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Effects of traffic enforcement cameras on macro-level traffic safety: A spatial modeling analysis considering interactions with roadway and Land use characteristics

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ABSTRACT

Nowadays, intelligent transportation system (ITS) planning has been often integrated into transportation planning stage. As a component of ITS, traffic enforcement cameras have been found to reduce dangerous behaviors, such as red-light running and speeding. However, with limited resource, it is important to understand the effects of enforcement cameras on macro-level safety, so that traffic policy-makers can better allocate those resources to improve traffic safety from the planning stage. In this paper, we examined the effects of various traffic enforcement cameras on regional traffic crash risk, considering their interactions with roadway and land use characteristics. The Kunshan city in Suzhou, China was selected in this study and a spatial modeling analysis was applied. According to the modeling results, several conclusions can be drawn: 1. Interaction effects on regional injury/PDO crash risk were found between traffic enforcement cameras and roadway/land use factors; 2. Traffic enforcement cameras were found to be associated with decreased regional crash risk. Among them, red-light running and speeding cameras were associated with the reduction of injury/PDO crash frequency, which can be further enhanced when being installed in certain area (e.g. industrial, commercial, residential land use) and on certain roadways (e.g. major arterials, local roads). Illegal lane changing cameras were associated with the decrease in PDO crash frequency, while such effect on reducing injury crashes was only found as significant on major arterials; 3. The main effects of certain land use and roadway factors appeared to be mediated by traffic enforcement interaction terms. For example, the main effect of industrialized land use was found as insignificant, while the interaction term between industrial area and speeding cameras showed a significant effect of reducing injury/PDO crash frequency. Based on those findings, traffic enforcement cameras, as one of the major components of ITS, need to be carefully considered at the transportation planning stage. In general, this study provides valuable information for policy-makers and transportation planners to improve regional traffic safety, by properly allocating traffic enforcement resources.

1. Introduction

Nowadays, intelligent transportation system (ITS) planning has been often incorporated into transportation planning process. By leveraging investments with ITS treatments, a more efficient, safer, economically-sound, and environmentally-sensitive transportation system can be expected. As a common ITS treatment, traffic enforcement cameras have been implemented in many cities across the world to monitor aberrant and aggressive driving behaviors. It has been proven that traffic enforcement cameras can effectively reduce diving violations and in turn improve overall traffic safety (Li and Graham, 2016; Porter et al., 2013; Vanlaar et al., 2014; Ruiz et al., 2019; Goldenbeld et al., 2019). Red-light running camera and speeding camera are the two common types that have been extensively installed. With the development of sensing technology and computer vision techniques, other traffic enforcement camera types have been emerging, which are able to detect other high-risk driving behaviors such as illegal lane change, right-of-way violation, and illegal parking (Penmetsa and Pulugurtha, 2017; C. Wang et al., 2019; X. Wang et al., 2019. However, policy-makers and transportation planners often encounter an issue that ITS investments are limited by governments' budget or strategic plans. Thus, in order to ensure transportation safety to the largest extent from the planning stage, it is necessary and important to understand the best way to allocate various traffic

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enforcement cameras with limited ITS investments.

Traditionally, the effects of planning-related factors on macro-level/regional safety were often examined by spatial crash modeling techniques, which provided valuable information and guidance for transportation planners and policy-makers to allocate planning resources. Planning-related factors include roadway features (e.g. roadway length, road density, roadway type, the number of intersections, et al.), land use factors (e.g. industrial land use, commercial land use, et al.), traffic characteristics (e.g. average daily volume, average volume over capacity, et al.), and social-economic factors (population density, lower-income household, employed population, et al.) (Abdel-Aty et al., 2011; Lee et al., 2015; Xu and Huang, 2015; Saha et al., 2018; Xie et al., 2019; C. Wang et al., 2019; X. Wang et al., 2019). However, the effects of ITS treatments, especially traffic enforcement cameras, on regional safety have not been identified. Moreover, it is unknown the interaction effects between traffic enforcement cameras and roadway/land use environment. Interaction effects could be important to reveal the impacts of certain factors depending on other factors (Ahmed et al., 2018). Since ITS has been increasingly incorporated into transportation planning process, investigating the main and interaction effects of traffic enforcement cameras on regional crash risk would provide transportation planners and policy-makers better ideas of how to allocate traffic enforcement cameras. However, to our best knowledge, research on this topic is still lacking.

In light of these, in this paper, we examined the effects of traffic enforcement camera on macro-level transportation safety, considering their interactions with roadway and land use characteristics. A spatial modeling technique will be utilized to model regional crash risk, accounting for spatial auto-correlation. The purpose of this study is to deeply understand how to allocate traffic enforcement cameras to better improve transportation safety. The remainder of the paper are organized as follows: section 2 introduces methods used in this study, including research design, data preparation, and statistical analysis. Section 3 and section 4 presents modeling results and discusses research findings, respectively. Section 5 provides the research conclusion and future directions.

2. Method

2.1. Research design

To identify the effects of traffic enforcement cameras on regional crash risk, a typical county-level city, Kunshan, China, was select in this study. The Kunshan government launched their ITS development plan early in 2008 and over 700 traffic enforcement cameras had been installed in the central area (within the Kunshan Middle Ring Road) of Kunshan by the end of 2015. Two-year crash records of 2018 and 2019 were used for crash modeling, assuming that it took time (i.e. two years from 2016 to 2017) for most drivers to adapt themselves to camera enforcement. Since the focus is to provide insights for transportation planning, crashes were aggregated by regions (i.e. at macro-level) and spatial autocorrelations between adjacent regions were considered, when applying statistical crash modeling. Fig. 1 (a) displays the whole Kunshan area and 2018 crash records. Fig. 1(b) shows the traffic analysis zones (TAZ) of the central area and Fig. 1(c) displays the locations of traffic enforcement cameras (note that multiple cameras can be installed at the same location).

2.2. Data preparation

Two-year crash data between 2017 and 2018 were acquired from the Kunshan Police Department, which contain detailed information of drivers, roadway, and vehicles. For each crash record, there is a unique geodetic coordinate, which can be further used for locating each crash on a GIS map. Since the central area is our research focus, a total of 22,677 crash records (5538 for injury crashes and 17,139 for PDO crashes) located within this area were used for data analysis. Among injury crash records, there are 5170 slight injury crashes, 287 serious injury crashes, and 81 fatalities.

Based on crash records, a set of explanatory variables were developed, which include roadway characteristics, exposure, land use features, social-economic characteristics and traffic enforcement features. Roadway characteristics were gathered for each TAZ using ArcGIS tools, including the total number of intersections, the total length of major, minor and local roads, and roadway density. For those located on the boundary of TAZs, an equal weight was given for each TAZ (Sun and Lovegrove, 2010). Annual average daily traffic (AADT) and population data was provided by the Kunshan Urban Planning Institute, while violation frequency was derived from the Kunshan Traffic Police Department. To note, other exposure data were not available, such as trip generation and attraction.

According to planning data from the Kunshan urban planning institute, four major land use types need be considered, including residential area, commercial area, industrial area, and public and administrative area. For each TAZ, the percentage of each land use type was recorded. Regarding traffic enforcement features, six types of traffic enforcement cameras were identified including illegal lane changing, lane right-of-way violation, red-light running, right-of-way violation, speeding, and illegal parking. For each TAZ, the average density of the six camera types (# of cameras per km) was collected. To note that, cameras with multiple functions were considered as multiple cameras. For example, if an enforcement camera can detect both illegal lane-changing and speeding, two cameras will be counted. Similarly, for those on the boundary of TAZs, an equal weight was given for each TAZ (Table 1).

In order to identify interaction effects of traffic enforcement cameras and other planning factors, two combinations were considered, including traffic enforcement camera * roadway characteristics and traffic enforcement camera * land use features. Thus, there are totally $6^*(3 + 4) = 42$ interaction terms. Before applying crash modeling, multi-collinearity tests were conducted and those variables with VIF larger than 10 were removed before entering the model. Finally, 21 explanatory variables were used for crash modeling. Table 2 presents the descriptive statistics of those variables.

2.3. Statistical analysis

As for spatial crash modeling, many different models were employed before (Besag et al., 1991; Lee et al., 2014; Huang et al., 2016; Cheng et al., 2017; Xu et al., 2017; Wen et al., 2019), including: Poisson lognormal model, negative binomial spatial model, Poisson lognormal spatial model, geographic weighted Poisson regression model, Bayesian spatial varying-coefficient model, and Bayesian Spatial-temporal model. Since the major focus of this study is to identify the effect of traffic enforcement cameras, Bayesian log-normal models with conditional autoregressive (CAR) priors were used to analyze crash data, since they have been widely applied in many different research fields such as epidemiology.

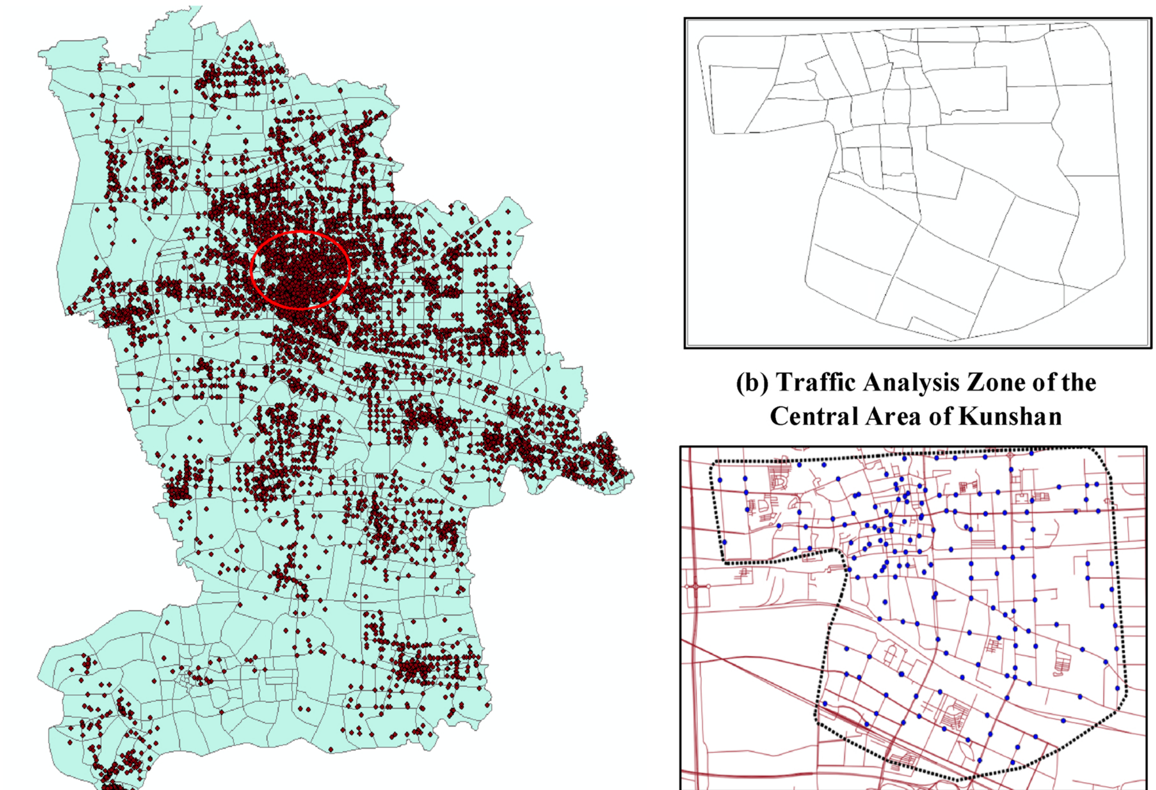
A generalized Bayesian log-normal model with CAR prior can be presented below:

$$Y_i \sim Poisson(\lambda_i) \tag{1}$$

$$\ln(\lambda_i) = \beta_0 + \beta_k X_{ik} + \theta_i + \phi_i \tag{2}$$

Where Y_i is the annual number of crashes for region i; λ_i is the expected mean of crash occurrence for region i; β_k is the parameter coefficient of kth variable; X_{ik} is the kth variable for i_{th} observation, θ_i is the unstructured error, often assumed as a prior normal distribution, ϕ_i is the spatial correlation.

For the spatial correlation term ϕ_i, the Intrinsic conditional autoregressive prior (IAC prior) can be defined as (Besag et al., 1991):



(b) Traffic Analysis Zone of the Central Area of Kunshan

(a) 2016 Crash information of Kunshan, China

(c) Traffic Enforcement Cameras

Fig. 1. the overall information of the subject area.

Table 1
Descriptive Statistics of explanatory variables entering crash model.

Variable	Minimum	Maximum	Mean
Illegal lane changing (# of detector per km)	0.023	1.407	0.423
Red-light running (# of detector per km)	0.108	1.819	0.603
speeding (# of detector per km)	0.212	1.621	0.676
Illegal parking (# of detector per km)	0.000	0.882	0.108
Major Arterial length (km)	2.232	26.54	12.4181
Road Density (km/km^2)	0.482	2.244	1.432
Average Intersection spacing (km)	0.221	0.502	0.401
Commercial Land use (%)	0	81.896	16.142
Area (km^2)	0.155754	2.947565	755,373
Total number of violation frequency (10^3)	0.721	41.939	6.949
Average annual daily traffic (10^3 pcu km)	0.839	37.523	18.639
Population (10^3)	1.144	71.234	38.542
Illegal lane changing* Residential Land use	0.341	10.356	8.614
Illegal lane changing * Major Arterial	1.032	30.159	7.208
Red-light running * Commercial Land use	0.440	29.644	14.322
Red-light running * Industrial Land use	0.000	21.655	7.512
Red-light running * Residential Land use	6.375	33.112	15.914
speeding * Industrial Land use	5.732	33.823	18.627
speeding * Residential Land use	1.243	33.923	8.141
speeding * Major Arterial	7.001	37.009	17.688
Illegal parking * Local Roads	0.000	18.790	1.242

$$\phi_i \mid \phi_{-i}, W, \tau^2 \sim N\left(\frac{\sum_{i\neq j}\phi_i m_{ij}}{\sum_{i\neq j} m_{ij}}, \frac{{\tau_c}^2}{\sum_{i\neq j} m_{ij}}\right) \tag{3}$$

Where m_{ij} is binary entries of proximity matrix (1 represents adjacency while 0 indicates non-adjacency). τ_c is the precision parameter, assumed as a prior gamma distribution.

In essence, the conditional expectation ϕ_i is the average of spatial correlations of adjacent areas; conditional variance τ^2 is inversely proportional to the number of adjacent areas.

A Cressie autoregressive prior can be written as (Stern and Cressie, 1999):

$$\phi_i \mid \phi_{-i}, W, \tau^2 \sim N\left(\rho\frac{\sum_{i\neq j}\phi_i m_{ij}}{\sum_{i\neq j} m_{ij}} + (1-\rho)\frac{\sum_{j=1}^{n}\phi_i}{n}, \frac{{\tau_c}^2}{\sum_{i\neq j} m_{ij}}\right) \tag{4}$$

Different from IAC priors, the conditional expectation of ϕ_i is modified into the weighted average of the average of adjacency area and the average of the entire area. Weight parameters ρ indicates the intensity of spatial auto-correlation. When $\rho = 0$, it indicates a complete spatial independency, with the increase of ρ, spatial auto-correlation increases. When $\rho = 1$, the Cressie model degenerates to an intrinsic CAR model. In this study, we applied Cressie auto-regressive prior for crash modeling.

Three performance indicators were used to measure the goodness-of-fit of the proposed Bayesian models, including deviance information criterion (DIC), mean absolute deviation (MAD), mean absolute percentage error (MAPE). MAD and MAPE can be calculated as:

$$MAD = \frac{1}{N}\sum_{1}^{N} |Y_i - \lambda_i| \tag{5}$$

$$MAPE = \frac{100\%}{N}\sum_{1}^{N} \left|\frac{Y_i - \lambda_i}{Y_i}\right| \tag{6}$$

Where N is the total number of observations. DIC can be written as:

$$DIC = \widetilde{D} + p \tag{7}$$

Where $\widetilde{D}$ is the posterior mean deviance for assessing the model fit, and p is the number of parameters in the model, as a measure of model complexity. A model with a lower DIC has better goodness-of-fit than that with a higher value.

Table 2
Posterior Estimates for Bayesian CAR model (Injury Crashes).

Variable	Posterior mean b	95 % BCI	% change (100*[$e^b - 1$])
Red-light running	−0.212	(−0.048, -0.383)	−19.1%
speeding	−0.302	(−0.039, −0.562)	−26.1%
Road Density	0.331	(0.214, 0.442)	+39.24 %
Average Intersection Spacing	−0.484	(−0.212, −0.742)	−38.4%
Population	0.002	(0.001, 0.003)	+0.2 %
AADT	0.001	(7.2E-04,0.0013)	+0.1 %
Commercial land use (%)	0.018	(0.006,0.031)	+1.81 %
Major Arterial	0.041	(0.025,0.057)	4.19 %
Illegal lane changing * Major Arterial	−0.014	(−0.005, −0.022)	−1.39 %
red-light running * Commercial land use (%)	−0.027	(−0.006, −0.047)	−2.66 %
red-light running * Residential Land use (%)	−0.028	(−0.012, −0.044)	−2.76 %
speeding * Industrial Land use (%)	−0.038	(−0.017, −0.058)	−3.72 %
speeding * Major Arterial	−0.021	(−0.008, −0.033)	−2.08 %
Illegal parking * Local roads	−0.018	(−0.005, −0.031)	−1.78 %
$\tau_c{}^2$	0.004	(0.001, 0.011)	–
ρ	0.389	(0.067, 0.722)	–
DIC	333.7		
MAD	5.20455		
MAPE	10.26139		

3. Results

According to previous research (Huang et al., 2019), injury and non-injury (PDO) crashes were examined separately. Based on modeling results, a few traffic enforcements features have been found as significant to regional injury/PDO crash risk. The summary of the significant model estimates (i.e. main and interaction effects) is shown in Tables 2 and 3. Note that the potential endogenous issue of traffic violation frequency was examined, since it was considered as an endogenous variable to crash risk in previous literature (Hong et al., 2019). By excluding the factor, the overall model performance had been improved. Thus, the total traffic violation frequency was not included in the final model.

3.1. Injury crash

Regarding enforcement cameras, red-light running and speeding cameras were both found to be associated with decreased effects (−19.1 % and −26.1 %) on regional injury crash risk, respectively. Other enforcement camera types were not found as significant, in terms of main effects. Roadway density was associated with a significant 39.24 % increase in injury crash frequency at TAZ level. Meanwhile, an increase in average intersection spacing was associated with a 38.4 % reduction in injury crash frequency. The increase in arterial length (per km) was associated with a significant 4.19 % increase in injury crashes. As for land use factors, one percentage increase in commercial land use was associated with a 1.81 % increment in regional injury crashes. AADT (10^3 pcu km) was found to be associated with an increase (+ 0.1 %) in injuryl crashes. Population was also found to be significantly correlated with increased injury crash risk (+ 0.20 %), which is consistent with previous literature (Lee et al., 2015). Area was not found as significant.

Six interactions terms were found as significant, including illegal lane changing * major arterial, red-light running * commercial land use, red-light running * residential Land use, speeding * industrial land use, speeding * major arterial, and illegal parking * local roads. With the existence of interaction terms, some main effects of traffic enforcement cameras have been mediated. To note, for interaction effects, the percentage change was calculated for enforcement cameras depending on land use/roadway factors.

As for red-light running and speeding cameras, their interactions with roadway and lane use characteristics were identified. The effect of red-light running cameras on decreasing injury crash risk (−19.1 %) could be even magnified by −2.66 %, when there is one percentage increase in commercial land use. Similarly, the effect of red-light running cameras on reducing injury crash risk could be enhanced by 2.76 %, when residential land use increases by one percentage.

Speeding cameras were associated with an enhanced effect on

Table 3
Posterior Estimates for Bayesian CAR model (PDO Crashes).

Variable	Posterior mean b	95 % BCI	% change (100*[e^b-1])
Illegal lane changing	−0.175	(−0.089, −0.261)	−16.1 %
Red-light running	−0.232	(−0.032, −0.432)	−20.7 %
speeding	−0.275	(−0.024, −0.526)	−24.0 %
Road Density	0.362	(0.174, 0.55)	+43.62 %
Average Intersection Spacing	−0.432	(−0.113, −0.751)	−35.1 %
AADT	0.001	(9.8E-04, 0.0011)	+0.1 %
red-light running * Commercial land use (%)	−0.039	(−0.01, −0.068)	−3.92 %
red-light running * Residential Land use (%)	−0.033	(−0.009, −0.057)	−3.25 %
speeding * Industrial Land use (%)	−0.031	(−0.006, −0.056)	−3.05 %
speeding * Residential Land use (%)	−0.023	(−0.007, −0.039)	−2.27 %
speeding * Major Arterial (%)	−0.028	(−0.01, −0.046)	−2.76 %
Illegal parking * local roads (%)	−0.016	(−0.003, −0.029)	−1.59 %
$\tau_c{}^2$	0.003	(0.001, 0.008)	–
ρ	0.337	(0.045, 0.629)	–
DIC	378.5		
MAD	25.43221		
MAPE	16.02335		

reducing injury crash risk of industrial area (−3.72 %). The main effects of major arterial on increasing regional injury crash risk can be mitigated by installing speeding cameras (one camera per km could result in a 2.08 % decrease in crash risk).

Lane changing enforcement camera was associated with a 1.39 % decrease in injury crash frequency, when being installed on major arterials. Previous studies found that industrial land use was associated with increased injury crash risk. However, with the incorporation of an interaction term between lane changing enforcement camera and industrialized land use, the main effects of industrialized land use were no longer significant.

Although no main effects were found for parking enforcement cameras, the interaction between local roads and parking enforcement cameras was associated with a significant decrease (−1.78 %) in injury crashes.

3.2. PDO crash

Significant main effects on regional PDO crash risk include red-light running camera (−20.7 %), speeding camera (−24.0 %), AADT (+0.1 %), road density (+43.62 %), and average intersection spacing (−35.1 %). Speeding cameras were found to be associated with enhanced effects on reducing PDO crash risk, when being installed in industrial area (−3.05 %) and on major arterials (−2.76 %). Red-light running cameras were associted with a magnified effects on decreasing PDO crash frequency, when being installed in commercial (−3.92 %) and residensial area (-3.25 %). Illegal car parking cameras installed on local roads were assocatied with decreased PDO crash risk (−1.59 %). Note that those were very similar to injury crash modeling results.

New significant effects were identified for regional PDO crash risk. Illegal lane changing was found to be associated with the decreased risk of PDO crash frequency (−16.1 %). The interaction between red-light running and residential land use was found to be associated with a reduction in (−2.27 %) PDO crashes. In addition, some significant effects on injury crash risk were found as non-significant for PDO crash risk, including major arterial, population, and commercial land use.

4. Discussions

Both main and interaction effects of traffic enforcement cameras on regional crash risk have been identified. Red-light running camera was found to be associated with decreased injury/PDO crash risk. According to previous literature, red-light running cameras had been proven to effectively improve roadway safety, by enforcing red-light running behaviors. With the increase of red-light running cameras, the effects of commercial land use on increasing regional injury/PDO crash risk were mitigated. This indicates the importance of implementing red-light running cameras in commercial land-use area, with where pedestrian/bicyclist activity could be high. By enforcing red-light running behaviors, pedestrian/bicyclist risk exposure could be reduced. Likewise, red-light running cameras need to be installed in residential area, since the interaction term was associated with the decreased injury/PDO crash risk.

Speeding cameras were found to be more effective in reducing both injury and PDO crash risk of industrial area and major arterials. In industrial area, the percentage of heavy truck is usually large, which normally have limited braking performance under high operating speed. Speeding enforcement could effectively control their operating speed. The operating speed of major arterials is high, where speeding behaviors could be more hazardous. With speeding automated enforcement, the speeding behaviors on major arterials could be effectively reduced. In addition, when speeding cameras are installed in residential area, regional PDO crash risk could be further reduced.

Lane changing enforcement camera was only associated with the decreased PDO crash risk. Such enforcement cameras can effectively prevent illegal lane changing behaviors, which could cause traffic conflicts to other vehicles rather than vulnerable road users (e.g. pedestrians/bicyclists). Only when being installed on major arterials, this camera type showed effects on reducing injury crash risk. The operating speed on major arterial is relatively high so that a lane-change crash could have large impact force, causing driver/occupant injuries. With the enforcement of lane changing cameras, illegal lane changing behaviors could be effectively decreased, resulting in fewer lane-change conflicts and safer traffic environment.

Parking enforcement cameras were associated with lower injury/PDO crash risk when being installed on local roads. In China, many local roads are very narrow so illegal on-street parking can block non-motorist lanes, resulting in potential safety issues. For example, non-motorists could be forced to share a motorized lane with motor vehicles, increasing their traffic crash exposure. On the other hand, vehicles may be forced to use the opposite lanes to pass through since their right-of-way was blocked by illegally parked vehicles. By applying automated parking enforcement, fewer drivers would commit illegal on-street parking and risk exposure would in turn decrease.

Other factors were found to be consistent with previous literature. AADT was found to be associated with increased injury crash risk. This is reasonable since AADT and population were both often considered as traffic exposure variables (Huang et al., 2010). Population was only associated with injury crash risk. Area size was not found to be significant. This may indicate the distinct nature between epidemics and roadway crash occurrence. Area size is often considered as an important exposure variable in epidemics research. However, larger area may not be linked to higher crash frequency, due to effects of other factors such as roadway length, traffic volume, and so on. Higher roadway density and intersection density (i.e. smaller intersection spacing) were associated with higher regional crash risk. Those findings are consistent with previous literature (Aguero-Valverde and Jovanis, 2006; Xie et al., 2013; C. Wang et al., 2019; X. Wang et al., 2019). According to C. Wang et al., 2019; X. Wang et al., 2019, more turning traffic could result in more conflicts under higher roadway densities. On the other hand, shorter intersection spacing tend to induce more frequent lane change maneuvers, leading to more severe conflicts and higher crash risk.

5. Conclusion

In this paper, we examined the main effects of traffic enforcement cameras on macro-level traffic safety (i.e. injury/PDO crash risk), as well as their interactions with roadway and land use factors. A set of explanatory variables were collected for each TAZ in the central area of Kunshan, China, including exposure, roadway, social-economic, land use, traffic enforcement features, and interaction terms between traffic enforcement cameras and land use/roadway factors. A multi-collinearity test was applied to remove variables with high collinearity and Bayesian CAR models were developed to identify significant variables to regional injury/PDO crash risk, accounting for spatial auto-correlations. The results can be concluded as follows:

1 Interaction effects existed between traffic enforcement cameras and roadway/land use factors. Thus, traffic enforcement cameras need to be carefully considered at the planning stage, being one of the major components of intelligent transportation system.
2 Traffic enforcement cameras were found to be associated with decreased regional crash risk. Red-light running and speeding cameras were associated with the decrease in injury/PDO crash frequency, which can be further enhanced when they are installed in certain area (i.e. industrial, and commercial land use) and on major arterials. Speeding cameras were associated with enhanced effects on reducing PDO crash risk when being installed in residential area. Illegal lane changing cameras were associated with the decrease in regional PDO crash frequency, while such effect on reducing injury crash frequency was only found as significant on major arterials. Illegal car parking cameras had decreased effects on reducing

injury/PDO crashes, when being installed on local roads.
3 The main effects of land use and roadway factors were mediated by interaction terms of traffic enforcement cameras. For example, while the main effect of industrialized land use appeared to be insignificant, the interaction term between industrialized area and speeding cameras showed significant effects on reducing regional injury/PDO crash risk. In addition, the effect of commercial and residential land use on increasing regional crash risk can be mitigated by implementing red-light running cameras.

In general, this study provides valuable information for transportation planning incorporating ITS. Based on those findings, policy-makers can be more confident to allocate traffic enforcement cameras with limited resources. Admittedly, there are some issues that needs to be further addressed. First, some planning-related factors were not included in this paper, such as trip generation data. Those could be added in the model when they are available. Second, more complex model structure could be applied, such as Bayesian spatial-temporal model. However, since our major focus was to identify the main and interaction effects of traffic enforcement cameras, we leave this topic as our future research. Third, more interaction terms could be added into the model, such as three-way interaction effects among land use, traffic enforcement, and roadway characteristics. However, such effects may need to be more carefully examined and interpreted. Last but not the least, previous literature suggested that drivers could change their behaviors over time after camera installment (Vanlaar et al., 2014). In this study, only two-years' data were available for crash modeling. Thus, the trends of camera effects over time can be analyzed in the future, when more data are collected. We recommended that future research could be focused on those directions.

CRediT authorship contribution statement

Chen Wang: Conceptualization, Funding acquisition, Methodology, Supervision, Writing - review & editing. **Chengcheng Xu:** Conceptualization, Methodology, Resources. **Pengguang Fan:** Data curation, Methodology, Software, Writing - original draft.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2020.105659.

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