.00	0.00
Cluster52	3	0.00	0.00	0.00	0.00
Cluster53	19	0.00	0.00	0.00	2.51
Cluster54	104	–0.70	–0.21	–0.25	0.38
Cluster55	24	0.06	0.08	0.00	0.38
Cluster56	12	0.00	0.00	0.00	2.17
Cluster57	3220	–0.34	–0.79	–1.21	–1.05
Cluster58	3	0.00	0.00	0.00	0.00

(continued)

Table 4. (continued)

Row labels	Count	Prev_crash (Y_vs_N)	Prev_suspen (Y_vs_N)	Alc (Y_vs_N)	SingleVeh (Y_vs_N)
Cluster59	34	–1.61	–0.74	1.67	–0.54
Cluster60	15	–0.23	0.00	0.00	1.07
Cluster61	8	0.00	0.00	0.00	0.00
Cluster62	10	0.00	0.00	0.00	0.00
Cluster63	2317	–0.77	–1.13	–1.86	–2.49
Cluster64	34	–1.61	0.00	0.00	–1.30
Cluster65	6	0.00	0.00	0.00	0.00
Cluster66	1244	–1.66	–2.04	–1.83	–3.56
Cluster67	8	0.00	0.00	0.00	0.00
Cluster68	279	–3.77	–2.49	–1.94	0.00
Cluster69	16	0.00	0.00	0.00	0.00

Note: Prev_Crash (Y_vs_N) indicates previous crash experiences in last 5 years.

research is needed to explore the driver and occupant traits in these groups.

Conclusion

The U.S. economy benefits immensely from the effective movement of freight. An unprecedented peak in freight-hauling was recorded in 2015, the result of an economic uprising following the recession from 2007 to 2009. In the U.S., the amount of freight transported on a daily basis averaged 49.3 million tons and was valued at nearly $53 billion in 2015 (*49, 50*). In this study, TCA, a robust variant of CA, was applied to 6 years of fatal crashes obtained from FARS. This technique allows a powerful interpretation of the complex association of factors in multivariate events using two-dimensional maps. The method can handle complex data sets with many outliers, which fits the FARS data set perfectly as it only screened for large truck crashes. The findings of this study are as follows:

- Urban intersections are the setting for a disproportionate number of large truck fatal crashes.
- There is a strong association between two-way roadways with an unprotected median and large truck fatal crashes.
- Two distinct clusters (impaired driver's involvement in single-vehicle crashes, and drivers with the past crash record being involved in inclement weather crashes) indicate human error associated patterns in large truck fatal crashes.
- Driving in non-daytime hours is associated with a high number of truck-involved crashes.
- Individual-level TCA analysis identified 69 distinct clouds based on four prevalence driving behaviors. A total of 13 clusters show LOR values greater than zero for all prevalence behavioral groups. These clusters represent 8,339 LTDOs. Out of these 8,339 LTDOs, the people that possess these prevalence traits are over-represented.

The CA approaches focus on the associations between the covariates of crashes rather than the associations between each covariate with the frequency (or odds) of crashes. However, TCA determines the strength of the association of a variable with the frequency of crashes, as shown in the LOR analysis. Because of this, TCA results are more easily interpretable than CA results.

The TCA method, currently being more applied to a large database such as FARS, helps to understand the crash patterns and also to associate the contributing factors to fatal crashes. With the growing body of literature in large truck safety, this study explores TCA in uncovering the deeper relations of factors leading to fatalities. This study is not without limitations. Newer FARS data have been released in the recent years. The current study is limited to 2010–2016 FARS data. In addition, this analysis is limited to a broader group by defining it as large truck. There is a need to separate out large, medium, and very large trucks, which is not done in the current study. The current limitations can be improved in future studies.

Authors' Note

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Subasish Das; data collection: Subasish Das, and Anandi Dutta; analysis and interpretation of results: Subasish Das, Mouyid Islam, Anandi Dutta, and Tahmida Hossain Shimu; draft manuscript preparation: Subasish Das, Mouyid Islam, Anandi Dutta, and Tahmida Hossain Shimu. All authors reviewed the results and approved the final version of the manuscript.

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