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ORIGINAL PAPER
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ENHANCING PEDESTRIAN SAFETY BY PROVIDING A LIDAR-BASED ANALYSIS OF JAYWALKING CONFLICTS AT SIGNALIZED INTERSECTIONS

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ABSTRACT

Motives: In response to the inherent vulnerability of pedestrians in urban settings, this paper is driven by a commitment to enhancing their mobility and safety. Recognizing the prevalence of jaywalking as a significant concern, the study seeks practical solutions through the application of LiDAR sensors at signalized intersections. By delving into the complexities of jaywalking events and their contributing factors, the research aims to provide valuable insights that extend beyond mere statistical analysis. The motivations behind this endeavour lie in the imperative to comprehensively understand and address the risks associated with jaywalking, ultimately fostering a safer environment for pedestrians navigating urban crossroads.
Aim: The primary aim of this paper is to assess and analyse the diverse factors influencing the frequency of jaywalking at signalized intersections, leveraging the capabilities of LiDAR sensors for safety applications. Through a meticulous examination of 1000 jaywalking events detected over a six-month period, the study aims to pinpoint highly correlated independent variables to the frequency of jaywalking events. These variables include traffic signal controller patterns, signal phases, vehicle-pedestrian conflicts, weather conditions, vehicle volume, walking patterns toward the median, pedestrian volume, and the unique jaywalker's ratio. Employing advanced statistical regression models, the research seeks to identify optimal models and unravel key insights into the nuanced dynamics of jaywalking behaviour. The overarching goal is to equip decision-makers and transportation specialists with data-driven knowledge, enabling them to implement targeted safety measures that mitigate pedestrian risks and enhance safety infrastructure at critical urban crossroads.
Results: The outcomes of the study, derived from the optimal Poisson regression model, yield crucial insights into the multifaceted nature of jaywalking events at signalized intersections. The morning and mid-day signal controller patterns exhibit a substantial decrease of 44.7% and 34.4%, respectively, compared to the evening (PM) pattern, shedding light on temporal nuances in jaywalking behaviour. Additionally, the severity of vehicle-pedestrian conflicts escalates proportionally with the number of jaywalkers, emphasizing the importance of addressing pedestrian flow in mitigating potential conflicts. Notably, the presence of vegetation in the median emerges as a significant factor, significantly

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increasing the frequency of jaywalking. These results contribute to a nuanced understanding of the intricate interplay between environmental, temporal, and behavioural factors in jaywalking incidents. Decision-makers and transportation specialists can leverage these findings to formulate targeted safety interventions, fostering a safer pedestrian experience at crucial urban crossroads.

Keywords: LiDAR sensor, jaywalking event, vehicle-pedestrian conflicts, safety analysis, statistical regression models

INTRODUCTION

Jaywalking refers to crossing the road illegally and unsafely by a pedestrian (Norton, 2007). When a pedestrian cross against a red light or does not yield to oncoming traffic, it may also be considered jaywalking. There is no doubt that jaywalking can be extremely dangerous, however the danger of jaywalking may not seem obvious at first glance. According to the National Highway Traffic Safety Administration (NHTSA) released statistics (NHTSA, 2021), a total of 42,795 people were killed in motor vehicle crashes. The number of fatalities in 2022 dropped by about 0.3% as compared to 42,939 in 2021. According to Governors Highway Safety Association (GHSA) statistics (Association, 2022) in 2022, there continues to be an incredibly high death rate for pedestrians on roadways in the USA troubling trend of elevated pedestrian mortality rates has continued since 2020, with 2.37 pedestrian deaths per billion vehicle miles traveled (VMT) in 2022. The state of Maryland experienced 1.10 pedestrian fatality rate per 100,000 population and the report (Association, 2022) highlighted that California, Florida and Texas were responsible for over one-third (38%) of pedestrian fatalities in the first half of 2022. However, their combined population makes up only 28% of the total population in the United States. Warmer climates and large urban areas in certain states may explain the higher incidence of pedestrian-vehicle collisions. Factors contributing to increased pedestrian fatalities include economic growth, lower gas prices, distracted driving, and impaired driving. Other elements, like the proliferation of smartphones, legalization of recreational marijuana, and disparities in street infrastructure, further contribute to pedestrian crash rates, particularly in less affluent neighborhoods (Eluru et al.; 2008, Thomas et al., 2020; Tyndall, 2021).

Crossing the road outside of designated crosswalks, commonly known as jaywalking, can increase the chances of being involved in a vehicle-pedestrian collision. There are various reasons why pedestrians may choose to cross outside of a designated crosswalk. In certain instances, the distance between the available crosswalk and their intended destination, the presence of crosswalks may not be apparent to pedestrians or they might not be aware of the requirement to use them. Furthermore, pedestrians may attempt to cross if they are in a rush, especially if pedestrian signals malfunction, which could lead to serious or even fatal injuries.

It is crucial to recognize that jaywalking is generally considered illegal in the majority of states in the United States. Nonetheless, it is important to note that the specific laws and regulations regarding jaywalking can vary from state to state. In some states, jaywalking tickets may only be issued if the pedestrian is causing a traffic hazard. Jaywalking in California can result in a $196 ticket (VC, 2022). Other states, such as Florida, allow the pedestrian to cross outside of a crosswalk if they yield to oncoming traffic. In busy cities with a lot of pedestrian traffic, jaywalking laws are also more strictly enforced. To prevent car crashes and promote pedestrian safety, police may even conduct sting operations to catch people who are illegally crossing the street. Traditionally, jaywalking laws primarily focus on pedestrian behavior in relation to crosswalks and intersections. These laws are designed to ensure pedestrian safety and orderly traffic flow. At signalized intersections, pedestrian signal compliance becomes a critical issue. Pedestrian signals are an integral part of traffic control systems

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and are designed to regulate pedestrian movements and vehicle-pedestrian interactions. Compliance with pedestrian signals is essential for the safe and efficient operation of these intersections. Several factors can influence pedestrian signal compliance at signalized intersections. These factors may include pedestrian awareness and understanding of signal indications, pedestrian volume, signal timing, urban design, enforcement efforts, and the presence of amenities such as countdown timers and audible signals. Addressing the issue of jaywalking at signalized intersections may involve a combination of enforcement measures, educational campaigns, and infrastructure improvements. Law enforcement agencies may issue citations to violators, and public awareness campaigns can help educate pedestrians about the importance of following pedestrian signals.

Jaywalking can also contribute to traffic congestion. Jaywalkers can prompt drivers to abruptly brake or maneuver around them and leading to potential disruptions in traffic flow. A pedestrian may jaywalk if they are drunk, if they are not from the area (pedestrians who are visiting an area for the first time), or if pedestrians don't think jaywalking is a big deal (Guo et al., 2014; Pasha et al., 2015; TSS 2022).

This paper aims to address the application of accurate real-time traffic data collection and less-used statistical analysis models as the existing gaps in jaywalking studies by utilizing LiDAR technology, a recent and efficient technology to study jaywalking at signalized intersections. LiDAR technology offers an efficient and objective alternative to traditional manual or video-based methods for analyzing jaywalking conflicts at signalized intersections. LiDAR technology provides precise three-dimensional spatial information, facilitating accurate identification and assessment of pedestrian movements. The high-resolution data enables a nuanced understanding of jaywalking behaviors, expediting research and ensuring a reliable examination for enhancing pedestrian safety. By providing detailed and precise spatial data, LiDAR enables a comprehensive understanding of pedestrian behaviors at signalized intersections, identifying specific trends and potential conflict points. This rich dataset becomes the foundation for data-driven analyses, allowing for the development of targeted safety measures. The precision of LiDAR ensures that safety interventions are tailored to address specific jaywalking scenarios, ultimately contributing significantly to an effective and robust enhancement of pedestrian safety in complex urban traffic environments.

While LiDAR technology has been employed for various purposes, its application to investigate jaywalking in different traffic signal phases/patterns and in different weather conditions has not been explored. Hereupon, the effect of signal controller timing and phasing, daily patterns, and the potential risk of vehicle-pedestrian conflicts is investigated whether LiDAR has provided any additional insight over previous non-LiDAR-based studies. In light of the importance of jaywalking, it would be worthwhile to study the independent variables that affect the frequency of jaywalking and how people behave during jaywalking intervals. Thus, LiDAR sensor was used to record the trajectory of jaywalkers, and the conflicts between vehicles and pedestrians at Hillen Rd – E 33rd street intersection in Baltimore city, USA. The remainder of this article is structured as follows: Section 2: Literature Review, Section 3: Methodology, Section 4: Data Analysis, Section 5: Statistical modeling results, Section 6: Discussion, Section 7: Conclusion, and Section 8: References.

LITERATURE REVIEW

Pedestrian and bicyclist traffic crashes have become a critical safety issue worldwide (Mei, Xiaobao et al. 2013). Multiple crossing facilities have been designed to enhance pedestrian safety while crossing roadways including crosswalks at both signalized and unsignalized intersections, as well as pedestrian overpasses and underpasses, situated at intersections and midblock. These infrastructure facilitates pedestrians with safer and more accessible means of crossing, reducing the risk of crashes and enhancing overall pedestrian mobility and convenience (Ansariyar and Jeihani 2023). Pedestrians' crossing

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behavior is strongly influenced by human factors. Therefore, pedestrians may cross illegally rather than using crossing facilities. As a result of subjectivity and randomness, pedestrian behavior is complicated (Guo et al., 2014). Understanding and accommodating the diverse behaviors and needs of pedestrians is essential for creating safer and more efficient transportation facilities. This includes designing pedestrian-friendly infrastructure, improving crosswalks and signalization, implementing traffic calming measures, and promoting pedestrian education and awareness.

Different characteristics can affect the pedestrian's behavior when crossing intersections. The effect of low-income pedestrians in interaction with approaching vehicles at midblock road crossings was studied by Vasudevan et al. (2022). Financial limitations may restrict low-income individuals' access to transportation options, leading them to rely more on walking and crossing roads unsafely. To account for different pedestrian crossing paths, Vasudevan et al. (2022) developed a trajectory-based pedestrian modified Post-Encroachment Time (PET) model to account for the various possible pedestrian crossing trajectories. In terms of the new technologies application to study the behavior of jaywalkers, LiDAR technology was installed (Ansariyar & Jeihani, 2023) at one signalized intersection with high pedestrian injury rate to identify highly correlated independent variables associated with the frequency of jaywalking. Choi et al. (2013) by using human factor analysis highlighted that high-speed drivers are disproportionately involved in fatal crashes when it comes to incidents related to jaywalkers. The higher speeds of motorized vehicles reduce their reaction time and increase the severity of collisions to jaywalkers. Furthermore, other factors e.g., the vulnerable age group, road and environment factors, and dry/icy pavement conditions may increase the frequency and severity of jaywalker's conflicts. In another study, Li et al. (2023) demonstrated that improper signal timing often leads to higher delays and insufficient walk times for pedestrians, which could result in risky behaviors such as jaywalking. They (Li et al., 2023) developed a pedestrian behavioral data collecting system based on the emerging LiDAR sensor to analyze the pedestrian waiting time before crossing, their perception-reaction time to walk and their crossing speed at signalized intersections when the traffic signal performance is not properly. Ning-bo and Li-ying (2021) developed a microscopic simulation model for pedestrians and vehicles interactions at signalized intersections, which can include pedestrians' jaywalking. By using observed crossing speed, crossing trajectories, and conflicts between pedestrians and vehicles, the model provided a realistic representation of how pedestrians navigate and interact within the crossing environment. By collecting pedestrian trajectories, geometric and crosswalk characteristics using the video-graphic technique, Bansal et al. (2022) demonstrated that the independent variables e.g., gender, crossing pattern, type of signal at arrival, number of lanes, width of crosswalk, presence of guard rails and average pedestrian delay are crusial factors affecting on the probability of pedestrian jaywalking. Urban forms and environmental designs easily influence pedestrian behavior (Elvik et al., 2013). It is possible to design facilities in a way that encourages walking without compromising safety or convenience (Shriver, 1997). Waiting time and crossing distance (distance between the destination and crossing point) are also external factors (TSS, 2022) that may lead to unsafe crossings, such as jaywalking. A significant percentage of pedestrians fail to comply with pedestrian signal controllers or crossing facilities since they are in a rush or want to keep moving along the shortcut. The scholars e.g., Lambrianidou et al. (2013) and Li (2013) studied pedestrian behavior influenced by time and distance. Guo et al. (2012) by using the reliability theory examined the waiting behavior at street crossings. They (Guo et al., 2012) found that jaywalking violations enhanced significantly with a longer waiting time. Last but not least, Hamidun et al. (2021) studied the effect of surrounding factors that influenced the jaywalking e.g., the presence of median and vegetation on median, the location of land-uses and public transport stations near the intersection.

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As can be seen in the state-of-the-art studies, jaywalking may be taken into account as one of key reasons to decrease the safety of pedestrians in interaction with motorized vehicles. In areas without adequate pedestrian crossings or pedestrian traffic signals (Li et al., 2014; Museus & Park, 2015), jaywalking frequency may increase. The literature on jaywalking behavior at signalized intersections revealed a correlation with median locations, vehicle flows, and vehicle-pedestrian conflicts. While specific numerical values and findings may vary among studies due to different locations and methodologies, the overall body of research underscores the importance of designing safer pedestrian infrastructure, considering traffic volumes and speeds, and implementing measures to reduce jaywalking behaviors for improved pedestrian safety at intersections (Nassiri & Sajed, 2009). In terms of the "median locations", the literature review highlighted that intersections lacking medians or with narrow medians that do not provide a safe refuge for pedestrians are associated with higher instances of jaywalking. Regarding the "vehicle flows", higher vehicle flows and faster traffic speeds can influence pedestrian decision-making regarding jaywalking. Regarding "the correlation with vehicle-pedestrian conflicts", pedestrians who jaywalk, especially at signalized intersections, are at a greater risk of being involved in conflicts with vehicles. Hence, to investigate the potential risk of jaywalking at signalized intersections, the objective of this paper is to examine the highly correlated independent characteristics that associate with jaywalking frequency. To achieve this, the study employs LiDAR technology as a precise tool for collecting jaywalker's real-time data. The study also seeks to investigate the relationships between various independent variables, such as traffic signal controller patterns, signal phases, vehicle-pedestrian conflicts, weather conditions, vehicle volume, pedestrian volume, and jaywalker frequency, and the frequency of jaywalking events. The overarching objective is to elucidate how these variables interrelate and contribute to the observed occurrences of jaywalking, with the ultimate goal of enhancing pedestrian safety and mobility. By formulating clear hypotheses that delineate the expected relationships between these variables, the study endeavors to address the identified research problem comprehensively. For instance, it is hypothesized that an increase in vehicle volume or pedestrian volume may correlate positively with a higher frequency of jaywalking events, as pedestrians may perceive greater traffic congestion as an opportunity to engage in jaywalking behavior. Conversely, it is anticipated that the implementation of stricter traffic signal controller patterns or the presence of vegetation in the median may serve as deterrents, leading to a decrease in jaywalking occurrences. By elucidating these relationships, the study aims to contribute valuable insights towards developing targeted interventions aimed at reducing pedestrian risks and improving safety infrastructure at signalized intersections. While emphasizing its potential contribution to enhancing pedestrian safety, this study acknowledges the importance of situating its findings within the broader context of existing research in the field. By elucidating the hypotheses and research objectives, the study aims to not only build upon but also expand the current state of knowledge regarding jaywalking behavior at signalized intersections. Specifically, the research endeavors to provide a more nuanced understanding of the intricate dynamics influencing pedestrian decision-making processes and the factors contributing to jaywalking occurrences. By leveraging advanced LiDAR sensor technology and rigorous statistical analysis, the study seeks to introduce new perspectives and insights into the realm of pedestrian safety, ultimately paving the way for the development of more effective strategies and interventions aimed at mitigating the risks associated with jaywalking. Moreover, by explicitly highlighting the expected relationships between independent variables and jaywalking frequency, the study aims to contribute to the refinement and validation of existing theories while also advancing novel hypotheses for future exploration. Through this comprehensive approach, the research endeavors to make a meaningful impact on the state of knowledge surrounding pedestrian safety and jaywalking behavior, fostering a safer and more sustainable urban environment for vulnerable road users.

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MATERIALS AND METHODS

Materials

In this study, the LiDAR (Light Detection and Ranging) sensor technology was utilized as the primary tool for data collection and analysis at signalized intersections. LiDAR sensors offer several advantages for studying pedestrian behavior and jaywalking events due to their high-resolution spatial and temporal data capabilities. LiDAR sensors accurately track the movement of pedestrians within intersection areas, recording their positions and velocities with exceptional precision. This level of detail provides possibility to analyze pedestrian trajectories, assess compliance with signal indications, and identify instances of jaywalking with a high degree of accuracy. Moreover, LiDAR data can be collected continuously, allowing for comprehensive and long-term monitoring of pedestrian behavior, providing insights into variations over different times of the day, days of the week, or seasons. One significant advantage of LiDAR technology is its ability to operate effectively in various weather conditions and lighting scenarios, making it a versatile tool for year-round data collection. Unlike traditional methods that may be affected by adverse weather or low light conditions, LiDAR sensors reliably capture pedestrian behavior in diverse environments, ensuring data accuracy and consistency. Additionally, LiDAR data can be synchronized with other traffic-related data sources, such as traffic signal information or vehicle trajectories, to gain a comprehensive understanding of the interactions between pedestrians, vehicles, and signal timings. This interdisciplinary approach allows for a holistic analysis of jaywalking events, identifying potential correlations with traffic flow patterns or signal cycle lengths, and ultimately guiding evidence-based decisions to enhance pedestrian safety at signalized intersections.

Furthermore, the inclusion of LiDAR sensor technology in this study allows for real-time monitoring and assessment of pedestrian behavior at intersections. By comparing LiDAR data with signal information, instances where pedestrians cross outside designated crosswalks or against pedestrian signal indications can be identified. This synchronized approach offers insights into patterns of pedestrian non-compliance and jaywalking behavior, facilitating the implementation of automated warning systems or adaptive signal control strategies to enhance pedestrian safety.

Data sources

To ensure the accuracy and reliability of the data collected using LiDAR sensor technology, various data sources were employed in this study. These sources include:

1. Closed-circuit Television cameras (CCTVs) installed at the intersection: Recorded videos from CCTVs were used to double-check jaywalking paths provided by LiDAR sensors, ensuring the accuracy of recorded events.
2. Field observations: Road infrastructure characteristics such as the presence of medians, building entrances, side fences, vegetation on medians, and the presence of bus/taxi stops at each approach were recorded during field observations. These observations contribute to a more comprehensive understanding of factors influencing jaywalking conflicts at signalized intersections.
3. Previous studies: The accuracy of real-time traffic data collection by a LiDAR sensor was evaluated in the author's previous study (Ansariyar & Jeihani, 2023) and the results showed that the LiDAR sensor can collect the real-time jaywalking data with 99.4% accuracy rate. In order to analyze the behavior of jaywalking events and to develop statistical analysis of dependent and independent variables affecting the frequency of jaywalking, a daily database were prepared including the statistics of the frequency of jaywalking occurring in each pattern of the traffic signal controller (AM, MD, and PM patterns), the frequency of repeated signal controller phase(s) during each jaywalking event, frequency and severity of vehicle-pedestrian conflicts in each approach, weather conditions change throughout the day and at different times during jaywalking events, entering motorized vehicle volume to each approach (PCU/day), and the frequency of jaywalkers who were interested

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in walking toward the road median or public transport stations around the intersection. This previous research provides confidence in the reliability of LiDAR data for analyzing jaywalking events.

4. Daily database: A daily database was prepared to analyze the behavior of jaywalking events and develop statistical analysis of dependent and independent variables affecting the frequency of jaywalking. This database includes statistics such as the frequency of jaywalking occurring in each pattern of the traffic signal controller, frequency and severity of vehicle-pedestrian conflicts, weather conditions, motorized vehicle volume, and pedestrian preferences regarding walking toward road medians or public transport stations.

Overall, the combination of LiDAR sensor technology with complementary data sources allows for a comprehensive analysis of pedestrian behavior and jaywalking events at signalized intersections. This multidimensional approach enables evidence-based decision-making and targeted interventions to enhance pedestrian safety and improve traffic flow in urban environments.

Statistical methods

By using SPSS software, two regression models including Poisson and Negative Binomial were developed since the response variable is the number of jaywalking events per day. Poisson distributions and Poisson regressions are characterized by equidispersion, which means the mean and variance are equal (Consul & Famoye, 1992). Equation 1 shows the general mathematical form of Poisson Regression model.

$$\ln(y) = a_0 + a_1x_1 + a_2x_2 + \cdots + a_px_p \quad (1)$$

Where,

y: The dependent (response) variable
a_i: numeric coefficients, $i = 0, 1, \ldots, p$
x_i: The independent (the predictor/explanatory) variable

To determine whether the data follow the Poisson distribution and to evaluate the effectiveness of the Poisson test, the Chi-Squared Goodness-of-Fit test is used. In the Chi-Square Goodness-of-Fit test, the observed counts are compared to the expected counts based on the Poisson distribution. A p-value larger than 0.05 can result in failure to reject the null hypothesis (=The sample data follow the Poisson distribution).

In addition to Poisson regression, Negative Binomial Regression that can account for overdispersion (=when variance is greater than mean) in the data is also tested (Hilbe, 2011). Since the Negative Binomial Regression model has the same mean structure as Poisson regression and has an additional parameter to model over-dispersion, it is a generalization of Poisson regression. Compared to Poisson regression models, the confidence intervals for Negative binomial regression are likely to be wider if the conditional distribution of the outcome variable is over-dispersed (Ver Hoef & Boveng, 2007). In Negative Binomial Regression, the dependent variable (y) is modeled by mean parameter (μ) and reciprocal dispersion parameter (Ω) as shown in Equation 2. NegBin is the abbreviation of "Negative Binomial" that represents the Negative Binomial distribution, a probability distribution commonly used in regression analysis to model count data.

$$y|\mu, \Omega \sim NegBin(\mu, \Omega);$$
$$\log(\mu) = a_0 + a_1x_1 + a_2x_2 + \cdots + a_px_p \quad (2)$$

In Negative Binomial Regression, the relationship between the dependent variable (=y) and the mean parameter (=μ) along with the reciprocal dispersion parameter (=Ω) is modeled using the Negative Binomial distribution. The Negative Binomial distribution allows for the characterization of count data, such as the frequency of jaywalking events, by considering both the mean parameter and the dispersion parameter. The mean parameter represents the average count value for the dependent variable y, while the dispersion parameter accounts for the variability or overdispersion in the data.

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By incorporating the Negative Binomial distribution into the regression model, it becomes possible to account for the inherent variability in count data and effectively model the relationship between predictor variables and the frequency of jaywalking events.

Considering y has conditional probability mass function (=pmf, characterizes the distribution of a discrete random variable. It associates to any given number the probability that the random variable will be equal to that number) (NCSS), the fundamental negative binomial regression model can be expressed as shown in Equation 3.

$$\Pr\,(Y = y_i|\mu_i, \Omega) = \binom{y_i + \Omega - 1}{\Omega}\left(\frac{\Omega}{\mu_i + \Omega}\right)^{\Omega}\left(\frac{\mu_i}{\mu_i + \Omega}\right)^{y_i};$$
$$E(Y = y_i|\mu_i, \Omega) = \mu_i$$
$$\text{and } Var(Y = y_i|\mu_i, \Omega) = \mu_i + \frac{\mu_i^2}{\Omega} \qquad (3)$$

In Equation 3,

Y: Represents the dependent variable, which in this case refers to the count data being analyzed, such as the frequency of jaywalking events.

y_i: Denotes a specific count value of the dependent variable Y.

μ_i: Represents the mean parameter associated with the negative binomial distribution, indicating the average count value for the dependent variable.

Ω: Stands for the dispersion parameter, which accounts for the variability or overdispersion in the count data.

$Pr(Y = y_i|\mu_i, \Omega)$: Indicates the conditional probability mass function (pmf) of the negative binomial distribution, representing the probability of observing a specific count value y_i given the mean parameter μ_i and dispersion parameter?Ω.

$E(Y = y_i|\mu_i, \Omega)$: Refers to the expected value or mean of the count variable Y given the mean parameter μ_i and dispersion parameter Ω.

$Var(Y = y_i|\mu_i, \Omega)$: Represents the variance of the count variable Y given the mean parameter μ_i and dispersion parameter Ω.

To analyze the goodness-of-fit of the negative binomial regression model, the Likelihood Ratio Chi-Square test is used. It is worth mentioning that in the Likelihood Ratio Chi-Square test, the overall goodness-of-fit of the model is assessed, not specific predictors or assumptions. In negative binomial model, the dispersion parameter (=θ) is analyzed that represents the degree of over dispersion. Theta (θ) measures the extra variability in the data beyond what is accounted for by the mean. A lower value of Theta suggests a better fit to the data.

The choice of LiDAR sensors stems from their inherent capability to provide high-resolution spatial and temporal data, less-used device in the state-of-the--art to study jaywalking events, and facilitating precise tracking of pedestrian movements and behaviors within signalized intersections. The decision to employ Poisson and negative binomial regression models was driven by their suitability for analyzing count data and accounting for potential over dispersion, aligning with the nature of the jaywalking event frequency data collected in this study. Moreover, the selection of these models was guided by their ability to handle the inherent complexities and non-linearity often present in transportation data, ensuring robustness and reliability. Additionally, a thorough discussion of analytical assumptions is presented, including potential sources of bias or confounding factors, such as measurement errors in LiDAR data and temporal dependencies within the dataset.

Case study description

The LiDAR sensor was installed in the northeast side of the Hillen Rd – 33rd street intersection in Baltimore city, MD. This intersection was chosen as one of the signalized intersections in Baltimore City where vehicles and pedestrians have the highest conflicts. Additionally, in this intersection, pedestrians have a significant interest in crossing outside the cross section to reach Montobello Lake in the intersection's southbound direction. As can be seen in Fig. 1, E 33rd street is a primary east-west road with two lanes in each direction and Hillen Rd is a secondary north-south road with three lanes each

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way. As shown in Fig. 1, the LiDAR sensor installed on the pole is indicated by a red circle. The LiDAR sensor collects jaywalking characteristics around the area of the E 33rd-Hillen Rd signalized intersection through its high-resolution scanning capabilities. Positioned strategically in the vicinity of the intersection, the LiDAR sensor emits laser pulses that bounce off surrounding objects, including pedestrians. By measuring the time, it takes for these pulses to return, the LiDAR sensor creates precise 3D maps of the surrounding environment, capturing the positions and movements of pedestrians with exceptional accuracy. Specifically, when pedestrians deviate from designated paths and engage in jaywalking behavior, the LiDAR sensor detects these movements and records relevant data points, such as the time interval, geographical coordinates, duration, and speed of each jaywalking event. This comprehensive data collection process enables detailed analysis of pedestrian behavior and jaywalking occurrences.

As can be seen in Fig. 1, the sensor's location was selected to capture frequent instances of jaywalking, as southbound traffic often experiences higher pedestrian volumes due to factors such as nearby residential areas, commercial establishments, or public transportation stops. Additionally, the proximity to Montebello Lake may influence pedestrian movement patterns, making it an ideal spot for detecting jaywalking behaviors. Moreover, the chosen location offers strategic advantages for integrating with existing infrastructure, such as CCTV cameras at the intersection. By collocating the LiDAR sensor with these surveillance systems, it facilitates comprehensive monitoring of pedestrian activities, enhancing overall safety surveillance capabilities at the intersection. Furthermore, the decision to position the LiDAR sensor in the southbound direction was informed by considerations of optimal coverage of the internal space of the intersection.

The heat map in Fig. 2 illustrates the number of jaywalking events detected by the LiDAR sensor in each approach from December 2022 to May 2023. According to Fig. 2, 97.7% of jaywalking events occurred in the northern approach. Due to the location of residential land-uses and Montebello Lake on the southbound of the intersection, as well as a spacious median adorned with vegetation (grass), pedestrians may cross outside the designated crosswalk on the northern approach (south-bound). The blue color in Fig. 2 indicates locations where jaywalking occurs

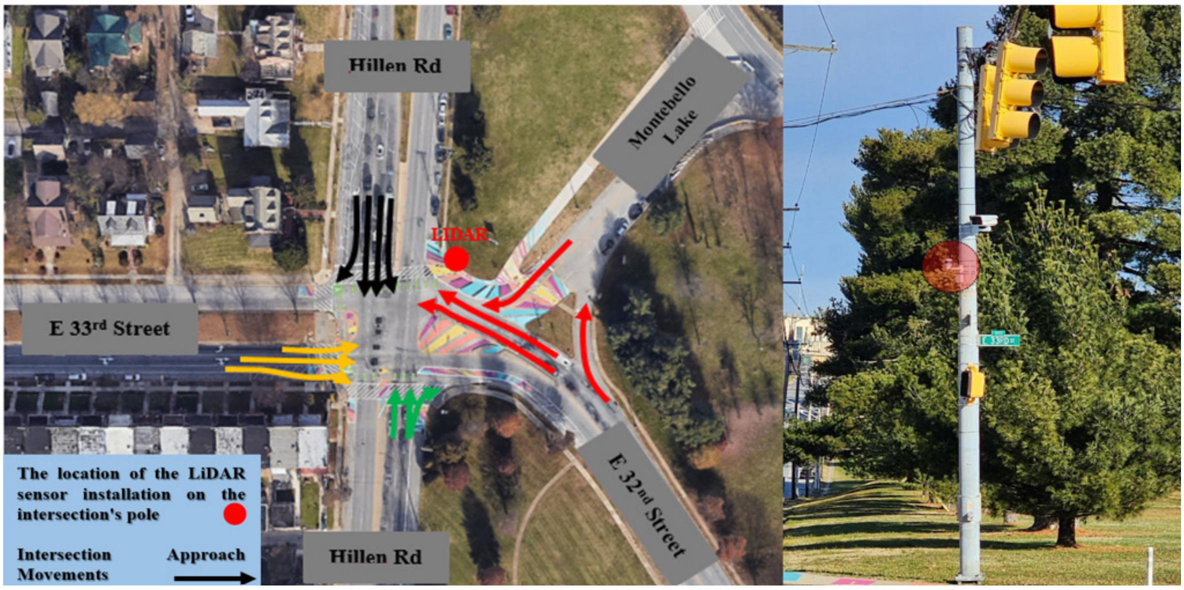

Fig. 1. Hillen Rd and E 33rd Street Intersection
Source: own elaboration.

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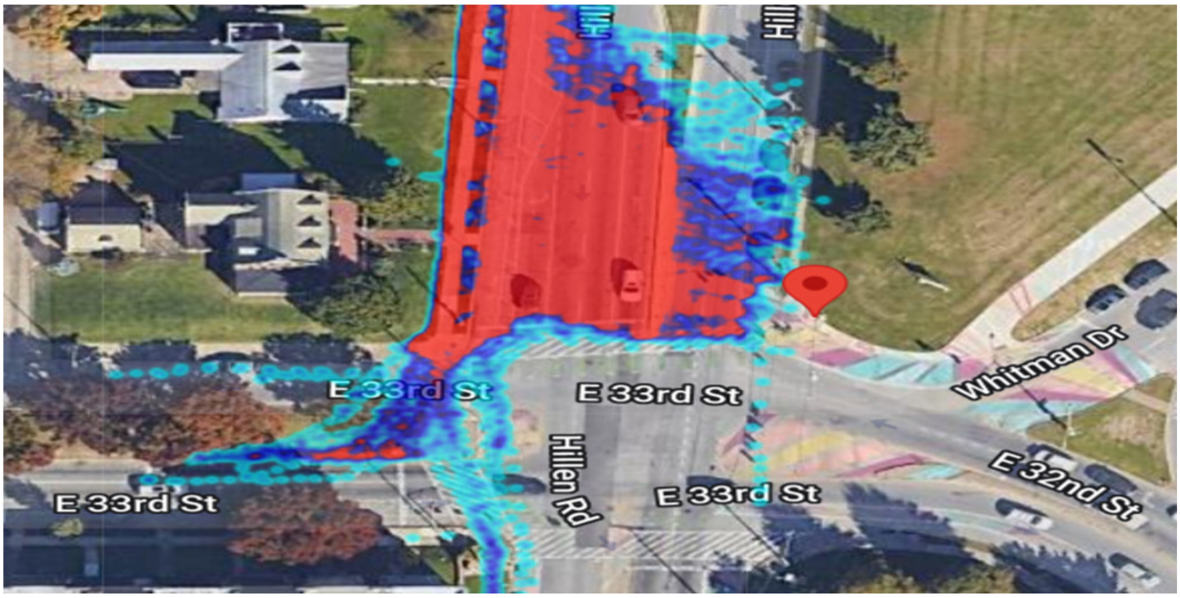

Fig. 2. Frequency Heat Map of Jaywalking Events in Diverse Intersection Approaches
Source: own elaboration.

less frequently and severely. On the other hand, red indicates a higher frequency of jaywalking events and a greater likelihood of severe conflicts between vehicles and pedestrians. As can be seen in Fig. 2, if a pedestrian crosses the road by following a path perpendicular to the direction of vehicular flow, the pedestrian will pass through some blue and some red zone. The differentiation in color signifies varying levels of risk associated with different segments of the crossing route. The blue zones suggest areas with a lower frequency of jaywalking events and, consequently, a reduced likelihood of severe conflicts between vehicles and pedestrians. These segments can be considered relatively safer for pedestrian crossings. Conversely, the red zones indicate higher frequencies of jaywalking events, highlighting areas where the risk of severe conflicts is greater. When an individual follows a path perpendicular to vehicular flow and traverses both blue and red zones, it implies that their route intersects locations with varying risk profiles. This nuanced representation allows stakeholders to pinpoint specific sections of the crossing route that may pose elevated risks and others that exhibit lower risks. From a technical perspective, this granularity in color representation on the heat map provides a spatially detailed understanding of the distribution of jaywalking incidents. The variation in colors enables a fine-grained analysis of risk along the entire crossing route, helping stakeholders identify precise locations where interventions may be needed. This tailored approach ensures that safety measures are targeted to address specific risk levels in different segments of the signalized intersection, enhancing the effectiveness of pedestrian safety interventions. Hereupon, statistical analysis of the northern approach is presented in this paper due to the significant safety concerns associated with this approach. An investigation was conducted into the trajectory of jaywalking events. The trajectory of jaywalkers over a six-month is shown in Fig. 3.

In conclusion to this section and in order to address the stages of this study with the research schema, the LiDAR sensor technology as the primary tool can accurately track the movement of pedestrians within intersection areas, recording their positions and velocities with exceptional precision. Moreover, LiDAR data can be synchronized with other traffic-related data sources, such as traffic signal information or vehicle

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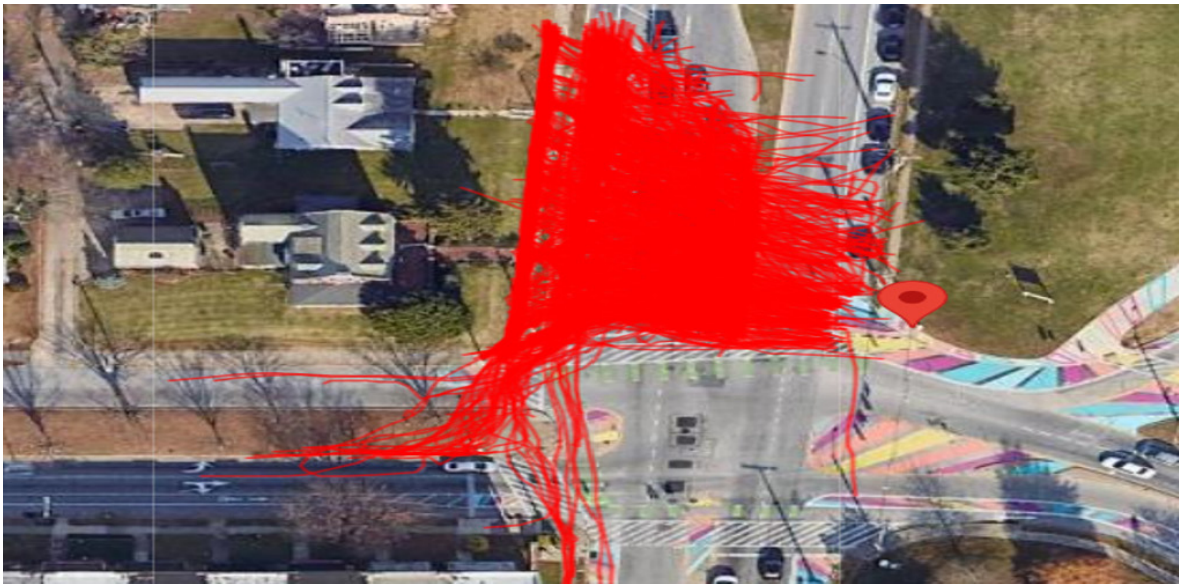

Fig. 3. Jaywalking Event Trajectories
Source: own elaboration.

trajectories, to gain a comprehensive understanding of the interactions between pedestrians, vehicles, and signal timings. This interdisciplinary approach allows for a holistic analysis of jaywalking events, identifying potential correlations with traffic flow patterns or signal cycle lengths, and ultimately guiding evidence-based decisions to enhance pedestrian safety at signalized intersections. To provide a clear visual representation of the methodology, a research schema was developed outlining the stages of the study. The stages include: (1) Data Collection Preparation, involving site selection, LiDAR sensor installation, and data synchronization setup; (2) Data Collection and Calibration, encompassing LiDAR data collection, CCTV video recording, and field observations; (3) Data Analysis and Validation, comprising trajectory analysis, cross-validation, and statistical modeling; (4) Integration and Synthesis, involving the integration of data sources and synthesis of findings; (5) Results Interpretation and Application, encompassing the interpretation of results and application of insights; and (6) Validation and Refinement, including the validation of recommendations and refinement of strategies. This structured approach ensures a comprehensive analysis of pedestrian behavior and jaywalking events, facilitating evidence-based decision-making and targeted interventions to enhance pedestrian safety and improve traffic flow at signalized intersections.

DATA ANALYSIS

Vehicle and pedestrian counts

The paper examined the average daily traffic and pedestrian counts per approach. The LiDAR sensor collected vehicle counts including cars, buses, trucks, trailers, and motorcycles, as well as pedestrian counts at 15-minute intervals. Fig. 4 illustrates the average daily vehicle counts (PCU per day), while Fig. 5 depicts the average daily pedestrian counts (in people per day) observed over a period of six months. It is worth mentioning that Fig. 5 does not include jaywalkers in the ADT of pedestrians. Considering Figures 4 and 5, the results demonstrate the considerable vehicle and pedestrian counts in the northern approach (SB) to the intersection.

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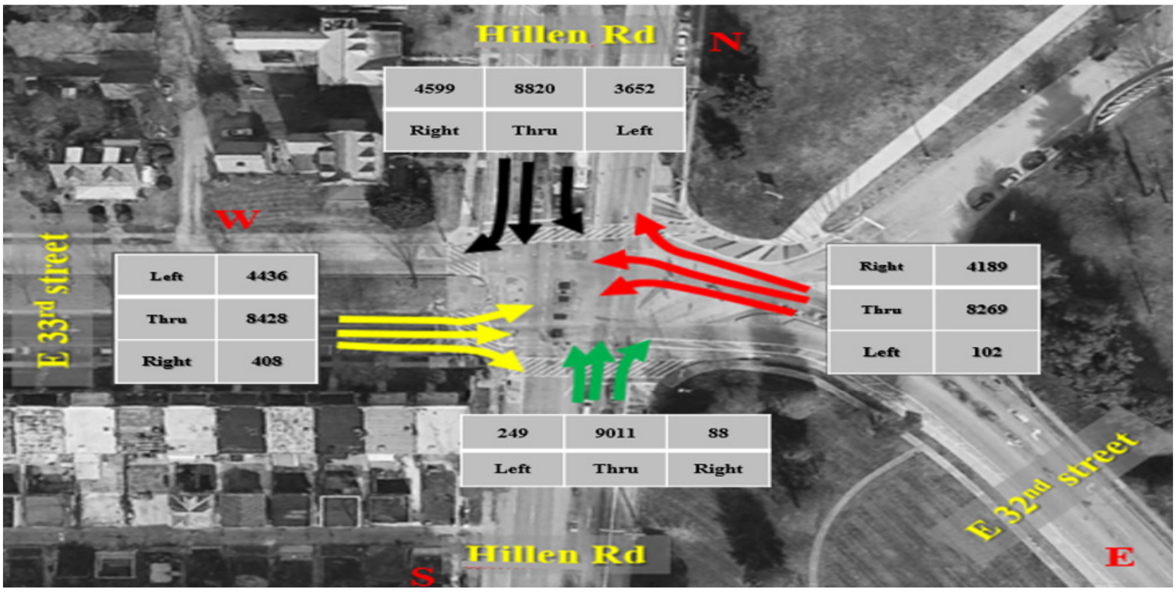

Fig. 4. Average Daily Traffic (ADT) of Motorized Vehicles at Intersection
Source: own elaboration.

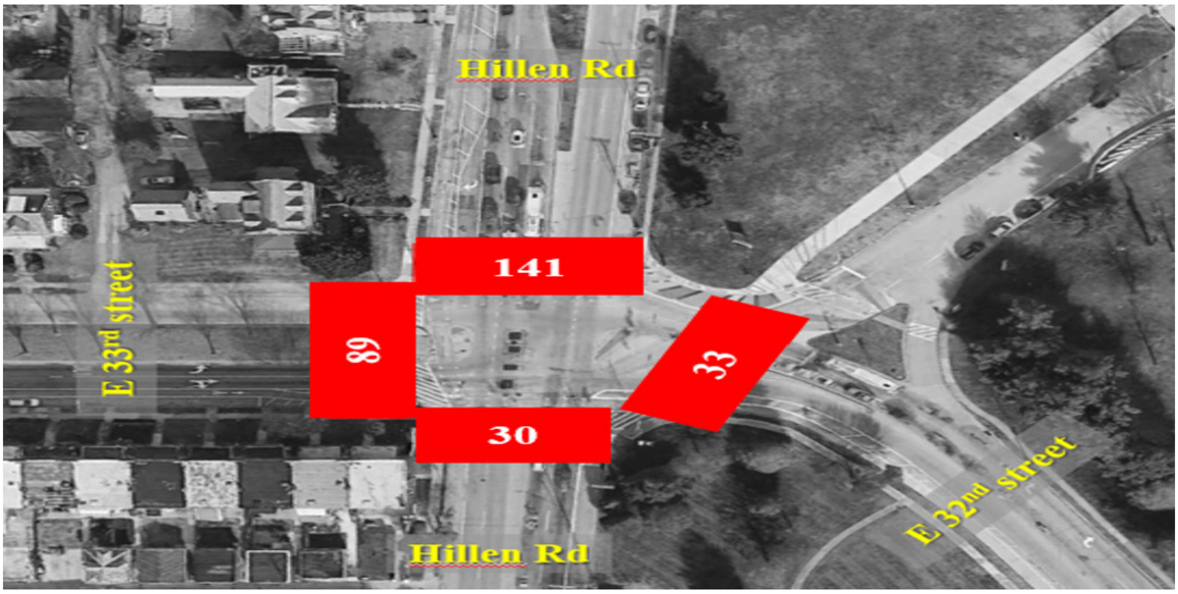

Fig. 5. Average Daily Pedestrian Traffic Counts at Intersection
Source: own elaboration.

Speed changes

At different approaches to the intersection, the speed of vehicles was monitored. A box chart of vehicle speed changes in the directions "east-west & west-east" and "north-south & south-north" is shown in Fig. 6. As can be seen in Fig. 6, the average vehicle speed in the north-south direction was changed from 33 to 49 km/hour, in the south-north direction was changed from 34 to 42 km/hour, in the east-west direction was changed from 35 to 39 km/hour, and in the west-east direction was changed from

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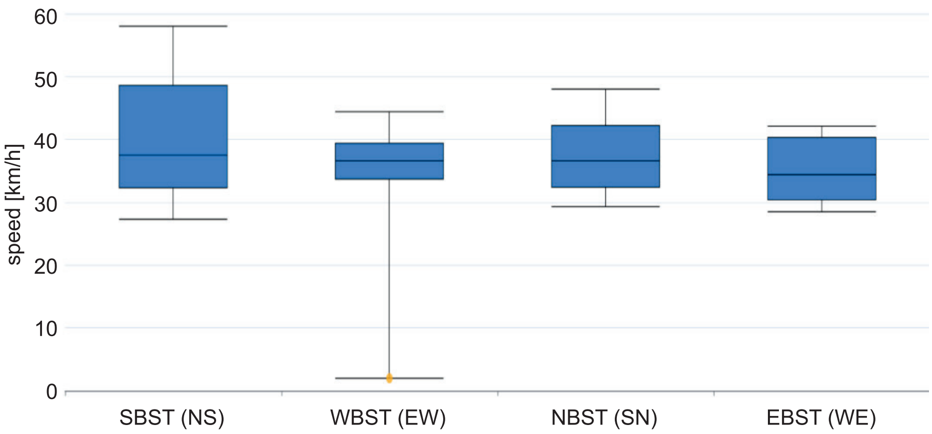

Fig. 6. Box Chart of Vehicle Speed Fluctuations
Source: own elaboration.

30 to 41 km/hour. Vehicle-pedestrian crashes are more likely to occur in north-south and south-north directions due to the higher average daily speed.

The speed of vehicles at a signalized intersection plays a crucial role in influencing the frequency of jaywalking conflicts, presenting a significant area of concern for urban traffic safety and pedestrian behavior studies. Higher vehicle speeds tend to correlate with an increased likelihood of jaywalking behavior. When vehicles are traveling at elevated speeds, pedestrians may perceive the crosswalk as less safe and hesitate to use it. This hesitation can result in pedestrians choosing to jaywalk, believing that they can cross the road more quickly and safely without having to wait for a green signal. Consequently, vehicle speed becomes a contributing factor to pedestrian non-compliance with traffic signals and crosswalks. Moreover, higher vehicle speeds also reduce the time available for drivers to react to pedestrians at crosswalks, increasing the risk of pedestrian-vehicle conflicts and crashes. This risk further discourages pedestrians from using designated crosswalks, as they may perceive them as unsafe due to the limited reaction time afforded to drivers. Therefore, mitigating the frequency of jaywalking conflicts necessitates a comprehensive approach that addresses not only pedestrian education and enforcement but also includes measures to reduce vehicle speeds, such as traffic calming strategies and improved intersection design, to create a safer environment that encourages pedestrian compliance with signalized crossings.

The frequency and severity of vehicle-pedestrian conflicts

The LiDAR sensor is capable of collecting hourly vehicle-pedestrian conflicts. Additionally, the sensor records the Post Encroachment Time (PET) values associated with these conflicts. PET refers to the time difference between the termination of encroachment by the first vehicle/pedestrian and the entrance of the second vehicle/pedestrian into the conflict zone (Ansariyar and Taherpour 2023). Non-zero PET values indicate crash proximity, while PET values of 0 indicate a crash. Lower PET values indicate a more severe crash, whereas higher PET values indicate a less severe crash. The LIDAR sensor collected 6709 vehicle-pedestrian conflicts over six months. The frequency of vehicle-pedestrian conflicts is shown in Table 1. The severity of conflicts was calculated by $\frac{1}{\sum \text{PET values}}$. The equation presented as the conflict's severity, which calculates conflict severity as the inverse of the sum of post-encroachment time (PET) values. PET is a recognized metric used to quantify the duration during which pedestrians are exposed to potential collision risk after entering a conflict zone. By summing up the PET values for

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all conflicts, the equation provides a comprehensive measure of pedestrians' overall exposure to collision risks at the intersection. Taking the inverse of this sum aligns with the concept that higher PET values correspond to lower conflict severity, as longer post-encroachment times indicate a greater safety buffer for pedestrians. Thus, by prioritizing conflicts with shorter PET values, which indicate more severe and potentially hazardous situations for pedestrians, the equation effectively quantifies conflict severity. This approach ensures that conflicts with shorter PET values contribute more significantly to the overall severity measure, emphasizing the urgency of addressing situations where pedestrians face higher collision risks within a shorter time frame.

The research utilized a predetermined PET threshold to delineate conflicts during jaywalking events at signalized intersections. The PET threshold may vary based on factors such as local traffic conditions, pedestrian volumes, and safety regulations. Typically, PET thresholds are determined based on safety standards and the desired level of risk mitigation. This study examined PET thresholds between 0 and 5. This threshold was carefully selected to identify instances where pedestrians' encroachment into vehicular space exceeded a predefined time duration, signifying potential safety risks. The incorporation of PET as a quantitative measure adds precision to the analysis, allowing for a standardized assessment of conflicts and facilitating a more nuanced understanding of pedestrian-vehicle interactions in the studied context.

This threshold was carefully selected to identify instances where pedestrians' encroachment into vehicular space exceeded a predefined time duration, signifying potential safety risks. The incorporation of PET as a quantitative measure adds precision to our analysis, allowing for a standardized assessment of conflicts and facilitating a more nuanced understanding of pedestrian-vehicle interactions in the studied context. To comprehensively measure the Post-Encroachment Time (PET) in conflicts between pedestrians and vehicles, the proposed methodology intricately incorporates the advanced capabilities of LiDAR for meticulous three-dimensional spatial data collection. The deployment of LiDAR sensors is strategically orchestrated to provide comprehensive coverage of the signalized intersection, enabling the capture of highly detailed trajectories for both pedestrians and vehicles. Subsequent trajectory analysis identifies precise instances of conflicts, delineating the exact initiation and resolution points within the spatial data. Leveraging LiDAR data, the temporal boundaries of the conflict are precisely defined, establishing the duration from conflict initiation until resolution when the pedestrian successfully clears the vehicular path. The calculation of PET involves determining the time elapsed between conflict resolution and the termination of the signal phase. This method capitalizes on the inherent high resolution and accuracy of LiDAR data, ensuring a meticulous quantification of the temporal intricacies inherent in conflicts, thereby providing a nuanced and detailed comprehension of pedestrian-vehicle interactions at signalized intersections.

Table 1 shows that more frequent and severe vehicle-pedestrian conflicts occurred in the WN (=EBL), EN (=WBR), WE (=EBT), and SN (=NBT) movements. As shown in Table 1, a significant percentage of conflicts between vehicles and pedestrians occur when either the origin or destination of the movement is in the north of the intersection. Considering the frequency and severity of conflicts in Table 1, the movements WN or EBL (=1381 conflicts with the severity 538.3), EN or WBR (=967 conflicts with the severity 353.5), and SN or NBT (=809 conflicts with the severity 299.1) have higher probability of vehicle-pedestrian crashes. The hourly frequency of vehicle-pedestrian conflicts was analyzed. As shown in Fig. 7, the intervals 14:00-15:00 PM (=10.2% of total conflicts), 08:00-09:00 AM (=9.4% of total conflicts), and 15:00-16:00 PM (=8.9% of total conflicts) were recognized as critical daily intervals.

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Table 1. Frequency and Severity of Recorded Conflicts by LiDAR Sensor

Movement*	Leading Object (Vehicle or Pedestrian)		Following Object (Vehicle or Pedestrian)		Total (Sum of Leading and Following Objects)	
	Frequency of collected conflicts	Severity of conflicts (1/PET)	Frequency of collected conflicts	Severity of conflicts (1/PET)	Frequency of collected conflicts	Severity of conflicts (1/PET)
EN	597	237.96	370	115.52	967	353.48
EW	445	180.39	128	40.77	573	221.17
ES	6	2.51	13	3.57	19	6.08
NW	452	196.5	307	90.01	759	286.51
NS	405	158.06	157	49.99	562	208.05
NE	480	214.32	192	61.51	672	275.84
WS	26	9.94	18	5.19	44	15.13
WE	642	279	226	73.48	868	352.74
WN	845	353.3	536	184.89	1381	538.22
SE	5	2.892	3	0.867	8	3.76
SN	625	238.212	184	60.884	809	299.09
SW	36	14.04	11	3.148	47	17.18
SUM	4564	1887.43	2145	689.86	6709	2577.29

* EN (=WBR), EW (=WBT), ES (=WBL), NW (=SBR), NS (=SBT), NE (=SBL), WS (=EBR), WE (=EBT), WN (=EBL), SE (=NBR), SN (=NBT), SW (=NBL)

Source: own elaboration.

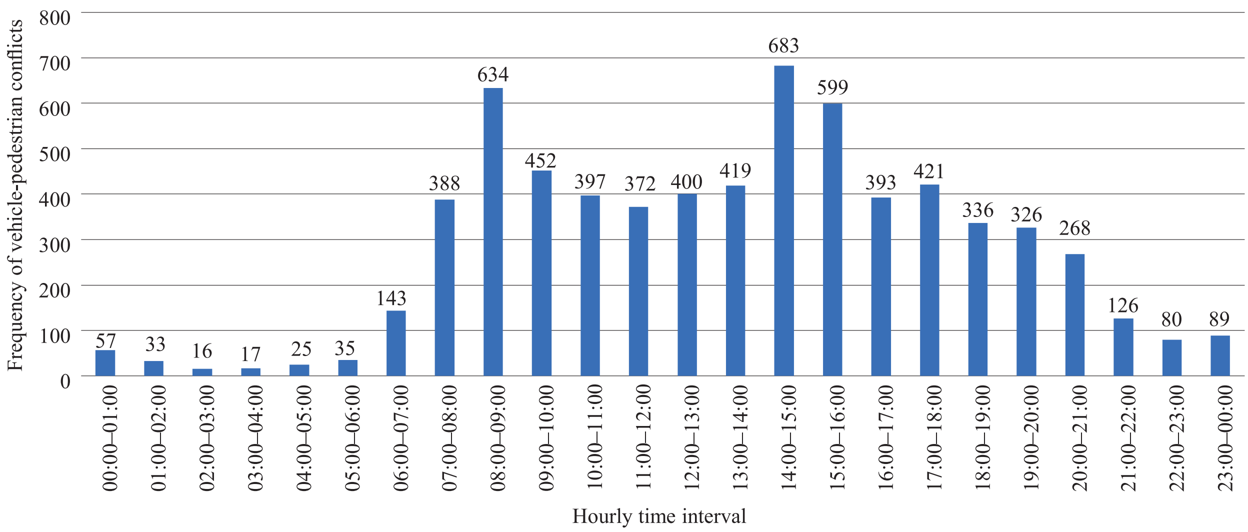

Fig. 7. Hourly Frequency of Vehicle-Pedestrian Conflicts, December 2022 – May 2023
Source: own elaboration.

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The frequency of jaywalking events

LiDAR sensor collected 1000 jaywalking events over a six-month interval, with a significant proportion occurring in the northern approach (=southbound) to the intersection. As shown in Fig. 8, the intervals 15:00–16:00 PM (=12.8% of total jaywalking events), 16:00–17:00 PM (=11.8% of total events), and 09:00-10:00 AM (=9.7% of total events) were recognized as critical daily intervals. As shown in Fig. 3, the trajectory of jaywalking events highlighted that a significant percentage of jaywalking events occurred in the southbound direction between residential land uses and the lake. Despite the pedestrian signal working well on all approaches to the intersection, pedestrians prefer to walk outside of the cross section in northern approach (southbound).

Traffic signal controller at Hillen Rd – E 33rd street intersection

The traffic signal at Hillen Rd – E 33rd street intersection is controlled as a pre-timed signal with three daily patterns including morning (AM), mid-day (MD), and afternoon (PM). The traffic signal is controlled from 00:00 – 06:30 by MD pattern with 110 sec cycle time and 46 sec offset, from 06:30 – 09:00 by AM pattern with 165 sec cycle time and 79 sec offset, from 09:00 – 14:30 by MD pattern, from 14:30 – 19:00 by PM pattern with 180 cycle time and 98 sec offset, and from 19:00 – 00:00 by MD pattern. The optimization of pedestrian crossing timings, phase splits, and phase sequences at signalized intersections is a critical aspect of traffic management and safety. When signal timings do not align with the natural flow of pedestrian activity or fail to accommodate the needs of pedestrians, it can create frustration and impatience, compelling individuals to take unnecessary risks by crossing the road outside designated crosswalks. For instance, during peak traffic hours, if the pedestrian phase is too short or infrequent, pedestrians may resort to jaywalking to save time, as they perceive the official crossing time as excessive. This misalignment between signal timing and pedestrian behavior can result in dangerous situations and heightened risks of crashes. In the United States, according to the Manual on Uniform Traffic Control Devices (MUTCD), which provides standards for traffic control devices including pedestrian signals, the "walk interval" for pedestrian is suggested a minimum duration of 7 seconds. This allows pedestrians to begin crossing the road safely. After the "Walk" interval, the MUTCD recommends that the "Flashing Don't Walk" interval should provide

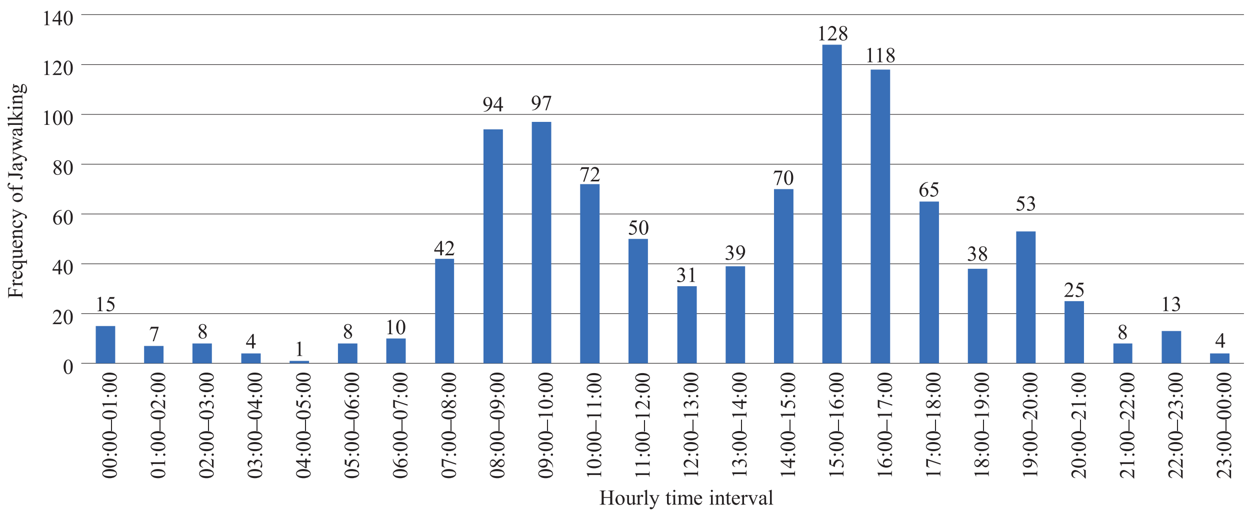

Fig. 8. Hourly Frequency of Jaywalking Events, December 2022 – May 2023
Source: own elaboration.

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a minimum of 3.5 feet per second of walking speed for pedestrians to complete their crossing. For example, if the road is 40 feet wide (=12.192 meters), the flashing "Don't Walk" interval should be a minimum of 11.4 seconds (40 feet / 3.5 feet per second). After the "Flashing Don't Walk" interval, there is often a clearance interval where the signal displays a solid "Don't Walk" indication. This allows any pedestrians who have already started crossing to finish safely. At Hillen Rd – E 33rd street intersection, the minimum "walk interval", flashing "don't walk" interval, and "acceptable clearance interval" are included.

Moreover, the issue of jaywalking frequency can also be exacerbated by inadequate synchronization between vehicle and pedestrian phases. When pedestrian crossings are not coordinated with vehicle green phases, pedestrians may be left waiting for extended periods, leading to impulsive decisions to jaywalk during gaps in traffic. Furthermore, during off-peak hours, signalized intersections often prioritize vehicular flow with longer green times, leaving pedestrians with limited opportunities to cross safely. In such cases, pedestrians may resort to jaywalking as a means of avoiding extended waiting times, further emphasizing the need for a comprehensive understanding of pedestrian behavior and careful consideration of pedestrian-oriented timing plans. It is worth mentioning that there has been an acceptable synchronization between vehicle and pedestrian phases at the intersection of Hillen Rd and E 33rd street. Fig. 9 shows how different approaches are controlled by the phases of the traffic signal controller.

Table 2 shows the frequency and severity of vehicle-pedestrian conflicts and the frequency of jaywalking in different phases of the traffic signal controller.

Table 2. Characteristics of Traffic Signal Controllers at E 33rd – Hillen Rd Intersection

Time interval	Signal Controller pattern	Signal Cycle Time (sec)	Frequency of jaywalking	Frequency of Veh-Ped Conflicts	Severity (1/PET) of Veh-Ped Conflicts
00:00–06:30	MD	110	53	255	131.8
06:30–09:00	AM	165	233	1092	549.2
09:00–14:30	MD	110	262	2382	888.9
14:30–19:00	PM	180	350	2091	788.7
19:00–00:00	MD	110	102	889	218.6

Source: own elaboration.

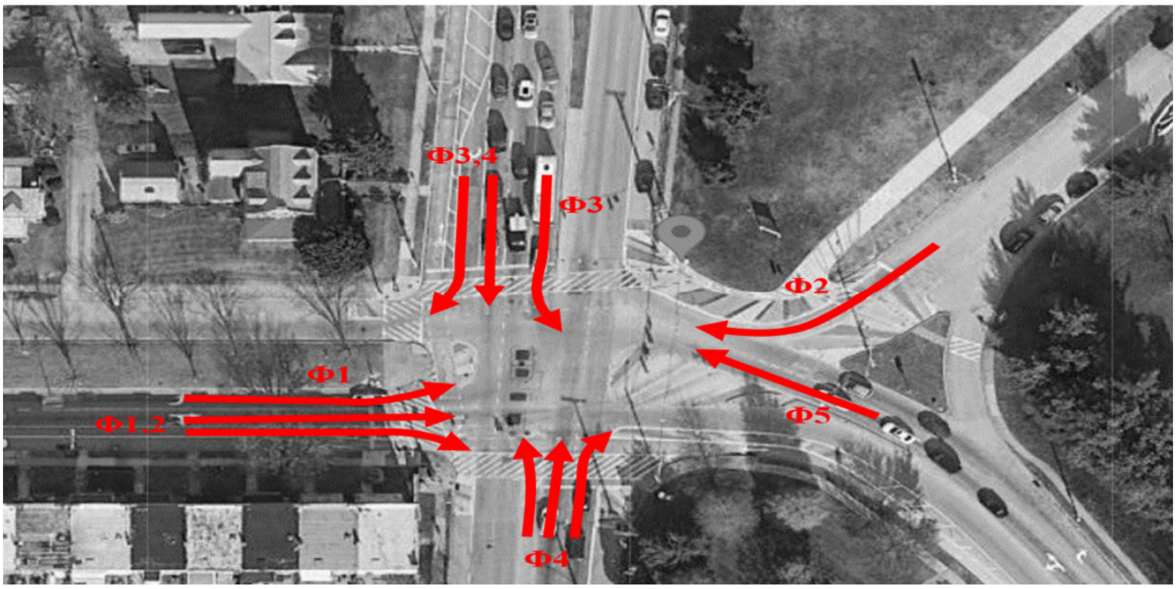

Fig. 9. Phases of Traffic Signal Controller at Hillen Rd - E 33rd Street Intersection
Source: own elaboration.

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As shown in Table 2, 2382 conflicts with severity 888.9 were collected in time interval 09:00 AM – 14:30 PM. The results emphasized that this particular time interval was crucial for jaywalkers due to the significant frequency and severity of vehicle-pedestrian conflicts. It is not entirely correct to claim that a higher cycle length at a traffic signal usually corresponds to heavier demands at intersections and that pedestrians are less likely to jaywalk in such situations. The relationship between cycle length and pedestrian behavior is more nuanced and depends on various factors. While it is true that longer cycle lengths can indicate a higher volume of traffic, they may not necessarily discourage jaywalking among pedestrians. In some cases, longer cycle lengths can lead to frustration and impatience among pedestrians, especially during peak hours when there is a substantial wait time for the pedestrian crossing signal to change. This can actually increase the likelihood of jaywalking, as pedestrians may perceive the official crossing times as too lengthy and decide to take risks by crossing outside designated crosswalks. Conversely, shorter cycle lengths might not always correspond to lighter demands at intersections. Shorter cycles are often implemented to prioritize pedestrian flow and reduce waiting times, which can be beneficial for pedestrian safety. Pedestrians are more likely to use designated crosswalks when they feel that the signal timing is responsive to their needs. Therefore, the relationship between cycle length and jaywalking is influenced by multiple factors, including pedestrian behavior, traffic volume, signal design, and urban context. It is essential to consider these factors comprehensively when designing signal timing plans to effectively address jaywalking concerns and promote pedestrian safety.

STATISTICAL MODELING RESULTS

Different independent variables were evaluated in order to establish a logical relationship to daily frequency of jaywalking events as dependent variable. The trajectory of each jaywalking event (=1000 events in total) during a six months' interval was evaluated. The location of trip attraction land-uses around the intersection, the attractiveness of vegetation in the median, the traffic signal controller pattern when a jaywalking event occurs, the phase(s) of the traffic signal controller when a jaywalking event occurs, the frequency and severity of vehicle-pedestrian conflicts, the vehicles and pedestrians volume entering different approaches where the jaywalking event occurs, the ratio of jaywalkers, and the weather conditions during each jaywalking event were investigated. Jaywalkers who walk towards the median and pass through it are considered to attract to the median. In order to identify the highly correlated independent variable(s) to the frequency of jaywalking, Pearson correlation test was conducted and the results showed there is a highly correlated relationship between the frequency of jaywalking event and the traffic signal control pattern (0.264^{**}), frequency of vehicle-pedestrian conflicts (0.678^{**}), severity of vehicle-pedestrian conflicts (0.712^{**}), walk toward the median (0.610^{**}), and the vehicle volumes/flow (0.956^{**}). A numerical value in parenthesis indicates the significance of each independent variable, and two stars indicate that there is less than 1% error for each independent variable. Table 3 shows the independent variables used in the statistical models. Two statistical regression models are explained below. It is worth mentioning that the distance to the crosswalk, time of day, and active phase at the controller were all taken into account based on the jaywalking events' trajectories.

The variability of traffic signal variables on a daily basis is justified by the dynamic nature of traffic patterns and signal control strategies. Traffic signals often operate under different signal plans based on time-of-day, accommodating variations in traffic demand. These variations can include adjustments in signal cycle length, phase sequences, and signal timings to optimize traffic flow. Furthermore, signal plans may be adapted for specific days of the week or to address events, leading to variations in signal operations. This adherence to traffic engineering principles ensures that signalized intersections are efficiently managed, and the study's consideration of daily variations in traffic signal variables aligns with standard practices in traffic signal control and

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Table 3. Statistical Analysis of Independent Variables

Independ Variable	Definition	Mean*	Standard Deviation*
Traffic Signal Controller Patterns	The pattern of traffic signal controller (AM, MD, and PM) when jaywalking occurs	AM: 1.39	AM: 1.60
		MD: 2.54	MD: 2.41
		PM: 2.13	PM: 5.10
Traffic Signal Phases	The phase(s) of the traffic signal controller when jaywalking occurs	Ø1: 2.59	Ø1: 1.55
		Ø1,2: 1.0	Ø1,2: 0
		Ø2: 1.18	Ø2: 0.4
		Ø3: 0	Ø3: 0
		Ø3, 4: 6.05	Ø3, 4: 6.35
		Ø4: 2.49	Ø4: 1.37
		Ø5: 2.46	Ø5: 1.43
Frequency of Vehicle-Pedestrian Conflicts	Number of vehicle-pedestrian conflicts collected by LiDAR when jaywalking occurs	3.15	5.36
Severity of vehicle-Pedestrian Conflicts	The severity $\left(\frac{1}{\sum PET}\right)$ of vehicle-pedestrian conflicts collected by LiDAR when jaywalking occurs	0.77	1.24
Weather Condition	When jaywalking occurs, the frequency of the weather conditions	Sunny: 2.22	Sunny: 4.30
		Cloudy: 2.76	Cloudy: 5.58
		Overcast: 0.58	Overcast: 1.50
		Rainy: 0.48	Rainy: 1.48
		Snowy: 0.01	Snowy: 0.08
Vehicles Volume	Vehicle counts (flow)	4354	3603.6
Walk Toward the Median	Walking toward the median based on jaywalkers' trajectory	Yes: 5.34	Yes: 5.73
		No: 0.72	No: 1.34
Pedestrians Volume	Pedestrian counts (pedestrian flow)	73.31	27.73
Jaywalker's Ratio	Jaywalker frequency divided by pedestrian frequency	0.08	0.07

* Each independent variable's mean and standard deviation based on the collected dataset.
Source: own elaboration.

management. The incorporation of AM (morning), MD (midday), and PM (afternoon) signal controller patterns is essential for a comprehensive analysis of daily variations in pedestrian behaviors at signalized intersections. The temporal segmentation of signal controller patterns aligns with real-world traffic dynamics, where distinct traffic conditions exist during different parts of the day. Through the independent analysis of AM, MD, and PM periods, variations in traffic demand, pedestrian volumes, and signal timings unique to each time segment are considered. This methodology amplifies the precision of the examination, enabling the identification of subtle patterns in jaywalking behavior linked to distinct signal controller configurations throughout the day.

Poisson regression model

The Poisson distribution represents the probability of a given number of cases happening in a set period of space or time if these cases happen at an identified constant mean rate. Several models were developed based on the frequency of jaywalking events as the dependent variable and the highest significant Poisson model was identified. Based on the p-values

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of independent variables and goodness-of-fit, Table 4 shows the proposed Poisson model results. As shown in Table 4, two categories for the walk toward the median (Yes as Category 1, and No as Category 2) were defined. Additionally, three categories were considered for the traffic signal controller pattern including AM as category 1, MD as category 2, and PM as category 3. The overall results of the model show that all error values are within 5% confidence intervals for all independent variables, indicating that the proposed Poisson regression model is accurate. As can be seen in Table 4, a significant relationship between the frequency of jaywalking events and independent variables e.g., traffic signal controller phases, frequency of vehicle-pedestrian conflicts, and weather condition was not obtained. Hereupon, these variables were excluded from the final model. In the statistical analysis, pedestrian volume was also taken into account. However, this variable error (p-value) exceeded 5%. Hereupon, pedestrian volume was excluded from the final model. Taking into account the limited amount of data for jaywalkers who are not interested in walking towards the median (category 2 – less than 2% of total data) and traffic signal controller pattern in the afternoon peak hour (PM) (category 3 – less than 15% of total data), the results indicated that changes in these two categories do not affect the frequency of jaywalking events.

Negative binomial regression model

A negative binomial regression model has the same form as a Poisson regression model. Unlike the Poisson distribution, the variance and the

Table 4. Results of Poisson Regression Model

Parameter Estimates										
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	1.227	.2100	.816	1.639	34.149	1	<.001	3.412	2.261	5.149
[Walk toward the median=1]	.336	.1678	.007	.665	4.010	1	.045	1.399	1.007	1.944
[Walk toward the median =2]	0[a]	.	.	.	.	.	.	1	.	.
Severity of Veh-Ped Conflicts	.183	.0113	.161	.206	265.867	1	<.001	1.201	1.175	1.228
[Traffic Signal Controller Pattern=1]	-.593	.0917	-.772	-.413	41.800	1	<.001	.553	.462	.662
[Traffic Signal Controller Pattern=2]	-.422	.0813	-.581	-.263	26.989	1	<.001	.656	.559	.769
[Traffic Signal Controller Pattern=3]	0[a]	.	.	.	.	.	.	1	.	.
Vehicles Volume (Flow)	.003	.0011	.001	.005	8.934	1	.003	1.003	1.001	1.005

Dependent Variable: Frequency of Jaywalking events
Model: (Intercept), Walk toward the median, Severity of vehicle-pedestrian conflicts, Traffic signal controller pattern, Vehicles volume (flow)
a. Set to zero because this parameter is redundant.
Source: own elaboration.

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mean are not equivalent. The variance of a negative binomial distribution is a function of its mean and has an additional parameter as called the dispersion parameter. Negative binomial distributions converge to Poisson distributions as the dispersion parameter increases. As shown in Table 5, the overall results of the model show that all error values are within 5% confidence intervals. Additionally, a significant relationship between the frequency of jaywalking events and independent variables e.g., traffic signal controller phases, severity of vehicle-pedestrian conflicts, and weather condition was not obtained. Hereupon, these variables were excluded from the final model.

As shown in Tables 4 and 5, the exclusion of weather conditions as a proportion in the model is justified by the statistical analysis, which revealed that the correlation between weather and jaywalking behavior lacked a high level of significance in both Poisson and negative binomial models. The decision to not represent weather as a proportion is based on the observation that this variable did not exert a substantial influence on the variation in jaywalking incidents. Prioritizing variables with stronger correlations and higher significance levels enhances the focus on factors that more significantly impact jaywalking behavior at signalized intersections, ensuring the model's effectiveness in capturing meaningful relationships. The limited correlation between weather conditions and the frequency of jaywalking events in the presented analysis can be attributed to several key factors. Firstly, pedestrians' decision to engage in jaywalking may be influenced more strongly by factors such as traffic signal patterns, pedestrian volumes, and vehicular flow, which might overshadow the impact of weather conditions. Additionally, the study area's climate may not exhibit extreme variations, diminishing the significance of weather in relation to jaywalking incidents. These factors collectively contribute to the observed lower significance of weather in the proposed Poisson and negative binomial models, leading to the decision not to represent it as a proportion in the analysis. The exclusion of pedestrian volume as a variable in the presented analysis is justified by the intricate nature of pedestrian behavior at signalized intersections. While pedestrian volume is undoubtedly a crucial factor, its direct correlation with the frequency of jaywalking events may be influenced by various nuanced dynamics. One reason for the decision is that the presence or absence of jaywalking incidents is likely not solely determined by the absolute number

Table 5. Results from Negative Binomial Regression Model

Parameter Estimates										
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	1.261	.2096	.850	1.672	36.188	1	<.001	3.529	2.340	5.322
[Traffic Signal Controller Pattern=1]	-.645	.0908	-.823	-.467	50.436	1	<.001	.525	.439	.627
[Traffic Signal Controller Pattern=2]	-.458	.0803	-.616	-.301	32.604	1	<.001	.632	.540	.740
[Traffic Signal Controller Pattern=3]	0[a]	.	.	.	.	.	.	1	.	.
[Walk toward the median =1]	.353	.1677	.024	.682	4.430	1	.035	1.423	1.025	1.977
[Walk toward the median =2]	0[a]	.	.	.	.	.	.	1	.	.
Frequency of Veh-Ped Conflicts	.042	.0026	.037	.047	258.375	1	<.001	1.043	1.037	1.048
Vehicles Volume (Flow)	.003	.0011	.001	.005	8.577	1	.003	1.003	1.001	1.005

a. Set to zero because this parameter is redundant.
Source: own elaboration.

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of pedestrians but rather by complex interactions involving other variables such as traffic signal patterns, vehicle volumes, and specific temporal conditions. Moreover, the observed lower correlation between pedestrian volume and jaywalking events may be attributed to the influence of traffic control measures and signal timings, which play a substantial role in regulating pedestrian movements. Pedestrian behaviors might be more responsive to signal changes and vehicular flow than solely contingent on the overall volume of pedestrians.

Optimal model

The Likelihood Ratio (LR) test was conducted to determine the most efficient model between Poisson and negative binomial regression models. As can be seen in Table 6, the likelihood ratio chi-square provides a test of the overall model by comparing it to a model without any predictors (a "null" model). In the comparison of calculated LR statistics between Poisson and negative binomial tests, the greater LR statistic implies a significantly better fit for the model. Additionally, models with low AIC are generally preferred over models with high AIC, as a general statement. Hereupon, considering the higher Chi-Square value and lower AIC, it is clear that the Poisson model provides better results.

DISCUSSION

As can be seen in the column Exp(B) of Table 4, jaywalking frequency can increase the severity of vehicle-pedestrian conflicts by 20% that showed the severity of vehicle-pedestrian conflicts appears to be significantly correlated with the frequency of jaywalking events in the Poisson model. Jaywalking in the morning and mid-day signal controller's pattern is 44.7% and 34.4% less compared to the PM's pattern, respectively. Lastly, there is a 39.9% higher probability that Jaywalkers will walk toward the median, resulting in an increase in frequency of jaywalking. In other

Table 6. Overall Results of Poisson and Negative Binomial Regression Models

Model	Independent variables	Wald Chi-Square	df	Sig	Likelihood Ratio Chi-Square	Deviance	Finite Sample Corrected AIC (AICC)b
Poisson	(Intercept)	43.900	1	<.001	311.714[a]	416.343	980.870
	Walk toward the median	4.010	1	.045			
	Severity of veh-ped conflicts	265.867	1	<.001			
	Traffic signal controller pattern	50.152	2	<.001			
	Vehicles volume (flow)	8.934	1	.003			
Negative binomial	(Intercept)	44.787	1	<.001	305.392[a]	422.665	987.192
	Traffic signal controller pattern	61.171	2	<.001			
	Walk toward the median	4.430	1	.035			
	Frequency of veh-ped conflicts	258.375	1	<.001			
	Vehicles volume (flow)	8.577	1	.003			

a. For df=5 and sig <.001
b. the AICC is interpreted as the sum of the" goodness of fit to the model" and the" model complexity penalty"
Source: own elaboration.

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word, this finding suggests that while vehicle volume does play a role in shaping pedestrian behavior, it is not the sole or predominant factor influencing jaywalking occurrences. This interpretation was provided based on the statistical analysis results that has examined the multifaceted nature of jaywalking behavior. Several other factors, such as pedestrian signal timing, infrastructure design, pedestrian perceptions of safety, and local enforcement practices, can have a more substantial impact on the occurrence of jaywalking. Therefore, the slight influence of vehicle volume, as indicated in the sentence, underscores the importance of considering a comprehensive set of factors when addressing jaywalking behavior and designing effective interventions to enhance pedestrian safety. The negative binomial model (Table 5) showed that the frequency of vehicle--pedestrian conflicts is significantly correlated with the frequency of jaywalking events. The frequency of jaywalking events is increased by 42.3% due to vegetation in the median. The Poisson model also yields similar results regarding the effect of vegetation in the median. The frequency of jaywalking can increase the frequency of vehicle-pedestrian conflicts by 4.3%. Jaywalking in the morning and mid-day signal controller's pattern is 47.5% and 36.8% less compared to the PM's pattern, respectively.

In order to compare the goodness-of-fit of Poisson and negative binomial regression models, the likelihood ratio (LR) Chi-Square test was conducted. In a Likelihood Ratio Chi-Square test, the observed frequency is compared with the expected frequency. The test compares the fit of two models so that the null hypothesis is that the smaller model is "best", it is rejected when the test statistic is large. Stronger support is indicated by a higher likelihood ratio. Considering the outcome of the Poisson model, this model better fits the data. Consequently, the Poisson model revealed that traffic signal controller patterns, jaywalker's interest walking toward the median, frequency of vehicle-pedestrian conflicts, and vehicles volume (flow) were correlated to jaywalking frequency.

The results of the statistical analysis from both the Poisson and negative binomial regression models provide valuable insights into the relationship between jaywalking behavior and the severity of vehicle--pedestrian conflicts at signalized intersections. In the Poisson model, the Exp(B) values in Table 4 indicate that jaywalking frequency can increase the severity of vehicle-pedestrian conflicts by 20%. This finding underscores the significant correlation between jaywalking events and the occurrence of conflicts between vehicles and pedestrians. Interestingly, the analysis also reveals variations in jaywalking frequency based on the signal controller's pattern, with jaywalking being 44.7% and 34.4% less prevalent during morning and mid-day patterns compared to the PM pattern. Furthermore, a 39.9% higher probability of pedestrians walking toward the median is associated with an increase in jaywalking frequency. These findings suggest that while vehicle volume plays a role in shaping pedestrian behavior, it is not the sole or predominant factor influencing jaywalking occurrences. This interpretation is consistent with previous studies highlighting the multifaceted nature of jaywalking behavior, wherein factors such as pedestrian signal timing, infrastructure design, pedestrian perceptions of safety, and local enforcement practices can have a more substantial impact on jaywalking occurrences.

The negative binomial model, as presented in Table 5, corroborates the findings of the Poisson model regarding the correlation between jaywalking frequency and the frequency of vehicle-pedestrian conflicts. Additionally, the negative binomial model highlights the impact of vegetation in the median, indicating a 42.3% increase in jaywalking events associated with its presence. Consistent with the Poisson model, the negative binomial model also demonstrates variations in jaywalking frequency based on signal controller patterns, with morning and mid-day patterns exhibiting lower levels of jaywalking compared to the PM pattern.

To assess the goodness-of-fit of the Poisson and negative binomial regression models, a Likelihood Ratio (LR) Chi-Square test was conducted. The results indicate that the Poisson model better fits the data, suggesting its superiority in explaining the relationship

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between jaywalking frequency and associated factors. Specifically, the Poisson model reveals that traffic signal controller patterns, pedestrians' inclination to walk toward the median, frequency of vehicle-pedestrian conflicts, and vehicle volume (flow) are correlated with jaywalking frequency.

In synthesizing the results gained from this study with findings from other research studies in the state-of-the-art, it becomes evident that jaywalking behavior is influenced by a complex interplay of factors. This study's emphasis on factors like signal controller patterns and pedestrian behavior tendencies aligns with previous research studies highlighting the multifaceted nature of jaywalking behavior. Notably, urban design, land use characteristics, and cultural norms have been identified as significant influencers in shaping pedestrian behavior. By contextualizing the findings within this broader framework, the study underscores the intricate interplay between various environmental and social factors in influencing jaywalking occurrences. The interpretation of these findings in the context of urban planning underscores their practical relevance, particularly in guiding the development of targeted interventions aimed at enhancing pedestrian safety. For instance, the identification of specific factors influencing jaywalking frequency provides valuable insights for optimizing crosswalk layouts to improve visibility and accessibility for pedestrians. Furthermore, the synchronization of pedestrian signal timings with vehicular phases can be strategically implemented to facilitate safer pedestrian crossings and minimize conflicts with vehicular traffic. In the realm of road infrastructure design, the study's insights offer opportunities for integrating pedestrian-friendly features into roadway environments. This may entail the incorporation of pedestrian amenities such as well-marked crosswalks, pedestrian islands, and refuge areas to enhance pedestrian safety and comfort. Additionally, strategic placement of vegetation can serve as a natural deterrent to jaywalking behaviors, effectively guiding pedestrian movement and promoting adherence to designated crossing areas. Overall, by considering the broader contextual factors and practical implications, the study contributes to the advancement of strategies aimed at creating safer and more pedestrian-friendly urban environments.

CONCLUSIONS

Jaywalking poses many risks, including injury, death, and traffic congestion. In order to cross the roads safely, pedestrians should always use crosswalks and look both ways before proceeding. The conclusion of this study underscores the imperative for a comprehensive strategy to mitigate the inherent risks associated with jaywalking, encompassing injuries, fatalities, and traffic disruptions. In addressing this concern at signalized intersections, the focus must prioritize pedestrian safety while minimizing adverse effects on traffic flow. The proposed solutions center on promoting pedestrian compliance with crosswalks and adherence to proper pedestrian signal indications. Essential to this approach is the role of public education campaigns in instilling the significance of utilizing designated crosswalks for secure road crossing, underscoring advantages such as heightened visibility to drivers and reduced exposure to traffic hazards. Furthermore, well-crafted crosswalks not only serve as visual guides but also contribute to an enhanced overall pedestrian experience, fostering increased safety and convenience. Moreover, the alignment of pedestrian signal timings with vehicular phases, particularly during peak hours, serves to minimize waiting times and encourage synchronized pedestrian behavior. The multifaceted nature of addressing jaywalking at signalized intersections necessitates a holistic strategy that integrates education, infrastructure enhancements, and effective enforcement. The concerted efforts towards fostering pedestrian adherence to crosswalks and synchronizing signal timings with pedestrian needs are pivotal for fostering a safer road environment and reducing jaywalking incidents.

Pedestrian crossing behavior is strongly influenced by human factors and traffic circumstances. The pedestrian's perception-judgment-decision-action process determines when and where to cross.

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An individual's crossing decision is influenced by a number of factors (e.g., origin and destination, complexity and length of route), infrastructure (e.g., pedestrian facilities, road geometry, and traffic conditions), and individual characteristics (e.g., age, gender, and safety awareness). According to the nature of human behavior, crossing behavior is subject to a significant amount of subjectivity and randomness. As a result, pedestrian crossing behavior may become risk-taking and result in conflicts with vehicles. Pedestrians will make their most satisfactory decision based on the type and location of the crossing facility. As a result, pedestrian behavior may be changed to do jaywalking on a case-by-case basis. To study jaywalking behavior at signalized intersections and in order to improve the safety of pedestrians as one of the vulnerable road users, a LiDAR sensor was installed at the intersection of Hillen Rd and E 33rd Street in Baltimore city. The LiDAR sensor can record the jaywalking events, including the time interval, the geographical coordinates, the duration, and the speed of each jaywalking event. The LiDAR sensor is able to recognize each jaywalking event from the moment the pedestrian attempts to walk out of the crosswalk to the moment the pedestrian terminates the jaywalking. Due to a recognized gap in the state-of-the-art and as the key contribution of this research, this paper attempted to investigate how the timing and phasing of the traffic signal controller and the pattern of signal controller affect the frequency of jaywalking at signalized intersections. In addition to the traffic signal controller characteristics, the paper highlighted a variety of highly correlated independent factors, including vehicle-pedestrian conflict frequency and severity, weather conditions, the volume of vehicles entering each approach, and the interest of jaywalkers toward vegetation-covered medians.

The inherent risk of being hit by other motorized vehicles passing through the intersection has risen as a result of jaywalking. Hereupon, the LiDAR sensor installed at the Hillen Rd – E 33rd street intersection has accurately collected the real-time conflicts between vehicles and pedestrians. In order to provide a safety analysis for pedestrians, the frequency of jaywalking events over a six-month interval from December 2022 to May 2023 was examined. LiDAR data showed 1000 jaywalkers, and 97.7% of total jaywalkers were found in the northern approach (=southbound) to the intersection. The paper emphasized the safety of the southbound due to safety concerns. Jaywalkers' trip origins and destinations, jaywalker's trajectories in terms of accessing to land-uses and public transport stops around the intersection, and the frequency and severity of vehicle-pedestrian conflicts were assessed. A daily-based dataset including the independent variables affecting the frequency of jaywalking was obtained and two statistical regression models including Poisson, and negative binomial were developed. Furthermore, pedestrian trajectories revealed that a significant percentage of pedestrians prefer to walk toward the median; this may lead to more jaywalking and more severe conflicts between vehicles and pedestrians. Vehicle-pedestrian conflicts can be made more severe and frequent by 20% and 4.3%, respectively, when jaywalking occurs more frequently. As a result of jaywalkers, drivers may be forced to abruptly brake, and causing disruptions to traffic flow. Consequently, traffic can back up and crashes can occur. Jaywalking causes pedestrian injuries, lead to deaths, and clog up traffic. Jaywalking can be prevented by being aware of the surroundings and following road rules. The frequency of jaywalking may be reduced by educating pedestrians only cross in crosswalks, providing them with safety equipment that alarms by audible or visible warnings, and providing real-time dynamic pedestrian safety messages to vehicles via roadside units (RSUs) that alert the location of pedestrians. As a result of this research findings, the most important independent variables influencing jaywalking frequency were identified. The researchers, policymakers, and practitioners can use the results as a basis for conducting future research, making practical rules, and improving pedestrian crossing facilities so that pedestrians crash risk is decreased.

This study underscores the imperative for a comprehensive strategy to mitigate the risks associated with jaywalking at signalized intersections,

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prioritizing pedestrian safety while minimizing adverse effects on traffic flow. Through the application of LiDAR sensor technology, significant insights were gained into the factors influencing jaywalking behavior and its impact on vehicle-pedestrian conflicts. The findings highlight the importance of promoting pedestrian compliance with designated crosswalks and synchronizing pedestrian signal timings with vehicular phases to enhance safety. Furthermore, the study identified the influence of environmental factors such as vegetation in the median on jaywalking frequency, emphasizing the need for urban planning interventions to enhance pedestrian safety infrastructure. While the study provides valuable insights, it is essential to acknowledge certain limitations. The study's duration of six months may not fully capture seasonal variations in pedestrian behavior, warranting longer-term data collection efforts. Additionally, the study did not explore demographic factors such as gender and age due to privacy concerns, representing a potential avenue for future research. Furthermore, the inability to analyze video recordings of jaywalking events due to privacy constraints highlights the importance of ethical considerations in data collection and analysis. While the study acknowledges limitations such as the limited time interval of data collection spanning six months and the lack of investigation into jaywalkers' gender and age due to privacy concerns, it could benefit from a more detailed discussion of their implications for the generalizability of results. For instance, the short duration of data collection may limit the representation of seasonal variations and long-term trends in jaywalking behavior, potentially impacting the extrapolation of findings to different time periods or geographical locations. Additionally, the absence of demographic information on jaywalkers may restrict the applicability of results to specific population groups or urban contexts, warranting caution in generalizing the findings to broader settings.

Looking ahead, future research endeavors should focus on addressing the identified limitations and further refining our understanding of pedestrian behavior and jaywalking phenomena. Longitudinal studies spanning multiple seasons could provide deeper insights into seasonal variations in jaywalking behavior and inform the development of targeted interventions. Additionally, incorporating demographic variables into the analysis could elucidate potential disparities in jaywalking patterns and inform equitable safety interventions. Moreover, advancements in machine learning techniques offer promising avenues for developing predictive models that integrate vehicle-pedestrian conflicts and jaywalking events, facilitating real-time safety assessments and proactive intervention strategies. State-of-the-art machine learning algorithms, such as deep learning neural networks, support vector machines (SVM), and random forests, can effectively capture complex patterns and interactions within vast datasets comprising variables related to pedestrian movement, traffic flow, infrastructure characteristics, and environmental factors. By harnessing the power of these advanced models, future studies can not only predict the likelihood of jaywalking events based on real-time data inputs but also identify key contributing factors and their relative importance in influencing pedestrian behavior. Additionally, ensemble learning techniques, which combine multiple models to enhance predictive accuracy, can further refine the reliability and robustness of jaywalking prediction models. Such predictive models hold the potential to revolutionize pedestrian safety research by enabling real-time safety assessments and proactive intervention strategies, thereby contributing to the development of smarter and safer urban environments.

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