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Research Paper

The influence of roadway characteristics and built environment on the extent of over-speeding: An exploration using mobile automated traffic camera data

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ABSTRACT

Over-speeding is a pivotal factor in fatal traffic crashes globally, necessitating robust speed management strategies to augment road safety. In 2021, the National Highway Traffic Safety Administration reported over 12,000 speed-related fatalities in the United States alone. Previous studies aggregated over-speeding tendency; however, the extent of over-speeding has a significant implication on the crash outcome. This study delves into the prevalence and magnitude of over-speeding in various scenarios, utilizing data from traffic cameras in Edmonton, Canada, and employing a negative binomial statistical model for analysis. The model elucidates the significance and likelihood of over-speeding tendencies by incorporating temporal and built environment variables—year, month, number of lanes, dwelling unit types, school-related, and open green space. Study results indicated that the aggregation of the over-speeding data tends to underestimate the influence of various factors. Notably, the estimated impact of the posted speed limit is up to over two times for the disaggregated models compared to the aggregated model. Further, the summer months exhibit a roughly 25% uptick in speed limit violations for aggregated models compared to about 40% for disaggregated approaches. Conversely, a discernible decline in over-speeding tendencies is observed with camera enforcement, showcasing a 25% reduction over four years. Built environment variables presented mixed results, with one-unit dwellings associated with a 12% increase in over-speeding, while proximity to schools indicated a 10% decrease. These pivotal findings provide policymakers and practitioners with valuable insights to formulate targeted interventions and countermeasures to curtail speed limit violations and bolster overall road safety conditions.

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1. Introduction

Over-speeding is one of the major contributors to severe traffic crashes, thus posing significant social and public health concerns (Anjerome Bedruz et al., 2018). It generally refers to the act of driving above the posted speed limit, indicating non-compliance with safety and legal speed restrictions on the road. In 2021, the United States witnessed over 12,000 fatalities attributed to over-speeding, underscoring the gravity of the issue (Almoshaogeh et al., 2021; Bombom et al., 2022; CrashStats - NHTSA - DOT, n.d.). The National Highway Traffic Safety Administration (NHTSA) has highlighted that nearly 30% of motor vehicle fatalities in recent years have involved over-speeding (Cai et al., 2021). Furthermore, NHTSA's crash report sampling system indicates that in 2021, over-speeding was a factor in approximately 12% of crashes leading to injuries or fatalities and 9% of crashes leading to property damage (CrashStats - NHTSA - DOT, n.d.; IIHS-HLDI, 2023).

The impact of roadway characteristics and the built environment on traffic crashes, especially those involving over-speeding, is a significant concern. Factors such as the number of lanes, road type, and posted speed limit can notably influence driving behavior and the propensity for over-speeding (Wang et al., 2022). For instance, wider roads with more lanes and higher speed limits may encourage drivers to speed, thereby increasing the risk of crashes. Similarly, the built environment, encompassing elements like land use, building density, and features like schools or parks, can influence over-speeding tendencies and crash rates. Areas with high residential density or school zones may have lower speed limits and more traffic calming measures, which can deter over-speeding and reduce the risk of crashes. Conversely, areas with less development or open green spaces may have higher speed limits and fewer traffic calming measures, potentially encouraging over-speeding and increasing crash risk (Filipovíc et al., 2022).

Various studies have utilized the data collected from automated speed cameras to understand the trend and factors associated with over-speeding (Factor et al., 2023; Kloeden et al., 2018; Shaaban et al., 2023; Wilson et al., 2010). The correlation between driving speed and the potential for accidents and fatalities is widely recognized and well-documented. Studies have consistently shown that higher speeds contribute to increased risks on the road (Speed, n.d.-b). Over-speeding has been identified to pose twice the relative risk of fatal injuries compared to other factors, establishing it as a primary cause of road traffic injuries (Al-Aamri et al., 2017).

While over-speeding has been a subject of previous research, exploring various factors influencing its extent appears insufficient. A particularly overlooked area is the impact of the posted speed limit on over-speeding. Most existing studies have adopted a somewhat simplistic view of over-speeding, often categorizing any speed above the posted limit as over-speeding, regardless of the extent. For instance, a driver exceeding a 75-mph speed limit by 10-mph and another exceeding a 20-mph limit by 20 mph are both considered over-speeding. However, the severity of potential crashes at these two speeds is drastically different, and it is reasonable to assume that the factors influencing drivers to exceed the speed limit in these scenarios may also differ significantly. This lack of differentiation in the analysis of over-speeding represents a significant gap in the current body of knowledge. It oversimplifies the complex nature of over-speeding behavior and its contributing factors, potentially leading to less effective speed management strategies.

To address this gap, this study utilizes a dataset from the city of Edmonton, Canada (Automated Traffic Enforcement Tickets Issued (by Month) | Edmonton - Open Data Portal, n.d.). It employs Negative Binomial Regression (NBR) analysis to explore the factors influencing the extent of over-speeding, focusing on the role of the posted speed limit and the built environment. The NBR model was adopted due to its proficiency in handling count data and its capability to manage over-dispersion, which is common in traffic violation data. The approach can effectively model the count of over-speeding incidents, which are discrete and non-negative, while accounting for the variance not equal to the mean (a phenomenon often observed in traffic data). By adopting this approach, the study seeks to provide a deeper understanding of over-speeding behavior, which could inform the development of more targeted and effective interventions to enhance road safety. The insights gained from this research could be instrumental in shaping speed management strategies considering the varying extents of over-speeding and their unique influencing factors.

The following section of this manuscript gives a comprehensive literature review, providing an overview of pertinent studies and articles that shed light on the factors influencing over-speeding. This is followed by a detailed discussion of the statistical analysis and methodology employed in this study. The study's findings are then presented and discussed, providing valuable insights into the extent of over-speeding and its influencing factors. The manuscript concludes with a summary of the key findings and recommendations for enhancing road safety measures and mitigating over-speeding incidents, thereby contributing to the broader discourse on traffic safety.

2. Literature review

Numerous studies have explored the issue of over-speeding and its implications for road safety. Researchers have recognized the significance of speed enforcement techniques in promoting safe driving practices and reducing traffic accidents and fatalities. Over-speeding has been identified as a significant contributing factor to accidents. This literature review delves into the critical factors associated with over-speeding, examines the analytical approaches used in the studies, and highlights the existing gaps and criticisms in the previous research (Al-Aamri et al., 2017; Atombo et al., 2016; Laapotti et al., 2003; Møller et al., 2014).

Factors influencing over-speeding have been investigated in several studies. Surface uniformity of paved roads has been found to contribute to higher speeding rates (Cai et al., 2021). Moreover, areas with lower speed limits often experience higher instances of over-speeding, while an increase in the (Afghari et al., 2018; Ece et al., 2018) number of lanes has been correlated with the extent of over-speeding. Temporal attributes, such as time of day, also play a role in over-speeding behavior, with drivers more likely to overspeed at night (Khaddar et al., 2023; Williams et al., 2006). Vehicle and driver characteristics, such as newer vehicles with higher speeds and better acceleration, younger drivers, sport utility vehicle drivers, and male drivers influenced by peer behavior, have also been associated with high-speed driving (Al-Aamri et al., 2017; Atombo et al., 2016; Laapotti et al., 2003; Møller et al., 2014). The analysis of factors influencing over-speeding underlines the complexity of the issue, as influenced by road characteristics, temporal aspects, and driver demographics.

Researchers have employed various analytical approaches to study over-speeding behavior. (Bhowmik et al., 2019) utilized a probit fractional split model to analyze factors influencing vehicle speed on arterial roads. From the model, analysis, and estimation of the significant factors that contribute to vehicle operating speed on arterial roads were determined. This model could predict increased speed from 20 to 25-mphin industrial areas exclusively; however, the study had some limitations. The analysis only considered two hours of speed data for each time slot, which suggests that conducting extended hourly records could provide additional insights. Another limitation is that the study exclusively examined conditions with potential traffic congestion, neglecting the inclusion of night hours. On the other hand, several studies that examined factors influencing vehicle over-speeding on arterial roads revealed that higher speeding was observed on paved roads due to their surface uniformity. This variety of analytical approaches used in these studies highlights the diverse methodologies employed to understand over-speeding, though they also reveal certain limitations in scope and data use.

Another study by Zahid et al. (2020) focused on traffic violations committed by taxi drivers. They used violation datasets considering georeferenced data, temporal attributes, road types, vehicle types, and violation types, and it was observed that almost 50% of the violations were over-speeding. While descriptive statistics provided such insights, hotspot analysis was conducted to identify areas with a higher prevalence of specific violation types. Over-speeding, the predominant violation, had three hotspots linked to it. Two were in the city center, and one was on a major highway in the city center (Zhang, 2012). Over-speeding in the city center was attributed to individuals' tendency to avoid traffic congestion. Conversely, highways, known for lower traffic density, were directly related to over-speeding due to larger headways (Bashir et al., n.d.; Zahid et al., 2020). Furthermore, researchers in a similar study focused on analyzing the operational factors influencing aggressive taxi over-speeders, characterized by high frequencies and severities of speeding (Zhou et al., 2021). Utilizing Fuzzy C-means clustering algorithm, they classified taxi drivers into restrained, moderate, and aggressive speeders based on their speeding patterns. The study employed Bayesian binary logistic Least Absolute Shrinkage and Selection Operator (LASSO) model to effectively manage multicollinearity and unobserved heterogeneity among drivers. Key operational factors such as daily driving distance, cruise distance, delivery time, hourly income, night driving, and driving on low-speed limit roads were identified as significant influences of aggressive speeding behavior. Interestingly, factors like lane changes and daily naps were found to have lesser impact on such behaviors. The study revealed that aggressive speeders were more sensitive to these factors compared to their moderate counterparts. In summary, these studies underscore the significant prevalence of over-speeding among taxi drivers, particularly in urban centers and highways, highlighting the need for targeted traffic enforcement and policy interventions in identified hotspot areas to address this issue effectively.

In another study promoting compliance with the speed limit in Maryland, speed cameras were to be installed on residential roads with speed limits of 35 mph or lower (Hu and McCartt, 2016). These cameras were aimed to capture the rear license plate of vehicles exceeding the speeding threshold within a defined roadway segment rather than just specific locations. Linear regression models were used to estimate the changes in space mean speeds, and logistic regression models, on the other hand, were utilized to determine the program's effect on the likelihood of vehicles exceeding speed limits by more than ten mph. In this study, the relative risk ratio was utilized instead of odds ratios as risk ratios are more suitable when investigating outcomes with a high incidence rate, such as over-speeding, as they offer a comprehensive and precise estimation of the relative risk by considering the baseline probability of the outcome (Hu and McCartt, 2016; Osborne, 2019). According to the linear regression model, there was a significant decrease in the space mean speed at camera sites. Additionally, the logistic regression model revealed that the likelihood of a vehicle exceeding the speed limit by more than ten mph at camera sites decreased by more than 50% (Hu and McCartt, 2016). These findings highlight the effectiveness of speed camera enforcement in promoting compliance with speed limits and reducing over-speeding behaviors. However, the study does not explain the extent of over-speeding as other vehicles might have traveled at 11 mph while others travel at 25 mph above the speed limit, but both are grouped as over-speeded vehicles. To identify the extent of over-speeding, another study utilized a sampled subset of spatial data with four categories of over-speeding clusters extracted: class 1 (over speed 1–5 mph), class 2 (over speed 5–10 mph), class 3 (over speed 10–20 mph), and class 4 (over speed more than 20 mph) (Analyzing Transportation Big Data with GIS: Detecting Over-Speeding Vehicles from Traffic GPS Data, n.d.). Results revealed that the extent of over-speeding by more than ten mph was most prominent at intersections of major highway segments and ramps. Additionally, violations were observed when the speed limit changed between two segments of local roads. The impact of speed camera enforcement demonstrates the effectiveness of such measures, although it suggests the need for more nuanced data on the extent of over-speeding.

Further studies explored the impact of temporal and spatial attributes on over-speeding frequency. The research utilized a random parameter negative binomial model to analyze observational data from specific count locations (Khaddar et al., 2023). The analysis examined the relationship between driver and vehicle characteristics and high-speed driving behavior by considering factors such as time of the day, road geometry, and the built environment. Drivers are more likely to speed in relatively new vehicles with higher speeds and better acceleration (Atombo et al., 2016). Temporal attributes, such as the time of day and weekdays versus weekends, also impact over-speeding behavior, with drivers more likely to speed at night (Khaddar et al., 2023; Williams et al., 2006). The findings revealed several notable differences between the two groups of drivers. High-speed drivers were found to be younger, newer vehicle drivers, and sport utility vehicle drivers. It was further noted that high-speed drivers were less likely to drive minivans (Williams et al., 2006). Additionally, studies suggest that male drivers are reported to overspeed more than their female counterparts due to peer influence. This exploration into the temporal and spatial influences on over-speeding frequency offers insights into how driver and vehicle characteristics correlate with high-speed driving behaviors.

In a recent study focusing on driving risks among regular speeders, researchers employed an innovative method to analyze speeding-related hard-braking events (SHEs) using low-frequency GPS trajectories (Zhou et al., 2024). The objective was to identify risky behaviors among regular speeders, particularly those leading to SHEs. To achieve this, the study compared average travel speeds between adjacent GPS points to the posted speed limits and examined the corresponding speed curves and travel distances. Methodologically, the study stood out by employing a range of advanced machine learning models in identifying regular speeders involved in SHEs. The key factors involved were the intensity and duration of speeding, specific road features, and the presence or absence of bicycle lanes and roadside parking. A critical finding was the identification of short-duration over-speeding as particularly hazardous. The study also leveraged explainable artificial intelligence (AI) to visually interpret the influence of these speeding behaviors on the likelihood of SHEs. This study stands out for its practical approach of targeting specific hazardous speeding behaviors using machine learning and AI.

Despite the valuable insights from prior research into over-speeding behavior and its influencing factors, notable gaps and limitations remain. These include the scarcity of studies focusing on over-speeding, as most previous studies considered over-speeding to be a binary outcome. Such a consideration does not provide insights into the extent of over-speeding, as regardless of the magnitude of over-speeding, all over-speeded vehicles are categorized in one category (Hu and McCartt, 2016). Furthermore, even categorizing over-speeding in various categories without quantifying the number of over-speeded vehicles in each category provides little insight (Chen et al., 2019). The existing literature also predominantly leans towards exploring the direct implications of over-speeding, with extensive research focusing on the underlying factors and the subtle intricacies that govern such behavior among drivers. Consequently, this study seeks to bridge the gap by employing the NBR model to analyze the extent of over-speeding, thereby dissecting the number of over-speeded vehicles within each speed category. This nuanced analytical approach not only promises to unveil the layered complexities embedded within over-speeding behaviors but also aims to equip policymakers and road safety practitioners with robust, data-driven insights. These insights, in turn, can be harnessed to formulate and implement finely tuned strategies and interventions, meticulously tailored to address the multifaceted dimensions of over-speeding, thereby enhancing road safety and mitigating the associated risks and repercussions. This effort to delve further into the complexities of over-speeding and to uncover its underlying causes has the potential to greatly add to the body of knowledge and pave the way for future road safety measures that are more well-informed, successful, and long-lasting.

3. Materials and methods

This study applies the Negative Binomial model to speeding data to examine the factors associated with the extent of over-speeding. The following sections describe the dataset, methodology, and analytical process used in this study.

3.1. Data Description

The study used a dataset from Edmonton, Canada (Automated Traffic Enforcement Tickets Issued (by Month) | Edmonton-Open Data Portal, n.d.), whose data collection started on March 8, 2019, and has been undergoing periodic updates. The dataset contains information related to the regulation of traffic speed, and it was created to share the number of mobile automated traffic enforcement tickets issued to the public. The information includes the approximate locations of the centroids of the enforcement zones, the number of tickets issued to drivers at different excess speed ranges, and the number of enforcement hours. This dataset contains about 12,800 unique data points with more than 682,160 tickets offered from January 2019 in 17 columns. The columns contain various information like site ID, location, road name, enforced speed limit, month-end date, deployment hours, and excess speed groups (ESGs) in which the tickets fall. These variables are presented in Table 1.

3.2. Analytical approach

In this study, the number of over-speeding instances per month at 589-speed camera locations was counted for the entire dataset and for specific groups of excess speed to the posted speed limit. The specific groups included the excess speed between 6–10 kph, 11–15 kph, 16–20 kph, and 21–50 kph. The dataset did not have the 0-5kph over-speeding category. Its exclusion may be based on the assumption that over-speeding up to 8 kph (5 mph) is less likely to pose safety issues (Mannering, 2009). Thus, this group of over-speeding was not included in the analysis.

Table 1
The description of field data variables.

Variable	Description
Site ID	The identification number for the site at which a ticket was issued
Road Name	Name of the road at which a ticket was issued
Speed_Limit	Posted speed limit for a road section
Date_Month	The date on which a ticket was issued (Date/Month/Year)
Covid_cat	Classification of the date (before, during, or after COVID-19)
Deployment Hours	The number of hours for which the enforcement was done
Excess speed groups	The group in which the excess speed of a vehicle relative to the posted speed falls
Total_tickets	The number of speed tickets given due to over-speeding at a given site
Latitude, Longitude	The location at which the posted speed violation took place
Land_use	The land use of the location at which the posted speed violation took place
NBRLANES	The land use of the location at which the posted speed violation took place
TRAFFICDIR	The direction of traffic at which the posted speed violation took place
ROADCLASS	The road classification at which the posted speed violation took place

Due to the count nature of the data, the Negative Binomial Regression (NBR) model was used to study the association of over-speeding and five explanatory variables, which are speed limits, months of the year, years, types of built environment, and number of lanes. These variables are considered to influence speed patterns and the extent of overspeeding directly or indirectly (Wilmot and Khanal, 1999). The NBR follows a similar distribution to the Poisson distribution but with different assumptions of the variance (Booth et al., 2003; Kutela et al., 2022). The Poisson model can estimate the number of over-speeding instances y_{it} for month i given variables X_{it}. With the assumption mean speed μ equals variance, the average speeds are assumed to follow the Poisson distribution with likelihood given as:

$$y_{it}\ \ \mathrm{Pois}(\mu) = f(y_{it}|X_i) = \frac{e^{-\mu i}\mu_i^{yit}}{y_{it}!} \tag{1}$$

Since the scenario of mean speed being equal to its variance is unrealistic due to multiple scenarios acting as different explanatory variables, the dependent variable is considered over-dispersed (Cox, 1983; Kutela and Teng, 2019). This scenario violates the regular Poisson distribution assumption, and the variability is included as the mixture distribution with conjugate gamma mixing (Booth et al., 2003). After the introduction of the over-dispersion parameter α, of the NBR model for over-speeding is given by:

$$Pr(Y_i = y_{it}; \alpha, \mu_i) = \frac{\Gamma(y_{it}+\alpha)}{\Gamma(\alpha)y_{it}!}\left(\frac{\alpha}{\mu_i+\alpha}\right)^{\alpha}\left(\frac{\mu_i}{\mu_i+\alpha}\right)^{y_{it}} \tag{2}$$

Where the expected mean and variance can be computed as μ_i and $\mu_i + \frac{\mu_i^2}{\alpha}$ respectively.

Since the Poisson model exists as a log-linear relationship, this tendency prevails between speeds y_{it} that are negatively binomially distributed with mean μ_i and the vector of explanatory variables X_{it} given by:

$$ln(E(y_{it}|x_{it}) = ln(\mu_i) = X_{itj}\beta \tag{3}$$

With, X_{itj} indicating the covariates row vector, y_{it} is the speed, and β is the matrix of regression coefficients.

4. Descriptive analysis

As described in the data description section, the dataset in this study provides information related to the regulation of traffic speed and the number of mobile automated traffic enforcement tickets issued to the public. Table 2 summarizes the descriptive statistics of this dataset, focusing on both the overall and ESG-specific distributions, namely: *Between 6–10 kph*, *Between 11–15 kph*, *Between 16–20 kph*, and *Between 21–50 kph*.

The dataset records tickets issued at various speed limits. The speed limits include *30 kph*, *40 kph*, *50 kph*, *60 kph*, *70 kph*, *80 kph*, *90 kph*, and *100 kph*. The most common speed limit for tickets issued is *50 kph* (30.7% of all tickets), followed by *100 kph* (27.1%). The least common speed limit for tickets is *40 kph* (1.0%). The most common speed limit for the ESG *between 6–10 kph* is *50 kph* (65.8%). The least common speed limit in the group is *60 kph* (0.7%). The speed limit of *50 kph* is also the most common in the ticketed groups, with over-speeding between 11–15 kph (37.6%). The least common speed limit in this group is *90 kph* (1.1%). Most tickets in the ESG between 16–20 kph are issued for a speed limit of *100 kph* (48.6%). For this ESG, *40 kph* has the lowest representation (0.5%). Lastly, for the ESG of between 21–50 kph, tickets are primarily issued for *100 kph* (46.4%). The speed limits of *50* and *30 kph* also have a significant presence, with 13.4% and 12%, respectively. The speed limit distribution shows that more over-speeding events on roadways with lower speed limits compared to those with higher speed limits except for roadways with 100 kph as speed limit. This may be attributed to the relatively lower number of roadways with mid-range speed limits. As a result, fewer speed cameras are available on those roadways.

Table 2
Descriptive statistics of the variables.

Variable		Overall		Between 6–10 kph		Between 11–15 kph		Between 16–20 kph		Between 21–50 kph	
		Count	Percent	Count	Percent	Count	Percent	Count	Percent	Count	Percent
Speed Limit	30 kph	96,400	14.4%	20,996	30.8%	46,603	14.2%	19,205	9.9%	9,589	12.0%
	40 kph	6,977	1.0%	1,814	2.7%	3,979	1.2%	892	0.5%	288	0.4%
	50 kph	205,673	30.7%	44,797	65.8%	122,986	37.6%	27,100	13.9%	10,710	13.4%
	60 kph	97,890	14.6%	459	0.7%	75,801	23.2%	15,469	8.0%	6,057	7.6%
	70 kph	28,626	4.3%			11,814	3.6%	11,753	6.0%	5,010	6.3%
	80 kph	39,606	5.9%			12,643	3.9%	18,696	9.6%	8,192	10.3%
	90 kph	13,151	2.0%			3,478	1.1%	6,759	3.5%	2,903	3.6%
	100 kph	181,746	27.1%			50,020	15.3%	94,600	48.6%	36,943	46.4%
Month of the year	January	43,459	6.5%	5,107	7.5%	21,147	6.5%	12,330	6.3%	4,849	6.1%
	February	36,098	5.4%	4,124	6.1%	17,390	5.3%	10,543	5.4%	4,020	5.0%
	March	57,725	8.6%	6,327	9.3%	29,036	8.9%	16,092	8.3%	6,233	7.8%
	April	58,282	8.7%	5,995	8.8%	29,541	9.0%	16,193	8.3%	6,513	8.2%
	May	70,334	10.5%	6,229	9.2%	34,867	10.7%	20,599	10.6%	8,577	10.8%
	June	71,492	10.7%	6,697	9.8%	34,795	10.6%	21,014	10.8%	8,929	11.2%
	July	73,249	10.9%	5,942	8.7%	35,829	10.9%	22,084	11.4%	9,338	11.7%
	August	58,413	8.7%	5,949	8.7%	28,663	8.8%	16,586	8.5%	7,165	9.0%
	September	60,144	9.0%	5,799	8.5%	28,929	8.8%	17,752	9.1%	7,605	9.5%
	October	67,675	10.1%	6,857	10.1%	31,966	9.8%	20,392	10.5%	8,409	10.6%
	November	41,488	6.2%	4,903	7.2%	19,559	6.0%	12,250	6.3%	4,742	6.0%
	December	31,710	4.7%	4,137	6.1%	15,602	4.8%	8,639	4.4%	3,312	4.2%
Year	2019	329,681	49.2%	39,991	58.8%	172,365	52.7%	82,788	42.6%	34,362	43.1%
	2020	112,244	16.8%	9,360	13.8%	53,936	16.5%	35,164	18.1%	13,680	17.2%
	2021	114,956	17.2%	10,185	15.0%	52,726	16.1%	36,952	19.0%	14,973	18.8%
	2022	113,188	16.9%	8,530	12.5%	48,297	14.8%	39,570	20.3%	16,677	20.9%
Built environment	One Unit Dwelling	274,849	41.0%	29,428	43.2%	138,657	42.4%	75,880	39.0%	30,683	38.5%
	School-related	53,239	7.9%	5,185	7.6%	24,593	7.5%	16,652	8.6%	6,752	8.5%
	Open green space	56,725	8.5%	4,562	6.7%	27,347	8.4%	17,629	9.1%	7,143	9.0%
	Semi-Detached Dwelling	22,067	3.3%	3,475	5.1%	12,089	3.7%	4,498	2.3%	1,988	2.5%
	Multi-Unit Dwelling	79,048	11.8%	7,076	10.4%	36,818	11.2%	24,699	12.7%	10,405	13.1%
	Others	184,141	27.5%	18,340	26.9%	87,820	26.8%	55,116	28.3%	22,721	28.5%
Number of lanes	One	68,141	10.2%	5,883	8.6%	31,714	9.7%	21,435	11.0%	9,055	11.4%
	Two	513,438	76.6%	53,096	78.0%	254,278	77.7%	146,252	75.2%	59,402	74.5%
	Three	21,017	3.1%	2,836	4.2%	11,001	3.4%	5,135	2.6%	2,039	2.6%
	Four	67,473	10.1%	6,251	9.2%	30,331	9.3%	21,652	11.1%	9,196	11.5%

The dataset is divided by the month in which tickets were issued. *May*, *June*, and *July* had the highest ticket issuance, with 10.5%, 10.7%, and 10.9% of the total tickets, respectively. In contrast, *December* had the lowest ticket issuance, with 4.7% of the total. *October* sees the highest ticket issuance (10.1%) in the ESG between 6–10 kph group, followed by June (9.8%). *February* and *December* have the lowest ticket issuance (both 6.1%). For the ESG, between 11–15 kph, May, June, and July have a higher proportion of tickets (10.7%, 10.6%, and 10.9%, respectively). In this ESG, December has the lowest share (4.8%). Like numeral ESGs, May, June, and July have a relatively higher number of tickets in the ESG between 16–20 kph (10.6%, 10.8%, and 11.4%, respectively). Also, December has the lowest number of tickets in this ESG (4.4%). Finally, May, June, and July have the highest number of tickets in the ESG between 21–50 kph (10.8%, 11.2%, and 11.7%, respectively), while December has the lowest (4.2%). According to the monthly distribution of tickets, it is evident that most tickets are issued during the summer season that spans between May and July. This trend may be attributed by factors such as increased community events and festivals. In addition to that, construction and maintenance projects also tend to take place during the summer due to favorable weather conditions. Speed limits may be reduced in construction zones, and law enforcement may be more vigilant in enforcing these limits hence increased speeding scenarios.

The dataset spans several years, with most tickets issued in 2019 representing 49.2% of the total observations. This is followed by 2021 (17.2%) and 2022 (16.9%). Fewer tickets were issued in 2020, accounting for 16.8% of the total observations. The distribution within the ESGs is as follows: *Between 6–10 kph*, the year 2019 accounts for the majority of tickets in this group (58.8%). *Between 11–15 kph*, 2019 is also the dominant year in this group (2.7%). *Between 16–20 kph*, 2019 remains the primary year (42.6%) for this ESG. Similarly, 2019 has the highest number of tickets (43.1%), followed by 2022 (20.9%). The occurrence of more speeding tickets issued in 2019 compared to the other years may be attributed to the fact that residents started noticing the presence of the speed cameras and abide to the speed limit.

The dataset classifies ticket locations into various built environments, including *One-Unit Dwelling*, *School-related*, *Open green space*, *Semi-Detached Dwelling*, *Multi-Unit Dwelling*, and *Others*. *One-Unit Dwelling* is the most common environment, accounting for 41.0% of all tickets. *Others* and *Multi-Unit Dwelling* are the next most common environments, with 27.5% and 11.8%, respectively. *One Unit Dwelling* and *Others* are the most commonly built environments in the ESG *Between*

6–10 kph (43.2% and 26.9%, respectively). *One-Unit Dwelling* and *Others* remain common environments in the ESG *Between 11–15 kph* (42.4% and 26.8%, respectively). For the ESG *Between 16–20 kph*, *One Unit Dwelling* and *Others* continue to be common built environments (39.0% and 28.3% respectively). *One Unit Dwelling* and *Others* are still the most common environments, with the most *Between 21–50 kph* ESG tickets (38.5% and 28.5%, respectively). The occurrence of more over speeding events along one-unit dwellings may be attributed to the presence of much lower speed limits along these locations, leading to failure to adhere to such low-speed limits for most drivers.

In the end, the dataset also categorizes ticket issuance based on the number of lanes on the road. The most common number of lanes is two, accounting for 76.6% of the total tickets. Four is the least common number of lanes, with 10.2% of the total tickets. The tickets are distributed in the ESGs as follows: *Between 6–10 kph*, two-lane roads have the highest ticket issuance in this group (78.0%). *Between 11–15 kph*, two-lane roads are also the most common (77.7%). *Between 16–20 kph*, two-lane roads remain the majority (75.2%). *Between 21–50 kph*, two-lane roads also dominate this group (74.5%). Two-lane roadways may be attributed to a higher number of speeding events due to limited passing opportunities, as drivers may encounter slower-moving vehicles, such as trucks or agricultural and construction machinery. This can lead to frustration and impatience among drivers, prompting them to speed when opportunities arise to pass slower vehicles.

5. Results and discussion

Table 3 presents the NBR results for the significance and likelihood of over-speeding based on different explanatory variables based on the five scenarios (speed limits, months of the year, years, types of built environment, and number of lanes) categorized into five sub-categories (overall and four ESGs described in the descriptive statistics.

5.1. Speed limit

In the analysis presented in Table 3, a notable observation is that nearly all vehicle speeds, except the 40 kph speed limit, were statistically significant at a 90% confidence level. The exception observed at 40 kph might be linked to the functional classification of these roads, often street roads where drivers typically begin to accelerate to merge onto higher-speed roads. A crucial point to note is the substantial increase in the likelihood of over-speeding as the speed limit ascends from lower (30 kph) to higher limits (100 kph). Specifically, the likelihood of over-speeding at 100 kph is more than 16 times higher than at 30 kph (OR = 16.54). This pattern might be attributed to the structural design of roads with higher speed limits, which often feature a larger number of lanes, thereby inadvertently encouraging over-speeding. Interestingly, the analysis also unveils that the likelihood of over-speeding at an 80 kph speed limit is significant, yet it does not adhere to the same trend as other speed limits. This anomaly could be rooted in the fact that 80 kph is a common cruising speed at which many vehicles travel and where a majority of drivers feel at ease (Nyamawe et al., 2014). Examining the excess speed between 6–10 kph, it is evident that all speeds were statistically significant in terms of over-speeding at a 90% confidence level. The probability of over-speeding at a 50 kph limit in this excess range was the highest, 1.75 times higher than at a 30 kph limit. Conversely, over-speeding at a 60 kph limit was 0.09 times lower than a 30 kph limit (Kusumawati et al., 2019). The overarching analysis of speed limits indicates a clear and significant increase in the likelihood of over-speeding as speed limits rise. This observation aligns with previous research underscoring the pivotal role of speed limits in shaping driving behavior and influencing the incidence of traffic accidents (Kusumawati et al., 2019).

5.2. Month of the year

The Month of the Year variable analysis in Table 3 reveals significant variations in over-speeding patterns throughout the year, with weather conditions playing a substantial role. June, October, and December were statistically significant at a 90% confidence level, suggesting a strong correlation between these months and the likelihood of over-speeding. In terms of Odds Ratio (OR), October has the highest likelihood of over-speeding (OR = 1.40), followed by June (OR = 1.28) and July (OR = 1.27). The lowest likelihood is observed in December (OR = 0.68) and November (OR = 0.97). This pattern can be attributed to the weather conditions prevalent during these months. For instance, the summer months (June, July, and October) are associated with increased travel and the absence of snow and ice on roads, leading to a higher likelihood of over-speeding. This is consistent with a study by the Bureau of Transportation Statistics (Bureau of Transportation Statistics, n.d.), which reported increased travel for vacation, sightseeing, or leisure during the summer months in North America. On the other hand, the winter months (December and November) are characterized by snow and ice weather conditions, which decrease skid resistance on road surfaces and increase the risk of crashes when over-speeding. This explains the lower likelihood of over-speeding during these months. The analysis of excess speed ranges further corroborates these findings. For the excess speed range between 6–10 kph, December is the only month with statistically significant speeds at a 90% confidence level. The highest likelihood of over-speeding is observed in October, followed by June and May, while the lowest likelihood is in December. For the excess speed range between 11–15 kph, October is the only month with statistically significant speeds at a 90% confidence level. The highest likelihood of over-speeding is in October (OR = 1.41), followed by July (OR = 1.28), while December (OR = 0.70) and November (OR = 0.98) have the lowest likelihood. The patterns observed in the "Month of the Year" variable analysis provide valuable insights for transportation planners aiming to reduce

Table 3
Negative Binomial Regression Results.

	Overall			Between 6–10 kph			Between 11–15 kph			Between 16–20 kph			Between 21–50 kph		
	Estimate	OR	*P*-value	Estimate	OR	*P*-value	Estimate	OR	*P*-value	Estimate	OR	*P*-value	Estimate	OR	*P*-value
Speed Limit															
40 kph	0.151	1.16	0.052	0.406	1.50	<0.001	0.297	1.35	<0.001	−0.316	0.73	0.001	−0.717	0.49	<0.001
50 kph	0.599	1.82	<0.001	0.560	1.75	<0.001	0.819	2.27	<0.001	0.189	1.21	<0.001	−0.143	0.87	0.001
60 kph	1.265	3.54	<0.001	−2.461	0.09	<0.001	1.721	5.59	<0.001	1.057	2.88	<0.001	0.899	2.46	<0.001
70 kph	2.070	7.92	<0.001				1.976	7.22	<0.001	2.735	15.41	<0.001	2.649	14.14	<0.001
80 kph	1.565	4.78	<0.001				1.190	3.29	<0.001	2.413	11.17	<0.001	2.288	9.86	<0.001
90 kph	2.203	9.05	<0.001				1.628	5.09	<0.001	3.144	23.20	<0.001	3.008	20.24	<0.001
100 kph	2.806	16.54	<0.001				2.249	9.48	<0.001	3.772	43.47	<0.001	3.553	34.93	<0.001
Month of the year															
February	0.074	1.08	0.306	0.054	1.05	0.575	0.079	1.08	0.302	0.078	1.08	0.350	0.041	1.04	0.660
March	0.196	1.22	0.005	0.138	1.15	0.131	0.195	1.22	0.009	0.253	1.29	0.002	0.220	1.25	0.015
April	0.150	1.16	0.035	0.139	1.15	0.137	0.158	1.17	0.037	0.196	1.22	0.016	0.209	1.23	0.023
May	0.223	1.25	0.002	0.148	1.16	0.113	0.242	1.27	0.001	0.267	1.31	0.001	0.285	1.33	0.002
June	0.247	1.28	<0.001	0.169	1.18	0.065	0.236	1.27	0.001	0.321	1.38	<0.001	0.358	1.43	<0.001
July	0.237	1.27	0.001	0.071	1.07	0.444	0.245	1.28	0.001	0.298	1.35	<0.001	0.407	1.50	<0.001
August	0.181	1.20	0.010	0.138	1.15	0.132	0.177	1.19	0.018	0.279	1.32	0.001	0.331	1.39	<0.001
September	0.213	1.24	0.002	0.071	1.07	0.431	0.231	1.26	0.002	0.259	1.30	0.001	0.307	1.36	0.001
October	0.338	1.40	<0.001	0.310	1.36	0.001	0.345	1.41	<0.001	0.385	1.47	<0.001	0.416	1.52	<0.001
November	−0.030	0.97	0.666	−0.059	0.94	0.519	−0.025	0.98	0.740	0.035	1.04	0.664	0.001	1.00	0.994
December	−0.386	0.68	<0.001	−0.378	0.69	0.000	−0.364	0.70	0.000	−0.397	0.67	0.000	−0.466	0.63	<0.001
Year															
2020	−1.439	0.24	<0.001	−1.281	0.28	<0.001	−1.423	0.24	<0.001	−1.446	0.24	<0.001	−1.578	0.21	<0.001
2021	−1.552	0.21	<0.001	−1.671	0.19	<0.001	−1.523	0.22	<0.001	−1.536	0.22	<0.001	−1.625	0.20	<0.001
2022	−1.596	0.20	<0.001	−1.710	0.18	<0.001	−1.567	0.21	<0.001	−1.624	0.20	<0.001	−1.712	0.18	<0.001
Built environment															
School-related	−0.093	0.91	0.050	−0.011	0.99	0.862	−0.110	0.90	0.030	−0.108	0.90	0.049	−0.069	0.93	0.266
Open green space	−0.056	0.95	0.320	−0.097	0.91	0.192	−0.068	0.93	0.257	−0.014	0.99	0.834	−0.072	0.93	0.325
Semi-Detached Dwelling	−0.381	0.68	<0.001	−0.231	0.79	0.034	−0.415	0.66	<0.001	−0.363	0.70	<0.001	−0.231	0.79	0.036
Multi-Unit Dwelling	−0.106	0.90	0.038	−0.045	0.96	0.504	−0.110	0.90	0.043	−0.091	0.91	0.120	0.010	1.01	0.884
Others	−0.113	0.89	0.003	0.044	1.05	0.372	−0.129	0.88	0.001	−0.100	0.91	0.021	−0.095	0.91	0.050
Number of lanes															
Two	−0.014	0.99	0.784	0.088	1.09	0.192	0.005	1.01	0.927	−0.055	0.95	0.360	−0.097	0.91	0.149
Three	−0.139	0.87	0.108	0.183	1.20	0.096	−0.159	0.85	0.085	−0.141	0.87	0.157	−0.218	0.80	0.053
Four	0.017	1.02	0.803	0.112	1.12	0.216	0.044	1.05	0.550	−0.010	0.99	0.903	−0.003	1.00	0.976
Intercept	4.075	58.85	<0.001	2.502	12.21	<0.001	3.319	27.62	<0.001	2.437	11.44	<0.001	1.811	6.12	<0.001

over-speeding. Appropriate measures can be implemented to enhance road safety by understanding the influence of weather conditions on over-speeding patterns.

5.3. Year

The temporal analysis of over-speeding behavior, as indicated by the 'Year' variable in Table 3, reveals significant insights. The analysis was conducted for 2019 to 2022, considering similar ESGs with 2019 data as a constant. The results indicate a statistically significant decrease in the likelihood of over-speeding over these years for all speed groups. This trend suggests a possible increase in public awareness and understanding of the consequences of over-speeding over time. However, this interpretation requires further validation through additional studies. The decrease in over-speeding is more pronounced in the lower speed range (6–10 kph), indicating that drivers over-speeding at lower ranges decrease at a higher rate than those at higher ranges. This finding is consistent with the study by (Rao and Chandra, 2022) who found that a significant proportion of drivers were traveling above the speed limit, with a small percentage traveling at speeds higher than the 98th percentile speed. The study also suggested that appropriate speed limits could help control road accidents. Another study in Mexico City evaluated road safety policies implemented from 2015 to 2019 and found that policies including high economic penalties for over-speeding effectively decreased traffic mortality (Quintero Valverde et al., 2022). This finding provides an additional perspective on our study's observed decrease in over-speeding over the years, suggesting that stringent penalties could have contributed to this trend. However, it is essential to note that these findings are specific to the community studied and may not be generalizable to other settings. Further research is needed to validate these findings and explore the factors contributing to the decreased over-speeding over time.

5.4. Built environment

The built environment, precisely the type of dwelling, appears to significantly influence the likelihood of over-speeding. As per the results in Table 3, semi-detached dwellings exhibited statistically significant speeds at a 90% confidence level for overall speed and excess speeds between 11–15 kph and 16–20 kph groups compared to single-unit dwellings. The semi-detached dwelling environment had the lowest likelihood of over-speeding compared to other environments, with the highest likelihood observed in open-grass spaces for overall speed (OR = 0.95) and excess speed between 11–15 kph (OR = 0.93) and between 16–20 kph (OR = 0.99). This could be attributed to higher speed limits and lower traffic in these areas, which offer larger headways and facilitate over-speeding (Bashir et al., n.d.; Zahid et al., 2020). A study by Vos et al. supports these findings, suggesting that the built environment and the type of road can significantly influence speeding behavior. The study found that drivers were more inclined to speed on road sections with lower speed limits, possibly because it is the norm among drivers (De Vos et al., 2023). An Intelligent Speed Assistance (ISA) system was found to be an effective way of reducing speed on these road sections. The study also found that the ISA system was particularly effective on rural roads with a speed limit of 60 km/h, which is inferred from context rather than speed signs. In the context of the built environment, the study suggests that ISA can be useful for drivers by informing them of local speed limits. This is particularly relevant for truck drivers operating in international transport who might not be fully aware of the many rules for enforced speed limits for trucks in different countries. Therefore, these results may suggest that ISA can be a valuable tool for drivers by informing them of local speed limits.

5.5. Number of lanes

In analyzing the number of lanes, the significance and likelihood of over-speeding were examined for roadways with two, three, and four lanes, using a single-lane roadway as the reference category. As per the results presented in Table 2, none of the groups demonstrated statistically significant speeds at a 90% confidence level. This suggests that the number of lanes is not a significant predictor of over-speeding probability when a single-lane roadway is used as the reference. However, the likelihood estimates indicate that the propensity for over-speeding increases with the number of lanes for the overall speed. This trend, however, varies as the excess speed ranges from lower to higher values. For instance, a three-lane roadway exhibits the highest likelihood for over-speeding in the 6–10 kph excess speed range (OR = 1.20), while a four-lane roadway shows the highest likelihood for over-speeding in the 11–15 kph (OR = 1.05), 16–20 kph (OR = 0.99), and 21–50 kph (OR = 1.00) excess speed ranges. This observation aligns with the findings of a recent study by (Zahid et al., 2020) and (Bashir et al., n.d.) which suggests that as lanes increase, the likelihood of over-speeding also increases. This can be attributed to the higher speed limits typically associated with multi-lane roads, which provide larger headways and facilitate over-speeding. Further research is needed to explore the complex interplay between the number of lanes, speed limits, and over-speeding behavior. Future studies could also investigate the impact of other roadway characteristics, such as lane width and separation, on over-speeding.

6. Conclusion and future studies

In exploring over-speeding behavior within Edmonton, Canada, this study analyzed data derived from mobile automated traffic enforcement tickets, utilizing the Negative Binomial Regression (NBR) models. The models facilitated a thorough investigation into the relationship between the extent of over-speeding and an array of predictors, such as speed limits, temporal variables (months and years), built environment types, and the number of lanes, with over-speeding categorized into four groups based on speed ranges.

Overall, the study found that aggregation of over-speeding data tends to underestimate the influence of various attributes. A pivotal finding of the study is the significant role of speed limits in predicting over-speeding, where higher speed limits were correlated with an escalated likelihood of over-speeding. Additionally, June, October, and December were identified as periods with statistically significant speeds, while a gradual decline in over-speeding likelihood was noted over the years. The built environment also presented varied findings, with semi-detached dwellings and open-grass spaces being associated with the lowest and highest likelihoods of over-speeding, respectively, compared to single-unit dwellings. Notably, the number of lanes did not emerge as a significant predictor of over-speeding despite an increased likelihood with more lanes. From these findings, several critical implications and conclusions are drawn:

- **Policy and design implications**: The strategy of matching the posted speed limit with the operating speed does not inherently deter over-speeding. A more nuanced approach, potentially focusing on roadway design that intrinsically moderates drivers' behaviors, such as modifying roadway configurations and introducing varied roadside features, might be more effective.
- **Seasonal enforcement**: The pronounced incidence of vehicle over-speeding during the summer months in the northern hemisphere, potentially due to heightened vehicle miles of travel (VMT) for leisure activities and more favorable weather conditions, signals a need for strategic adjustments. Enhanced enforcement, perhaps through augmented police patrols during this period, might be a viable countermeasure.
- **Technological interventions**: The diminishing trend in over-speeding since 2019 implies that mobile automated traffic cameras might be an effective tool in mitigating speeding tendencies across all speeding extents, even those involving high-speed violations.
- **Spatial considerations**: While open spaces, often characterized by higher speed limits and larger headways, are typically associated with over-speeding, this study did not find a statistically significant difference between such locations and single-unit dwellings. This suggests that further research, incorporating additional variables, might be necessary to derive more conclusive insights.
- **Roadway characteristics**: Despite the non-significant association between the number of lanes and over-speeding in this study, future research might explore the interaction between the number of lanes and speed limit, given that roadways with more lanes typically have higher posted speed limits.

This study has several limitations that should be addressed in future research. Firstly, the study did not consider the interaction between the number of lanes and the speed limit, which could potentially influence over-speeding behavior. Secondly, the study was limited to Edmonton, Canada, and the findings may only be generalizable to other locations with similar traffic regulations and driving behaviors. Future research should aim to replicate these findings in different geographical locations and consider additional variables that may influence over-speeding behavior.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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