This item was submitted to [Loughborough's Research Repository](#) by the author.
Items in Figshare are protected by copyright, with all rights reserved, unless otherwise indicated.

Investigating vehicle roadway usage patterns on the Shanghai urban expressway system and their impacts on traffic safety

PLEASE CITE THE PUBLISHED VERSION

<https://doi.org/10.1080/15568318.2020.1722869>

PUBLISHER

Taylor & Francis

VERSION

AM (Accepted Manuscript)

PUBLISHER STATEMENT

This is an Accepted Manuscript of an article published by Taylor & Francis in International Journal of Sustainable Transportation on 3 February 2020, available online:
<http://www.tandfonline.com/10.1080/15568318.2020.1722869>.

LICENCE

CC BY-NC-ND 4.0

REPOSITORY RECORD

Yu, Rongjie, Yiyun Wang, Mohammed Quddus, Jian Li, Xuesong Wang, and Ye Tian. 2020. "Investigating Vehicle Roadway Usage Patterns on the Shanghai Urban Expressway System and Their Impacts on Traffic Safety". Loughborough University. <https://hdl.handle.net/2134/11877702.v1>.

Investigating Vehicle Roadway Usage patterns on the Shanghai Urban Expressway System and Their Impact on Traffic Safety

Rongjie Yu^{a,b}, Associate Professor

E-mail: yurongjie@tongji.edu.cn

Yiyun Wang^{a,b,*}, Graduate Research Assistant

*** Corresponding Author**

E-mail: 1731347@tongji.edu.cn

Mohammed Quddus^c, Professor

E-mail: M.A.Quddus@lboro.ac.uk

Jian Li^{a,b}, Ph.D. , Associate Professor

E-mail: tongji_lijian@163.com

Xuesong Wang^{a,b,d}, Professor

E-mail: wangxs@tongji.edu.cn

^a The Key Laboratory of Road and Traffic Engineering, Ministry of Education,
201804, Shanghai, China

^b School of Transportation Engineering, Tongji University
4800 Cao'an Road, 201804, Shanghai, China

^c School of Architecture, Building and Civil Engineering, Loughborough University,
Loughborough LE11, 3TU, United Kingdom

^d National Engineering Laboratory for Integrated Optimization of Road Traffic and Safety
Analysis Technologies,
88 Qianrong Rd, Wuxi 214151, China

1 **ABSTRACT**

2 Driving behavior has been identified as the most critical factor for crash occurrence. The
3 turbulent traffic flows, attributed by mixed vehicle types and heterogeneous driving
4 behaviors, are main reasons for crash occurrence. Previous studies have investigated the
5 impacts of traffic flow compositions on safety from the aspects of vehicle type (e.g. trucks,
6 passenger cars, motorcycles) and vehicle territory (e.g. local/non-local vehicles). Little
7 research considers how vehicle road use patterns (based on vehicle traveling rates on a
8 roadway system) affect traffic safety and this is the focus of this study. The empirical
9 analysis was conducted based on data from the Shanghai urban expressway system. First,
10 the license plate recognition (LPR) data were utilized to classify the vehicles and identify
11 road use patterns among them using latent class cluster analysis (LCCA). Then, random-
12 effects hurdle Poisson (REHP) and hurdle negative binomial (REHNB) models were
13 developed with hourly based crash frequency data. The hourly data were used in order to
14 capture the time varying feature of vehicle road use patterns. While considering the
15 excessive zero crash counts and unobserved heterogeneity, random-effects models were
16 employed. From the modeling results it indicated that higher proportions of vehicles with
17 the low-level road use pattern would substantially enhance the possibility of crash
18 occurrence. While proportions of vehicles with the medium-high-level road use pattern had
19 negative impact on crash occurrence likelihood. Finally, the implications for safety
20 improvement from the education and management aspects were discussed.

21
22
23 **Keywords:** Vehicle traveling rate; Vehicle road use pattern; Hourly based crash frequency
24 analysis; Latent class cluster analysis; Random-effects hurdle model
25
26
27

INTRODUCTION

Traffic safety has become one of the most important issues in transportation. More than 12.5 million people worldwide die each year due to traffic crashes. It is widely acknowledged that more than 90% of traffic crashes are attributed to human factors (1). The heterogeneous attitudes toward driving and risky behaviors such as violations, aggressiveness or inattention to the roadway environment are all related to crash occurrence. The various driving behaviors are mainly attributed to the drivers' personal characteristics (e.g. driving experience, age and gender), and their familiarity with the roadway infrastructure and operational conditions (1).

Since traffic flow is composed with a diverse range of drivers, roadway segments with the same level of traffic volume and road geometry are, therefore, experienced with a varying level of traffic safety. One common consequence is that under the same level of service (LOS), more crashes occurred on holidays in comparison to workdays. A case for this phenomenon is presented in Figure 1, which compares the hourly crash frequency distribution for national holidays and workdays with different traffic volumes on the Shanghai urban expressway system. Under the same volume interval, the mean crash frequency for the roadway network during holidays is about 20 times higher compared to workdays. In regard to this phenomenon, traffic engineers often argue that there are more tourist drivers traveling on holidays, who demonstrate a lack of driving experience for both road and traffic conditions. Therefore, roadway segments with a larger proportion of these drivers are more likely to incur a higher percentage of crashes compared to roadway segments with that of commuting drivers. However, this kind of hypothesis has never been examined and validated with empirical data.

FIGURE 1 Hourly Crash Distribution Between Holidays and Workdays in Shanghai

In this paper, we use a terminology - *road use pattern of vehicles* and this is described as whether vehicles sporadically or regularly travel on a roadway system, i.e. spatial and temporal characteristics of traveling rates of vehicles on a roadway system. Figure 2 shows the perspective of present traffic component-related studies and how the focus of this study differs.

FIGURE 2 Present Traffic Component-Related Studies

As for vehicle road use pattern analysis, it aims at understanding motorized travel features and their influencing factors. Vehicles were classified by travel purpose (commercial, recreation and business [2]) and travel frequency (low, medium, and high-level traveling rates [3]). The results of this kind of analysis are critical to traffic planning, operation and management policy. For instance, it will help to: (i) understand a vehicle road use pattern's relationship with urban characteristics (4) and residential environment (5), (ii) evaluate the effect of vehicle road use pattern on traffic flow (6), and (iii) analyze the policies to control urban traffic congestion (6).

This unprecedented study aims to link vehicle road use patterns on a roadway system with traffic safety through an hourly based crash frequency analysis. The empirical analysis was conducted based on data from the Shanghai urban expressway system. First, the LPR data were utilized to classify vehicles (according to their traveling rates) with the latent class cluster analysis (LCCA) technique. The heterogeneous road use patterns of different vehicles that travel on the Shanghai urban expressway system were identified. In order to avoid important information loss (7) and erroneous parameter estimates (8) during the data aggregation procedure, hourly based crash frequency data were formulated to capture the time varying flow components (9, 10). Finally, accounting for the substantial zero crash counts and unobserved heterogeneity, random-effects hurdle Poisson (REHP) and hurdle negative binomial (REHNB) models were applied.

LITERATURE REVIEW

This section focuses on the methods employed to identify different vehicle road use patterns based on vehicle traveling rates on a roadway system and the crash frequency analysis models adopted to investigate the relationship between vehicle road use patterns and traffic safety.

Vehicle Traveling Rates Analyses

To identify the heterogeneity among vehicle road use patterns based on traveling rates, both equal width method and clustering method have been applied. For instance, Li *et al.*, (3) proposed an equal width method, taking 0.33 and 0.67 as cut-off points for traveling rate to split vehicles into low, medium, and high-level categories. However, without looking into data characteristics, the equal width method may lead to biased clusters. Cluster analysis, an unsupervised learning technique, was used to divide a heterogeneous dataset into homogeneous subgroups or clusters (11). Guo *et al.*, (2) employed K-means clustering method and identified three sub-groups, which have travel characteristics of commuting vehicles (with high-level traveling rate on workdays), business vehicles (with low-level traveling rate on all types of days), and recreation vehicles (with high-level traveling rate on holidays and low-level on workdays). However, K-means clustering method could be affected by outliers (12), and the statistical properties of this distance-based clustering algorithm are unknown (13, 14), thus it is hard to decide the optimal number of clustering groups.

Whereas the statistical properties of probability-based clustering technique known as latent class cluster analysis (LCCA) are better understood (15, 16). The LCCA technique has been frequently adopted in transportation studies to deal with the traffic accident heterogeneity issue (14, 17, 18) and describe the unobserved heterogeneity of drivers (3).

1 In addition, the LCCA model outperforms K-means clustering method since LCCA can
2 analyze relationships in categorical data and the data used in the analysis do not need to
3 have the same scale or have equal variances (19). Additionally, the model can be
4 statistically tested to identify the best number of classes (20). In this study, the LCCA model
5 is therefore applied to identify the heterogeneity road use patterns among the vehicles
6 traveling on the roadway system.

8 **Hourly Based Crash Frequency Analyses**

9 For hourly based crash frequency analyses, there are several issues that need to be
10 discussed. First, the rare event of crash observations would cause excess zeros within the
11 dataset. In the literature, zero-inflated models have been widely adopted to deal with the
12 excessive zeros (21, 22). The model is developed based on the assumption that the presence
13 of extra zeros may come from two states: a true-zero state (where the zones are inherently
14 safe) and a non-zero state (which happen to record zero crashes in an observation period)
15 (23). However, intrinsically safe roadway segments would not exist in reality, which makes
16 this fundamental assumption logically fallacious (24, 25). Recently, hurdle models were
17 investigated to be employed as an alternative analysis approach (26). As a two-part model,
18 the first part of the hurdle model is used to decide whether the count value is zero or positive.
19 Given the value is positive, the second part is applied as a count distribution (27). This
20 assumption, where the existence of the zero record was decided by a ‘hurdle’, is more
21 realistic for traffic crash frequency analysis (28). Hojun et al. (29) utilized a hurdle model
22 to identify the dangerous locations and their contributing factors. Chen et al. (30) applied
23 a hurdle model to investigate the real-time characteristics influencing the traffic safety.

24
25 If observations are repeated by roadway segment, and if there are unidentified factors at
26 the segment level (often referred to as the unobserved heterogeneity), then the underlying
27 statistical model has to control for unobserved components in panel data. This would,
28 otherwise, lead to biased parameter estimations and incorrect inferences (31). To deal with
29 this issue, individual roadway segment-based random effects are usually introduced to the
30 model, capturing the unobserved heterogeneity factors for each specific roadway segment
31 (32). Chin (33) developed a random-effects model to examine traffic accident occurrence
32 at signalized intersections. Chen et al. (34) applied a site-specific random-effects model to
33 investigate the real-time environment’s impact on crash occurrence. It has been proved that
34 the utilization of random-effects models enhance the model goodness-of-fits (35, 36). In
35 this study, considering the excessive-zeros and unobserved heterogeneity issues for hourly
36 based crash frequency analysis data, the site-specific REHP and REHNB models were
37 established to analyze factors influencing crash likelihood and crash frequency.

DATA

This study utilized the Shanghai urban expressway system as the study area. The study time period was set on October 2012, considering the data availability from different resources period. The data included 7 national holidays (National Day and Mid-Autumn Festival), 6 weekends, and 18 workdays. A total of three datasets were employed: (i) LPR data; (ii) traffic crash data; and (iii) roadway segment geometric data. LPR data were utilized to extract vehicle traveling rate variables and traffic operational status variables, combined with geometric data and crash data, to form the hourly crash frequency analysis data.

License Plate Recognition Data

For the Shanghai urban expressway license plate recognition system, 268 detector points along the system were employed to detect and record the information for each vehicle. Table 1 lists the recorded parameters and the descriptions.

TABLE 1 Description of LPR Data

Parameters	Descriptions
TIME	Time when a vehicle passes through the detector point
TRANSECT ID	ID number of detector points
LANE NO	Number of lanes of the segment on which a vehicle is traveling
VEHICLE ID	License plate number of vehicles
COLOR	License plate color of vehicles: 01-yellow: large vehicle 02-blue: light vehicle 06- black: foreign enterprise or embassy vehicle 25-white: special vehicle
VEHICLE REGION	Region of vehicles
SPEED	Vehicle speed: km/h

After the data cleansing process, more than 3 million individual light vehicles were detected along the expressway system. Three features were introduced to describe the vehicle traveling rate characteristics:

$$(i) \text{ Workday Traveling Rate (vehicle's traveling rate on workdays)} = \frac{n_{wo}}{N_{wo}} \quad (1)$$

$$(ii) \text{ Weekend Traveling Rate (vehicle's traveling rate on weekends)} = \frac{n_{we}}{N_{we}} \quad (2)$$

$$(iii) \text{ Holiday Traveling Rate (vehicle's traveling rate on holidays)} = \frac{n_{ho}}{N_{ho}} \quad (3)$$

Where n_{wo} , n_{we} and n_{ho} is the number of days that specific vehicle has traveling record on workday, weekend and holiday. N_{wo} , N_{we} and N_{ho} equals to 18, 6 and 7 respectively

meaning the total number of days for workday, weekend and holiday.

The summary statistics and distribution illustrations for vehicle traveling rate features are shown in Table 2.

TABLE 2 Summary Statistics for Vehicle Traveling Rate Features

Traveling Rate Features	Mean	s.d.	15 th Percentile	50 th Percentile	85 th Percentile
Workday Traveling Rate	0.34	0.32	0.06	0.24	0.82
Weekend Traveling Rate	0.32	0.30	0	0.17	0.67
Holiday Traveling Rate	0.28	0.28	0	0.14	0.57

In order to develop the LCCA model, the continuous traveling rate feature parameters were discretized into categories. A percentile classification method was used here, which employed the 15th percentile, 50th percentile, and 85th percentile as cut-off. The categories under each traveling rate feature parameters were marked as levels 1-4 corresponding to the degree of traveling rate from low to high. The final classified categories are shown in Table 3. The obtained 12 categories will be used as variables in LCCA model to find heterogeneous road use patterns among vehicles.

TABLE 3 Categories under Each Traveling Rate Feature Parameter

Traveling Rate Feature Parameters	Categories	Values	Count	Proportion
Workday Traveling Rate	L1	<6%	820980	26%
	L2	6~24%	887398	28%
	L3	24%~82%	1070361	34%
	L4	>82%	395981	12%
Weekend Traveling Rate	L1	0	917184	29%
	L2	0~17%	713908	22%
	L3	17%~67%	1164131	37%
	L4	>67%	379497	12%
Holiday Traveling Rate	L1	0	916241	29%
	L2	0~14%	721632	23%
	L3	14%~57%	1137273	36%
	L4	>57%	399574	12%

Crash Frequency Analysis Data

For crash data, Figure 3 shows the hourly based temporal distribution of crash frequency on the entire expressway system. It demonstrates that the number of crashes reported during 23:00 to 06:00 was limited. The small magnitude of crashes would have minimal contribution to the statistical model and the potential non-reporting event could be included in the model, which therefore might produce biased estimation. Thus the time period of the

1 final dataset was set from 06:00 to 23:00. A similar time data processing approach can be
 2 seen in Mo et al.'s research (37).
 3

4
 5 **FIGURE 3 Hourly Distribution of Crash Frequency**

6
 7 A total of 1,659 crashes which occurred on the corresponding road segments were
 8 considered in the analysis. Crash data were aggregated into 1 hour interval data by 191
 9 roadway segments, which were split using on-ramps and off-ramps as dividing points (20).
 10 After the data aggregation procedure, crash frequency per hour has the mean of 0.0176 per
 11 roadway segment and the standard deviation of 0.1666, with the 98.63% of the roadway
 12 segments possess zero crash count.

13
 14 Geometric characteristics data for each roadway segment were obtained from on-line
 15 street-view maps. The summary statistics for geometric variables are shown in Table 4,
 16 with the ramp combination types indicated in Figure 4.

17
 18 **TABLE 4 Description of Geometric Variables**

Variable	Description	Summary Statistics
Length	Roadway segment length (m)	Mean: 923.9 s.d.: 536.64
Ramp Type	Ramp combination type: 1. Off-ramp and On-ramp	1: 64 2: 36

	2. Off-ramp and Off-ramp	3: 22
	3. On-ramp and Off-ramp	4: 69
	4. On-ramp and On-ramp	
Curve	If it is a curve section:	1: 92
	1. Curve section	0: 99
	0. Straight section	
Speed Limit Sign	If there is speed limit sign within the roadway segment:	1: 65
		0: 126
	1. Has speed limit sign	
	0. No speed limit sign	
Transition Length	The ratio of transition length of a roadway segment (m)	Mean: 182.5 s.d.: 175.04
Speed Limit Value	The level of speed limit value:	1: 78
	1. 50km/h and 60km/h	2: 113
	2. 80km/h	
DMS	If there is DMS within the roadway segment:	1: 57
	1. Has DMS	0: 134
	0. No DMS	
Main Lane	The level of lane numbers for the main road:	1: 61
	1. Has 2 lanes	2: 84
	2. Has 3 lanes	3: 46
	3. Has 4 lanes and above	
Access Lane 1	The level of lane numbers for the up-access road:	1: 26
	1. Has 1 lane	2: 165
	2. Has 2 lanes and above	
Access Lane 2	The level of lane numbers for the down-access road:	1: 26
	1. Has 1 lane	2: 165
	2. Has 2 lanes and above	

1

2

3

4

FIGURE 4 Ramp Type Illustration

It is worth mentioning that since no prior assumptions were used about the functional relationships between traffic operational parameters and crash frequency for the Shanghai urban expressway system, different functional forms were tested for the traffic volume and speed variables. This includes: volume and its quadratic form, vehicle miles travelled; speed and its quadratic form, and speed gap (speed limit value minus average speed). In the final analysis results, only the significant variables and the best functional forms were kept.

METHODOLOGY

Latent Class Cluster Analysis

The LCCA is a probability-based cluster analysis method (38). Like all cluster analysis methods, the LCCA separates the heterogeneous population into groups so that the similarity within the group is maximized and similarity between group elements is minimized (39). Different statistical criteria are available in LCCA output, which can be used to identify the appropriate number of clusters (17). In this study, the LCCA models were developed through a R package named poLCA (40).

Given the set of vehicle-level data, there are n_c latent classes to be estimated based on a set of $\mathbf{M}$ categorical vehicle traveling rate feature parameters ($M=3$ in this study, which are workday traveling rate, weekend traveling rate, and holiday traveling rate). Let the vector $Y_i = (Y_{i1}, \dots, Y_{iM})$ denote the individual vehicle i 's responses to the M items, where the Y_{iM} takes possible values $1, \dots, r_M$. Let $L_i = 1, 2, \dots, n_c$ be the latent class membership of observation i ; and let $I(y=k)$ be the indicator function, which equals 1 if y equals k , and 0 otherwise. Then the contribution by observation i can be expressed as:

$$P(Y_i = y) = \sum_{l=1}^{n_c} \gamma_l \prod_{m=1}^M \prod_{k=1}^{r_m} \rho_{mk|l}^{I(y_m=k)} \quad (4)$$

where γ is the prevalence or class-membership probability, and ρ is the item-response probabilities conditional on latent class membership.

To determine the number of clusters, Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) and Consistent Akaike Information Criteria (CAIC) are usually utilized. Percentage reductions in criteria between competing models were analyzed to determine the classification number (18).

Random Effects Hurdle Count Models

In this study, the REHP model and REHNB model were developed. Among which, Y_{it} represents the crash frequency with its observed value y_{it} for roadway segment i at time interval t . The conditional probabilities of responses for the random effects are given by:

$$p(y_{it}; \mathbf{b}_i) = \begin{cases} p_{it}^c(b_{i1}) & \text{if } y_{it} = 0 \\ (1 - p_{it}^c) \frac{g_i(y_{it}; \lambda_{it}^c(b_{i2}))}{1 - g_i(0; \lambda_{it}^c(b_{i2}))} & \text{if } y_{it} > 0 \end{cases} \quad (5)$$

logit $p_{it}^c(b_{i1}) = \Delta_{it1} + z_{it1}^T b_{i1}$, p_{it}^c is the probability of the i^{th} roadway segment to be in the zero state at time interval t .

For Poisson distribution:

$$g_i(y_{it}; \lambda_{it}^c(\mathbf{b}_{i2})) = \frac{\exp(-\lambda_{it}^c(b_{i2})) \lambda_{it}^c(b_{i2})^{y_{it}}}{y_{it}!} \quad (6)$$

and for negative binomial distribution:

$$g_i(y_{it}; \lambda_{it}^c(\mathbf{b}_{i2})) = \frac{\Gamma(v^{-1} + y_{it})}{\Gamma(v^{-1}) y_{it}!} \left(\frac{1}{1 + v \lambda_{it}^c(b_{i2})} \right)^{v^{-1}} \left(\frac{v \lambda_{it}^c(b_{i2})}{1 + v \lambda_{it}^c(b_{i2})} \right)^{y_{it}} \quad (7)$$

logit $\lambda_{it}^c(b_{i2}) = \Delta_{it2} + z_{it2}^T b_{i2}$, λ_{it}^c is the expected number of crashes on the i^{th} roadway segment at time interval t . Δ_{it1} and Δ_{it2} are connector functions corresponding to the $\mathbf{b}_{i1}$ and $\mathbf{b}_{i2}$ with their regressors z_{it1}^T and z_{it2}^T , respectively.

$\mathbf{b}_i$ is the random-effects vector for the i^{th} roadway segment, and it obeys distribution:

$$\mathbf{b}_i = \begin{pmatrix} \mathbf{b}_{i1} \\ \mathbf{b}_{i2} \end{pmatrix} \sim N(\mathbf{0}, \Sigma) \quad (8)$$

where $\mathbf{b}_{i1}$ and $\mathbf{b}_{i2}$ are random vectors of the zero part and the positive count part. They are assumed to be independent to each other. Thus, the variance-covariance matrix for them is given as:

$$\Sigma = \begin{pmatrix} d_1^2 & 0 \\ 0 & d_2^2 \end{pmatrix} \quad (9)$$

The models were built with NLMIXED procedure in SAS (41). For the model goodness-of-fit evaluations, both Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) values were adopted. The AIC is defined as:

$$AIC = -2l + 2p \quad (10)$$

and BIC is defined as:

$$BIC = -2l + p \ln(n) \quad (11)$$

where l is log-likelihood, p is the number of parameters and n is the number of samples. The smaller AIC or BIC value indicates a better fitted model.

MODELING RESULTS

Vehicle Road Use Patterns Identification

To identify the optimal number of homogeneous classes representing vehicle traveling rates on the Shanghai urban expressway system, LCCA models with 1-class to 7-class clusters

were estimated. Figure 5 shows the evolutions of BIC, AIC and CAIC for the 7 models. As the number of clusters increases from 1-class to 3-class, the values of BIC, AIC and CAIC reduces substantially. However, the BIC, AIC and CAIC values hardly show additional improvement over the 4 clusters. Thus, the model with 4 clusters was selected, ensuring the classification interpretability and maintaining the model succinct (14, 42). The probabilities for 4 clusters under different traveling rate characteristics are shown in Table 5 and the characterizations for each cluster are given in Table 6.

FIGURE 5 Identification of Number of Clusters for Vehicle Road Use Patterns

TABLE 5 Probabilities of Membership to Each Cluster

Parameters	Categories	cluster1 (%)	cluster2 (%)	cluster3 (%)	cluster4 (%)
WO (workday)	L1	0	4	40	95
	L2	1	18	45	0
	L3	33	64	14	3
	L4	66	14	1	2
WE (weekend)	L1	0	4	47	92
	L2	0	15	35	2
	L3	20	71	18	6
	L4	80	10	0	0
HO (holiday)	L1	1	11	51	0
	L2	2	18	28	47
	L3	26	57	20	52
	L4	71	14	1	1

(L1 to L4: vehicle traveling rates range from low to high)

Cluster 1: 99%, 100% and 97% of the vehicles in this cluster have either the 3rd or the 4th level traveling rates on workdays, weekends and holidays. This cluster has high traveling rate as 66%, 80% and 71% of the vehicles are categorized as the 4th level. We refer to this cluster as “high-level road use pattern”.

Cluster 2: 88%, 81% and 71% of the vehicles in this cluster have either the 3rd or the 4th level traveling rates on workdays, weekends and holidays. This cluster is different from Cluster 1 as it only has 14%, 10% and 14% of the vehicles categorized as the 4th level. This cluster is referred to as “medium-high-level road use pattern”.

Cluster 3: This cluster has 85%, 82% and 79% of the vehicles with a low level of traveling rates (i.e. 1st and 2nd level) on workdays, weekends and holidays. We refer to this cluster as “low-medium-level road use pattern”.

Cluster 4: This cluster contains 95% and 92% of the vehicles that travelled at the 1st level on workdays and weekends, while 53% of the vehicles travelled at the 3rd level or 4th level on holidays. This cluster is referred to as “low-level road use pattern”.

TABLE 6 Characterizations for Each Cluster

Cluster	Characterization	Proportion (%)
1: high-level road use pattern	vehicles with a high level traveling rate on all the types of days	9
2: medium-high-level road use pattern	vehicles with a medium-high level traveling rate on all the types of days	35
3: low-medium-level road use pattern	vehicles with a low-medium level traveling rate on all the types of days	52
4: low-level road use pattern	vehicles merely travel on holidays	4

Hourly Based Crash Frequency Analyses

For the hourly based crash frequency analyses, REHP model and REHNB model were established. A total of four types of variables were found to be significant: roadway geometry characteristics, temporal features, traffic operational statuses and vehicle road use pattern proportions. Multicollinearities between variables were tested before estimating the model, and there was no correlation found between the variables.

The modeling results were shown in Table 7. From the model goodness-of-fit indexes, the REHNB model provided slightly better fitness. Therefore, the following section will only introduce the modeling results of REHNB model.

1
2
3

TABLE 7 Modeling Results for REHP and REHNB Models

Variable	REHP			REHNB		
	Coff.	s.d.	p value	Coff.	s.d.	p value
Binary part						
Intercept	-2.34	0.65	<0.001	-2.34	0.65	<0.001
<i>Roadway geometry characteristics</i>						
Ramp Type 2	0.70	0.21	<0.001	0.70	0.21	<0.001
Ramp Type 3	0.99	0.24	<0.0001	0.99	0.24	<0.0001
Ramp Type 4	1.15	0.17	<0.0001	1.15	0.17	<0.0001
<i>Temporal features</i>						
Workday	-1.22	0.24	<0.0001	-1.22	0.24	<0.0001
Morning Peak	0.94	0.24	0.0001	0.94	0.24	0.0001
<i>Traffic operational statuses</i>						
VMT	0.10	0.03	<0.001	0.10	0.03	<0.001
Log Average Speed	-0.58	0.13	<0.0001	-0.58	0.13	<0.0001
Shanghai Vehicles Proportion	-1.22	0.24	<0.0001	-1.22	0.24	<0.0001
<i>Vehicle road use pattern proportions</i>						
Low-Level Proportion	59.94	1.90	<0.0001	59.94	1.90	<0.0001
Medium-High-Level Proportion	-7.10	0.78	<0.0001	-7.10	0.78	<0.0001
Count part						
Intercept	-3.60	1.04	<0.001	-4.25	1.18	<0.001
<i>Roadway geometry characteristics</i>						
Ramp Type 2	0.54	0.24	<0.05	0.59	0.27	<0.05
Ramp Type 3	0.65	0.26	<0.05	0.71	0.29	<0.05
Ramp Type 4	0.52	0.22	<0.05	0.56	0.24	<0.05
Log Length	0.43	0.14	<0.05	0.46	0.15	<0.05
<i>Traffic operational statuses</i>						
Shanghai Vehicles Proportion	-0.54	0.23	<0.001	-0.56	0.25	<0.001
<i>Vehicle road use pattern proportions</i>						
Low-Level Proportion	13.19	3.53	<0.001	14.25	4.11	<0.001
Medium-High-Level Proportion	-2.67	1.33	<0.05	-2.92	1.56	<0.05
Beta	-		-	1.44	0.91	0.1149
d1	0.44	0.08	<0.0001	0.42	0.09	<0.0001
d2	0.79	0.07	<0.0001	0.79	0.07	<0.0001
-2log-likelihood		11676			11665	
AIC		11718			11709	
BIC		11786			11780	

1
2
3 *Binary part as logistic model*

4 The binary part of the REHNB model identifies the influencing factors for the possibility
5 of having crashes within the observation time period, where a positive regression
6 coefficient implies an increasing trend.

7 **Roadway geometry characteristics**

8 Ramp Type variable was found to be significant, for which Ramp Type 1 was selected as
9 the reference category. Compared to Ramp Type 1, Ramp Type 2, 3 and 4 are significant
10 with positive signs while Ramp Type 4 has the largest estimated coefficients. These indicate
11 the higher probability of crash occurrence on Ramp Type 2, 3 and 4 comparing to that on
12 Ramp Type 1. It implies that the off-on ramp type combination (Ramp Type 1) is the safest
13 among the other ramp types, while the on-on ramp type combination is among the most
14 dangerous.

15 **Temporal features**

16 For temporal features, Workday and Morning Peak variables were found to be significant.
17 The regression coefficient for Workday is negative, indicating that workdays are less likely
18 to incur hourly crashes as opposed to weekends and holidays. In terms of Morning Peak
19 variable, it has a positive sign, which implies that it is more likely to incur crashes during
20 morning peak hours.

21 **Traffic operational statuses**

22 With respect to traffic operational statuses, the VMT (vehicles miles traveled) variable was
23 found to be positive. Crashes have higher probabilities of occurrence as the VMT increases.
24 Average speed variable was included in the model with an exponential form, and found to
25 be significant with a negative sign. It is implied that the higher probability of crashes lies
26 in segments with lower average speed. Moreover, the proportion of vehicles with a
27 Shanghai license plate was found to be significant with a negative sign. It concluded that
28 roadway segments with a higher composition of local vehicles are expected to have a lower
29 possibility of crash occurrence.

30 **Vehicle road use pattern proportions**

31 In terms of vehicle road use pattern compositions, the regression parameter for Low-Level
32 Proportion variable is significant with a positive sign. It indicates that segments with a
33 larger proportion of vehicles with the low-level road use pattern are more likely to incur
34 crashes. On the contrary, the Medium-High-Level Proportion variable is negative, which
35 implies that the segments that have a larger proportion of vehicles with the medium-high-
36 level road use pattern are associated with less crashes.

37
38 *Count part as negative binomial model*

39 As a counterpart to the binary part, the count part of the REHNB model reveals the

1 impacting factors for the crash frequency, where positive regression coefficients indicate
2 the increasing number of crash occurrence.

3 **Roadway geometry characteristics**

4 For the roadway geometry characteristics, two variables were found to be significant:
5 Ramp Type and Log Length. The Ramp Type variables showed similar results as the binary
6 part. Ramp Type1 was used as the reference category, and the regression coefficients of
7 Ramp Type 2, 3 and 4 were all positive, where Ramp Type 3 had the largest estimated value.
8 It is indicated that segments with off-on ramp combination type (Ramp Type 1) have the
9 least number of crashes and segments with on-off ramp type combination (Ramp Type 3)
10 contain the most. It is consistent with the research performed by Yu et al. (20). Log Length
11 variable has a positive coefficient, which indicates that the number of crashes would
12 increase along with the length of roadway segment. A similar modeling result was found
13 in a study investigated by Chen (30).

14 **Traffic operational statuses**

15 Shanghai Vehicles Proportion variable was found to be significant with a negative sign,
16 which means that roadway segments with a higher composition of local vehicles are
17 expected to reduce the crash number.

18 **Vehicle road use pattern proportions**

19 With respect to vehicle road use pattern composition, similar to the binary part, Low-Level
20 Proportion variable and Medium-High-Level Proportion variable were found to be
21 significant. Low-Level Proportion variable is significantly positive, which indicates
22 segments that have a larger proportion of vehicles with the low-level road use pattern are
23 more likely to have more hourly crashes. Medium-High-Level Proportion variable is
24 negative, which implies that the segments that have a larger proportion of vehicles with the
25 medium-high-level road use pattern are associated with less crashes.

28 **DISCUSSION AND CONCLUSION**

29 In this study, a relationship was developed between vehicle road use patterns (based on
30 vehicle traveling rates) on a roadway system and traffic safety through an hourly based
31 crash frequency analysis. LPR data were utilized, *for the first time*, to identify the
32 heterogeneous vehicle road use patterns with the LCCA technique. Both REHP (random-
33 effects Hurdle Poisson) model and REHNB (random-effects Hurdle NB) model were
34 established to deal with the excess zeros and unobserved heterogeneity issues.

36 Several interesting findings are concluded: (i) a higher proportion of vehicles with the low-
37 level road use pattern on a roadway system would increase the possibility of crash
38 occurrence and the number of crashes. This type of vehicles is normally making leisure
39 trips and traveling from the suburban area or the outside of the city. Their unfamiliarity

1 with the roadway and traffic conditions might have led to less experienced driving
2 behaviors and unexpected hazardous driving scenarios, which further increase the crash
3 occurrence likelihood; (ii) A higher proportion of vehicles with the medium-high-level road
4 use pattern would reduce the crash likelihood. These vehicles might travel on the Shanghai
5 urban expressway much more frequent and their drivers are familiar with the traffic
6 dynamics, bottlenecks and road configurations which reduce the crash occurrence risk;
7 (iii) A higher proportion of vehicles with Shanghai license plate was also found to reduce
8 the crash likelihood and the number of crashes. It could also be explained by their
9 familiarity with the infrastructures and traffic operational conditions of the roadway
10 network.

11
12 Based on the modeling results, several recommendations are put forward. First, education,
13 campaign and driver training would be the key to reduce traffic crashes during holidays
14 and weekends targeting at drivers who make leisure trips to unfamiliar areas. Second,
15 previous safety control and management measures were mostly based on the volume
16 indicator (e.g. UK motorway control algorithm adopts similar variable-speed limit sign
17 (VSLs) control strategy under the same volume level [43]). However, the proportions of
18 vehicles making trips for different purposes (e.g. commuting, leisure, business) would vary
19 significantly under the same volume level, which would lead to different degrees of crash
20 occurrence risk. Therefore, implementing the measures (e.g. variable message signs)
21 suitable for workdays may not be effective during weekends and holidays. Traffic control
22 and management strategies aimed at different drivers should further be investigated.
23 Furthermore, future studies could be conducted to understand the operational
24 characteristics at vehicle-level (i.e. lane changing behavior, driving speed) to unveil the
25 differences in driving behaviors between drivers who frequently use a roadway system and
26 the drivers who rarely use the same roadway system.

27
28
29 **Acknowledgements:** This study was jointly sponsored by the Chinese National Natural
30 Science Foundation (NSFC 71771174 and 71531011) and the 111 Project (B17032).

31
32
33 **Author contribution statement:**

34 The authors confirm contribution to the paper as follows: Study conception and design:
35 Yu, R. and Wang, Y, data collection: Wang, Y. and Yu, R. analysis and interpretation of
36 results: Yu, R., Wang, Y., Quddus, M. draft manuscript preparation: Yu, R., Wang, Y.,
37 Quddus, M, Li, Jian, Wang, X. All authors reviewed the results and approved the final
38 version of the manuscript
39

2 **REFERENCE**

- 3 [1] Treat, John R. Tri-level study of the causes of traffic accidents: an overview of final
4 results. *Proceedings: American Association for Automotive Medicine Annual Conference*.
5 1977.
- 6 [2] Guo, X., and C. Chen. Study of Traffic Characteristics and Vehicle Using Features
7 Based on Vehicle License Plate Data: A Case Study of Shanghai. *China Transportation*
8 *Review*, 2016.
- 9 [3] Li, D., T. Miwa, and T. Morikawa. Modeling Time-of-Day Car Use Behavior: A
10 Bayesian Network Approach. *Transportation Research Part D: Transport and*
11 *Environment*, 2016. 47: 54-66.
- 12 [4] Wan, X., J. Chen, W. Hu, and Y. Jing. Empirical Analysis of the Relationship between
13 Car Use Behavior and Urban Characteristics: Case Study of China. In *2008 International*
14 *Conference on Intelligent Computation Technology and Automation (ICICTA)*, 2008. 2:
15 358-363.
- 16 [5] Wang, F., and D. Wang. Characteristics and determinants of car use in Beijing, *Acta*
17 *Geographica Sinica-Chinese Edition*, 2014. 69.6: 771.
- 18 [6] Chen, X., X. Yang, and Q. Shi. Estimation of Vehicle Usage Rate Based on Capture-
19 Recapture Model with License Plate Recognition Data. *11th International IEEE*
20 *Conference on Intelligent Transportation Systems*, 2008.
- 21 [7] Lord, D., and F. Mannering. The Statistical Analysis of Crash-Frequency Data: A
22 Review and Assessment of Methodological Alternatives. *Transportation Research Part A:*
23 *Policy and Practice*, 2010. 44.5: 291-305.
- 24 [8] Coburn, T. C. Statistical and Econometric Methods for Transportation Data Analysis.
25 *Technometrics*, 2004. 46.4: 492-493.
- 26 [9] Chen, F., X. Ma, and S. Chen. Refined-Scale Panel Data Crash Rate Analysis Using
27 Random-Effects Tobit Model. *Accident Analysis & Prevention*, 2014. 73: 323-332.
- 28 [10] Ma, X., F. Chen, and S. Chen. Modeling Crash Rates for a Mountainous Highway
29 Using Refined-Scale Panel Data. In *Transportation Research Board Meeting*, 2015.
- 30 [11] Berry, J.A., M., and G. S. Linoff. *Data Mining Techniques: For Marketing, Sales, and*
31 *Customer Support*. John Wiley & Sons, Inc., 1997.
- 32 [12] Rai, P., and S. Shubha. A Survey of Clustering Techniques. *International Journal of*
33 *Computer Applications*, 2010. 7.12: 1-5.
- 34 [13] Fraley, C., and A. Raftery. Model-Based Clustering, Discriminant Analysis, and
35 Density Estimation. *Journal of the American statistical Association*, 2002. 97.458: 611-
36 631.
- 37 [14] Depaire, B., G. Wets, and K. Vanhoof. Traffic Accident Segmentation by Means of
38 Latent Class Clustering. *Accident Analysis & Prevention*, 2008. 40.4: 1257-1266.
- 39 [15] Bock, H. H. Probabilistic Models in Cluster Analysis. *Computational Statistics &*

1 *Data Analysis*, 1996. 23.1: 5-28.

2 [16] Fraley, C., and A. E. Raftery. Model-Based Clustering, Discriminant Analysis, and
3 Density Estimation. *Journal of the American Statistical Association*, 2002. 97.458: 611-
4 631.

5 [17] de Oña, J., G. López, R. Mujalli, and F. J. Calvo. Analysis of Traffic Accidents on
6 Rural Highways Using Latent Class Clustering and Bayesian Networks. *Accident Analysis
7 & Prevention*, 2013. 51: 1-10.

8 [18] Sasidharan, L., K.-F. Wu, and M. Menendez. Exploring the Application of Latent Class
9 Cluster Analysis for Investigating Pedestrian Crash Injury Severities in Switzerland.
10 *Accident Analysis & Prevention*, 2015: 219-228.

11 [19] Schreiber, J. B. Latent Class Analysis: An Example for Reporting Results. *Research
12 in Social and Administrative Pharmacy*, 2017. 13.6: 1196-1201.

13 [20] Yu, R., X. Wang, and M. Abdel-Aty. A Hybrid Latent Class Analysis Modeling
14 Approach to Analyze Urban Expressway Crash Risk. *Accident Analysis & Prevention*,
15 2017. 101: 37-43.

16 [21] Lee, J., and F. Mannering. Impact of Roadside Features on the Frequency and Severity
17 of Run-off-Roadway Accidents: an empirical analysis. *Accident Analysis & Prevention*,
18 2002. 34.2: 149-161.

19 [22] Chin, H., and M. Quddus. Modeling Count Data with Excess Zeroes. *Sociological
20 methods & research*, 2003. 32.1: 90-116.

21 [23] Shankar, V., J. Milton, and F. Mannering. Modeling Accident Frequencies as Zero-
22 altered Probability Processes: An Empirical Inquiry. *Accident Analysis & Prevention*, 1997.
23 29.6: 829-837.

24 [24] Lord, D., S. P. Washington, and J. N. Ivan. Poisson, Poisson-Gamma and Zero-Inflated
25 Regression Models of Motor Vehicle Crashes: Balancing Statistical Fit and Theory.
26 *Accident Analysis & Prevention*, 2005. 37.1: 35-46.

27 [25] Lord, D., S. Washington, and J. N. Ivan. Further Notes on the Application of Zero-
28 Inflated Models in Highway Safety. *Accident Analysis & Prevention*, 2007. 39.1: 53-57.

29 [26] Hosseinpour, M., J. Prasetijo, A. S. Yahaya, and S. M. R. Ghadiri. A Comparative
30 Study of Count Models: Application to Pedestrian-Vehicle Crashes Along Malaysia
31 Federal Roads. *Traffic Injury Prevention*, 2013. 14.6: 630-638.

32 [27] Cragg, J. G. Some Statistical Models for Limited Dependent Variables with
33 Application to the Demand for Durable Goods. *Econometrica*, 1971. 39.5: 829-844.

34 [28] Kassahun, W., T. Neyens, G. Molenberghs, C. Faes, and G. Verbeke. Marginalized
35 Multilevel Hurdle and Zero-Inflated Models for Overdispersed and Correlated Count Data
36 with Excess Zeros. *Statistics in Medicine*, 2014. 33.25: 4402-4419.

37 [29] Son, H. D., Y.-J. Kweon, and B. B. Park. Development of Crash Prediction Models
38 with Individual Vehicular Data. *Transportation Research Part C: Emerging Technologies*,
39 2011. 19.6: 1353-1363.

- [30] Chen, F., X. Ma, S. Chen, and L. Yang. Crash Frequency Analysis Using Hurdle Models with Random Effects Considering Short-Term Panel Data. *International Journal of Environmental Research and Public Health*, 2016. 13.11: 1043.
- [31] Mannering, F. L., and C. R. Bhat. Analytic Methods in Accident Research: Methodological Frontier and Future Directions. *Analytic Methods in Accident Research*, 2014. 1: 1-22.
- [32] Agüero-Valverde, J. Full Bayes Poisson Gamma, Poisson Lognormal, and Zero Inflated Random Effects Models: Comparing the Precision of Crash Frequency Estimates. *Accident Analysis & Prevention*, 2013. 50: 289-297.
- [33] Chin, H. C., and M. A. Quddus. Applying the Random Effect Negative Binomial Model to Examine Traffic Accident Occurrence at Signalized Intersections. *Accident Analysis & Prevention*, 2003. 35.2: 253-259.
- [34] Chen, F., S. Chen, and X. Ma. Crash Frequency Modeling Using Real-Time Environmental and Traffic Data and Unbalanced Panel Data Models. *International Journal of Environmental Research and Public Health*, 2016. 13.6: 609.
- [35] Min, Y., and A. Agresti. Random Effect Models for Repeated Measures of Zero-Inflated Count Data. *Statistical modelling*, 2005. 5.1: 1-19.
- [36] Yu, R., M. Abdel-Aty, and M. Ahmed. Bayesian Random Effect Models Incorporating Real-Time Weather and Traffic Data to Investigate Mountainous Freeway Hazardous Factors. *Accident Analysis & Prevention*, 2013. 50: 371-376.
- [37] Mo, B., R. Li, and X. Zhan. Speed Profile Estimation Using License Plate Recognition Data. *Transportation research part C: emerging technologies*, 2017. 82: 358-378.
- [38] Magidson, J., and J. Vermunt. Latent Class Models for Clustering: A Comparison with K-means. *Canadian Journal of Marketing Research*, 2001. 20.1: 36-43.
- [39] Hair, JF, et al. *Multivariate data analysis with readings*. London: Macmillan, 1992.
- [40] B. Lewis, J., and D. A. Linzer. poLCA: An R Package for Polytomous Variable Latent Class Analysis. *Journal of statistical software*, 2011. 42.10: 1-29.
- [41] Wolfinger, Russell D. "Fitting Nonlinear Mixed Models with the New NLMIXED Procedure." *Proceedings of the 24th Annual SAS Users Group International Conference (SUGI 24)*. 1999.
- [42] Scheier, L. M., A. B. Abdallah, J. A. Inciardi, J. Copeland, and L. B. Cottler. Tri-city Study of Ecstasy Use Problems: A latent Class Analysis. *Drug and Alcohol Dependence*, 2008. 98.3: 249-263.
- [43] Allaby, P., B. Hellinga, and M. Bullock. Variable Speed Limits: Safety and Operational Impacts of a Candidate Control Strategy for Freeway Applications. *IEEE Transactions on Intelligent Transportation Systems*, 2007. 8.4: 671-680.