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A COMPUTER VISION APPROACH TO EVALUATING CROSSWALK SAFETY FOR VULNERABLE ROAD USERS

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With advancements in computer vision and cloud computing, Surrogate Safety Measures (SSMs) now provide actionable insights to mitigate safety concerns before collisions occur. This study, conducted as part of the STREET21 research project and contributes to the existing body of knowledge by examining Post-Encroachment Time (PET), a time-based SSM, at a high-traffic urban intersection which many young vulnerable users (university students) cross as pedestrians for their daily commuting needs. In total 513 traffic conflict events were identified and mapped for the purposes of the analysis. The spatial analysis provides critical insights into the patterns of traffic conflicts. Results of the quantitative analysis demonstrate that pedestrian conflicts predominantly involved right-turning vehicles, followed by through vehicles, potentially indicative of red-light violations. The applied methodology underscores the efficacy of video analytics as a scalable alternative to traditional crash data analysis, enabling the evaluation of intersection designs and temporary treatments before permanent implementation.

Keywords: Surrogate safety measures (SSMs), road safety, intersection, spatial analysis, vulnerable road users

1. Introduction

Among young people, road traffic injuries rank as the main cause of death; they also remain a major factor influencing mortality across all ages (WHO, 2023). This fact has raised awareness among policymakers and scholars by highlighting the crucial need of traffic safety research in transportation engineering. Under such conditions, the European Union (EU) has already developed strategies to significantly decrease road traffic fatalities and serious injuries (EC, 2022). Particularly, the EU has committed to achieving zero road fatalities by 2050, while has adopted interim targets aimed at halving the number of road deaths and serious injuries till 2030 (EC, 2020).

Figure 1 illustrates the trends in traffic fatalities for both vehicle occupants and pedestrians over the last fifteen years (2009-2023 period) in Greece. It is observed that the compound annual growth rate (CAGR) for the fatalities of vehicle occupants is -5.4%, while fatalities among pedestrians have a CAGR of -4.5%. According to that, measures implemented over the last years have been more effective (or more focused) in reducing fatalities among vehicle occupants than among pedestrians. Upon this, according to the Hellenic Statistical Authority (HSA), 17.1% of Greek road fatalities in 2022 refer to pedestrians, with 1 in 4 of these occurring in residential areas. In parallel, it is of particular interest that young pedestrians (aged 18 to 40) were involved in road traffic accidents at a rate exceeding 18%, which is relatively high, considering that this age group is characterized by quicker reaction times (HAS, 2025).

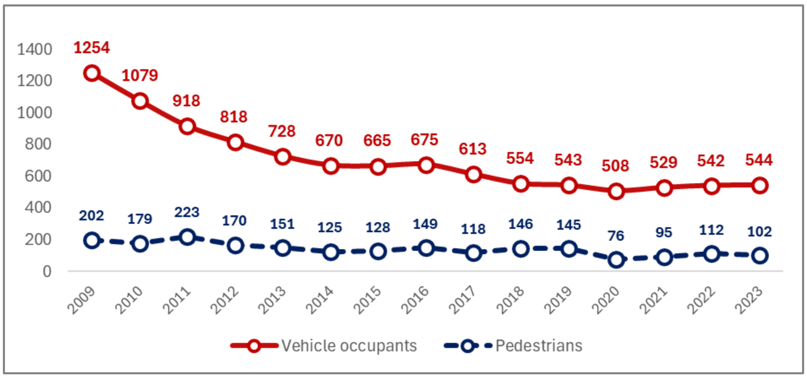

Figure 1. Trend in traffic fatalities in Greece

Significant body of past research has examined the factors that contribute to pedestrian road traffic fatalities, highlighting variables such as vehicle speed (Ang *et al*., 2020, Zhang *et al*., 2017), road congestion and traffic volume (Zhang *et al.,* 2017), road design (Lin *et al.,* 2019) and pedestrian behavior (Esmaili *et al*., 2021). Therefore, it is clear that road traffic events involving pedestrians in urban areas, especially intersections, may results from several contributing factors that might indicate for particular interventions. For example, a substantial portion of such events can be related to careless behavior or red-light violations, both on the side of motor vehicle drivers and pedestrians. Furthermore, the geometric design of intersections could increase potential risks by limiting road users' visibility while encouraging unsafe driving practices.

The lack of accurate and reliable historical crash statistical data on specific road intersections can contribute to difficult evaluations of the traffic safety, while the process of collecting crash statistics can be time-consuming (Anagnostopoulos, 2023). Surrogate Safety Measures (SSMs) can be applied as a quick method to examine safety concerns. Especially if someone considers that in recent years the use of artificial intelligence (AI) and the ability to effectively collect and process big data, SSMs can be an efficient method for the identification of vehicle and infrastructure issues, while minimizing the risk of accidents by proceeding with proactive measures.

There is a limited number of studies focusing on right-turn vehicle movements occur concurrently with a green phase for pedestrians, which may increase the risk of conflicts at the crossing point. The gap in the literature about the study of an urban signalized intersection examined in this article is on providing and comparing quantitative analysis and mapping the most dangerous interactions among pedestrians and motorized vehicles, under various signal timing scenarios and permitted movement configurations.

Hence, the main objective of this paper is to add to current knowledge and investigate SSMs at an urban intersection which many young vulnerable users (university students) cross as pedestrians for their daily commuting needs. The selection of this case study is also justified by the fact that the examined sample might be familiar with this intersection due to its regular use. This study, conducted as part of the STREET21 research project and focuses on analyzing the kinematic characteristics of both pedestrians and motorized traffic at a signalized intersection, providing valuable insights into their interactions and potential safety implications, under various signal timing scenarios and permitted movement configurations.

In this study, we used an artificial intelligence application “GoodVision Video Insights” (GoodVision, 2025) to extract vehicle and pedestrian trajectories and identify the traffic conflicts occurred at an urban signalized four-leg intersection, located in proximity to the Thessaloniki’s (Greece) university campus. Our approach integrated as well a semi-automatically process of using Geographical Information System (GIS) and Visual Basic for Application (VBA) procedures in spreadsheets in order to accurately calculate the Post-Encroachment Time (PET), a time-based SSM.

The present research is structured in four parts to reach the research objective. The first part (Section 2) includes a background of the previous literature and provides a comprehensive review of relevant existing literature and research. The second part (Section 3) describes the employed methodological framework to collect and process naturalistic trajectory data. The third part (Section 4) presents the results of the study providing a quantitative and spatial analysis. The fourth part (Section 5) summarizes the key findings of the study and suggests future research directions.

2. Research background

There has been a growing body of literature in recent years examining the intensified interactions between pedestrians and motorized traffic in urban areas, a trend largely attributed to rapid urbanization and the expansion of vehicular ownership (Tao *et al*., 2021).

Recent research highlights the growing importance of Surrogate Safety Measures (SSMs) in examining and analyzing vehicle-pedestrian interactions (Patel *et al*., 2023). The applications of indicators like Time-to-Collision (TTC) and Post-Encroachment Time (PET) demonstrate direct and cost-effective methods for accurately identifying pedestrian safety risks.

These indicators can offer valuable insights for public authorities to assess pedestrian safety at road intersections and to adopt robust data-driven tools for improving urban road safety management (Gagliardi *et al*., 2024, Zhang *et al.,* 2024). For example, Zhang *et al.* (2020) proposed in their study an LSTM neural network model to predict pedestrian-vehicle conflicts at signalized intersections using video-based detection and tracking of road users. Their model demonstrates strong potential for broader application, including integration into collision warning systems within connected vehicle environments.

Similarly, Li *et al.* (2023) introduced a probabilistic framework that estimates pedestrian-vehicle conflict risks at intersections by predicting trajectories with Gaussian process regression and incorporating vehicle maneuver probabilities. Validated on both simulated and real-world data, their approach offers a practical and scalable solution for proactive pedestrian safety management at intersections. In addition, Zhang and Abdel-Aty (2022) developed a real-time pedestrian conflict prediction model using CCTV video data and conflict indicators like PET and TTC. Their best-performing model could predict pedestrian conflicts one signal cycle (2–3 minutes) ahead, highlighting its potential for integration into Connected and Automated Vehicles (CAVs) systems to dynamically adjust signal timing and improve intersection safety.

Upon this, in recent years SSMs for vehicle-pedestrian intersections have gained a great deal of attention for developing intersection safety evaluation by implementing different traffic conflict indicators. In Italy, Gagliardi *et al.* (2024) proceeded in their recent study to a detailed analysis of 270 vehicle-pedestrian interactions at three intersections in Rome, focusing on conflict severity using SSM indicators such as TTC and PET. The results showed that PET was the most consistent in identifying conflicts, and a binomial logistic regression further revealed that longer red signal durations significantly increase the likelihood of conflicts, especially involving younger pedestrians.

The use of video analytics tools for the extraction of trajectories at specific time events to study the interactions among vehicles and pedestrians is being discussed in many studies (Anagnostopoulos and Kehagia, 2021). Such techniques can be applied either automatically or semi-automatically using proper software (Zhang *et al*., 2024). Both approaches come with advantages and disadvantages (Anagnostopoulos and Kehagia, 2021). More specifically, even if automatic procedures are time-efficient and facilitate big data analysis, the accuracy and the quality of the results are subject to debate.

Patel *et al.* (2023) introduced in their recent study an advanced artificial intelligence (AI)-based video analytics tool using YOLO-v5 and DeepSORT to accurately detect and track road user trajectories at six intersections in Glassboro, New Jersey. By analyzing 54 hours of video data, the researchers captured non-compliance behaviors, calculated surrogate safety measures (PET, TTC), and applied extreme value theory (EVT) to estimate crash frequency, ultimately ranking intersections by crash severity to support informed safety interventions by engineers and policymakers.

3. Materials and methods

3.1. Case study

A pedestrian crossing at an urban signalized intersection, located in Thessaloniki (Greece), and more specifically in proximity to the city's university campus, was selected as the case-study (Figure 2). The rationale for selecting the specific intersection is that many young vulnerable users (university students) cross it as pedestrians for their daily commuting needs. As this intersection experiences high pedestrian and vehicular traffic volumes, particularly during peak hours, a significant number of traffic conflict events can occur in the examined pedestrian crossing.

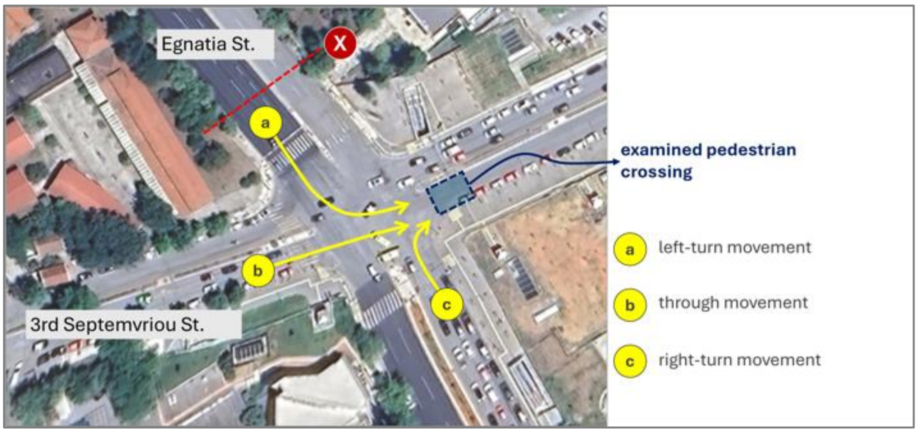

Figure 2. The examined pedestrian crossing

Three vehicle movements affect the pedestrian crossing being examined, as presented in the figure below. More specifically, (a) the left-turn movement, which comes from Egnatia St and continues to 3rd Septemvriou St; (b) the through movement, which includes the through movements along 3rd Septemvriou St from West to East; and finally (c) the right-turn movement of vehicles coming from Egnatia St and turning to 3rd Septemvriou St on the West.

For the first two cases (a and b), pedestrian movements across the crossing are prohibited, meaning that any observed traffic conflict indicates a violation on the part of the pedestrian. On the other hand, in the third case of right-turning vehicles, drivers must yield to pedestrians on the crossing under a flashing amber signal. Therefore, any observed traffic conflict for which vehicles proceeded before pedestrians is linked to vehicle-related violations.

3.2. Data collection

To select the appropriate time slots for the field surveys, a preliminary analysis was conducted according to the available traffic counts (annual average daily traffic (AADT) - hourly variation) for the study area. Available dataset (Table 1) provides insights into the temporal patterns of road usage, which can be critical for traffic management, infrastructure planning, and identifying congestion periods. Available traffic counts collected in the location "X" as presented in Figure 2, were further elaborated by the authors to identify the rush hours for the motorized traffic.

Upon this, given that the primary aim of this study is to investigate the traffic conflicts between pedestrians and vehicles, and pedestrian traffic counts s were not available, the selection of observation periods was informed by projected commuting trip patterns. As such, the morning and evening peak hours were chosen, under the assumption that these periods would reflect the highest pedestrian activity due to commuting flows.

Table 1. Hourly variations of available traffic counts (AADT) in the study area (location "X" in Fig. 2)

Hour	0:00	07:30-09:30	18:30-20:30	23:00
AADT (%)				

* Color scale shows hourly AADT variation, from minimum (green) to maximum (red).

Following the above-mentioned approach, the authors conducted field observations during the following two weekday peak periods: (a) 07:30 to 09:30, and (b) 18:30 to 20:30. Traffic monitoring was carried out for a weekday, according to the availability of resources, and more specifically on Tuesday, 15/10/2024. The sample was sufficient for the purposes of the analysis; therefore, no additional field surveys were considered necessary. It is estimated according to the AADT analysis that approximately 21% of the total daily motorized traffic demand was monitored during these hours.

Naturalistic driving behavior data were collected through a fixed camera attached to a tripod and positioned at a height of six meters at the multi-lane intersection. Figure 3 presents both the equipment and the field of view of the examined intersection during the field surveys.

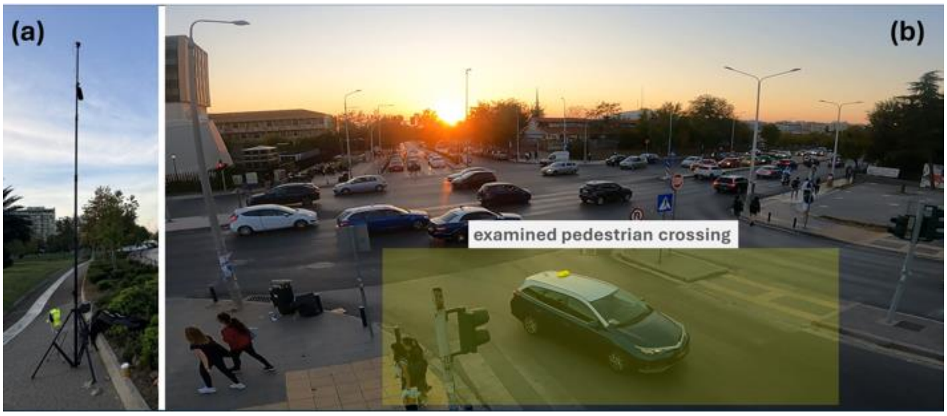

Figure 3. (a) The equipment and (b) the field of view of the examined intersection during the field surveys

It is noted that the elevated positioning of the tripods at the height of 6 meters not only enhances the scope and accuracy of the data collected but also plays a crucial role in ensuring compliance with privacy regulations, such as the General Data Protection Regulation (GDPR). By positioning the cameras at such a height, the focus remains strictly on the vehicle and traffic movements within the intersection, minimizing the visibility of identifiable details of pedestrians or drivers.

This approach safeguards personal privacy while still capturing the necessary traffic flow data for analysis. Moreover, all recorded footage is handled in strict accordance with GDPR guidelines, ensuring that it is stored securely and used exclusively for the intended purpose of the study. Any data not essential to the analysis was deleted promptly after the study's completion, reinforcing the project's commitment to ethical data management practices. This dual focus on technical excellence and privacy protection ensures the study maintains both its scientific integrity and public accountability.

3.3. Detection and mapping of conflict events and SSMs

Under the constant development of AI-based technologies during recent years, various tools and techniques have been developed for traffic data collection, replacing the traditional manual data collection methods. In this study, GoodVision software, an AI-powered tool designed for collecting and analyzing traffic data, was selected for the analysis and provided by the company GoodVision Ltd (GoodVision, 2025).

Following the definition of specific cells in the basemap of the collected videos, automatic detection and counting for both pedestrians and vehicles resulted in the development of origin-destination (OD) matrices concurrently with the illustration of the trajectories of each road user (Figure 4).

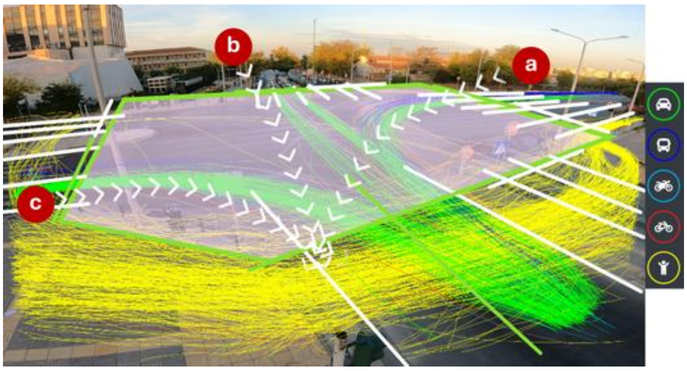

Figure 4. (a) Road users' trajectories as analyzed in GoodVision software, an AI-powered tool designed for collecting and analyzing traffic data

As thoroughly described in the sections above, surrogate safety measures (SSMs) are one of the most widely approached used in recent years for identifying future threats and evaluating the safety of both infrastructure and driving behavior. SSMs were calculated for the examined conflict events described above. In this study, the SSM Post-Encroachment time (PET) was considered for the analysis of the identified traffic conflicts.

PET can be described as the amount of time that elapses between when a leading road user (vehicle or pedestrian) departs from a conflict point to the moment that the following road user (vehicle or pedestrian) approaches that point (Figure 5). It is defined according to Equation 1.

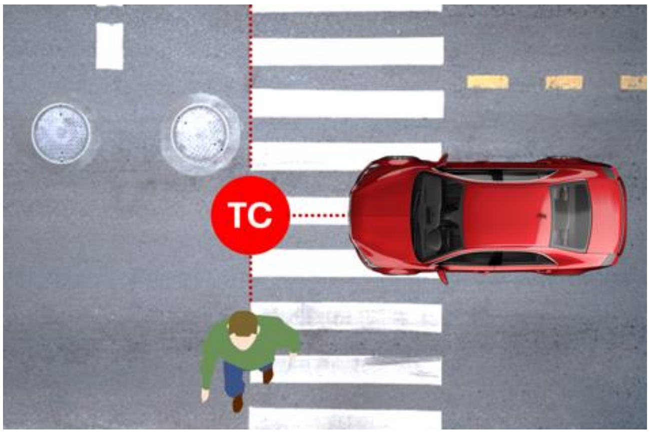

Figure 5. Definition of Post-Encroachment Time (PET) for a vehicle/pedestrian interaction

$$\mathrm{PET} = \mathrm{t}_2 - \mathrm{t}_1, \tag{1}$$

where, t_2 is the arriving time at a conflict point of the second road user, and t_1 is the time of the first road user departing the conflict point.

To identify and calculate the PET for each traffic conflict, a more extensive semi-automatic analysis was conducted in order to ensure the highest accuracy and quality of the calculated time-events. As SSMs refer to a small scale in terms of time (just a few seconds) and any deviation can lead to significantly erroneous conclusions, the authors deemed it appropriate to follow a more detailed analysis for the calculation of the indicators. In this way, the deviation from the initial data sample was checked, while the best possible accuracy approach regarding the developed sample was achieved. More specifically, for each traffic conflict, the critical timestamps for calculating the PET index were identified, recorded and then applied in Equation 1.

To identify traffic conflict severity, thresholds should be adopted. Thresholds values concerning vehicle-pedestrian conflicts vary across various studies (Almodfer *et al.*, 2015; Paul and Ghosh, 2019; Ahsan *et al.*, 2024). In most cases, thresholds vary between 1.0 seconds to 5.0 seconds. In this research, conflict severity is described according to the PET threshold values that are described in Table 2.

Table 2. Description of adopted severity thresholds for vehicle-pedestrian conflicts

PET threshold	Severity of conflict	Description
$0 \le PET \le 1$	high-risk conflicts	In this situation, the pedestrian rushed to cross the traffic lane, or the vehicle did not notice the presence of the coming vehicle, and the interaction was dangerous.
$1<PET\le1.5$	serious conflicts	In this situation, the pedestrian crossed the traffic lane, or the vehicle did not notice on time the presence of the coming vehicle, and the interaction is serious.
$1.5<PET\le3$	low-risk conflicts	In this situation, the pedestrian crossed the traffic lane, and the interaction with the vehicle is characterized as low-risk.
$3<PET\le5$	potential conflicts	The interaction between the vehicle and the pedestrian constitutes a potential traffic conflict, which warrants further analysis to better understand the contributing factors and to develop measures aimed at mitigating any increase in severity.

The analysis resulted in 513 total identified traffic conflicts for which the PET indicator was equal to or less than 5 seconds and therefore were used for the development of the overall database.

To map the identified traffic conflicts and develop a comprehensive database of calculated SSMs, the following process was followed:

- Timestamps were coded withing the proximity of a potential traffic conflict, based on vehicle and pedestrian trajectories, and speeds were subsequently calculated.
- The timestamps were exported on spreadsheets and by using Visual Basic for Application (VBA) procedures preliminary SSMs were calculated for each pedestrian movement, according to the closest-in-time vehicle trajectory.
- A threshold of 5 seconds was adopted to determine which traffic conflicts warranted further investigation.
- The shortlisted traffic conflicts were then identified in the video footage according to the recorded timestamps. The precise moments of interaction were manually verified through video observation, both to validate the extracted data and to provide more accurate and detailed calculations in the database.
- Simultaneously, the location of each traffic conflict was recorded in a GIS database.
- The GIS database was further developed through the recalculation of more accurate PET values based on video observation. In addition, vehicle speed data were integrated, along with estimates of pedestrian gender and age group, as derived from the video analysis.

Our approach integrated as well a semi-automatically process of using Geographical Information System (GIS) and Visual Basic for Application (VBA) procedures in spreadsheets in order to accurately calculate and illustrate the location points of the Post-Encroachment Time (PET) events.

4. Results

In total 513 traffic conflict points were identified for which the PET index was less than 5 seconds. To better understand the conflict severity, the sample was further divided into the following four categories as discussed in the literature review: (a) high-risk conflicts ($0\le PET\le1$), (b) serious conflicts ($1<PET\le1.5$), (c) low-risk conflicts ($1.5<PET\le3$), and (d) potential conflicts ($3<PET\le5$).

The results presented in the Table below indicate that seven traffic conflicts are characterized as high-traffic conflicts as these events have the potential to result in crashes. Moreover, the identification of additional 46 serious conflicts highlights the need for further investigation into the conditions under which these specific interactions between road users occurred. This suggests that both the intersection and the pedestrian crossing may require improvements, both in terms of geometric design and signal timing optimization, to reduce aggressive behavior and enhance road user interactions, promoting safer and longer time gaps during crossings.

Table 3. Severity classification of identified vehicle-pedestrian conflicts

PET threshold	Severity of conflict	Events
$0 \leq PET \leq 1$	high-risk conflicts	7
$1<PET\leq 1.5$	serious conflicts	46
$1.5<PET\leq 3$	low-risk conflicts	268
$3<PET\leq 5$	potential conflicts	192

The distribution of PET indices for the various turning movements and times of day reveals interesting descriptive statistics. As expected, right-turning movements predominate, as these turns are permitted simultaneously with pedestrian crossings. More specifically, drivers must yield to pedestrians on the crossing under a flashing amber signal. The proportion of pet events during the left-turn movements reveals that pedestrians that cross the traffic lane tend to be more cautious, due to lower visibility and ability to react to potentially dangerous situations.

Table 4. Distribution of PET indices for the various turning movements

Time of Day / Turning Movement	Through Movement PET / vehicles (%)	Right-Turn Movement PET / vehicles (%)	Left-Turn Movement PET / vehicles (%)	Total PET / vehicles (%)
Morning	42 / 146 (28.8%)	147 / 288 (51.1%)	42 / 163 (25.8%)	231 / 597 (38.7%)
Evening	120 / 259 (46.3%)	49 / 110 (44.5%)	113 / 335 (33.7%)	282 / 704 (40.1%)
Total	162 / 405 (40.0%)	196 / 398 (49.3%)	155 / 498 (31.1%)	513 / 1301 (39.4%)

The Figures below illustrate the share of observed traffic conflict events relative to the total number of pedestrian crossings during both the morning and evening peak hours. It is observed that, during τηε morning hours, pedestrian crossing volumes are relatively evenly distributed over time and correspond closely with the distribution of observed traffic conflict events.

However, this pattern appears only for the first hour of the evening peak. During the second hour, reduced visibility due to night-time period and darkness appears to weaken the correlation between pedestrian volumes and traffic conflict events.

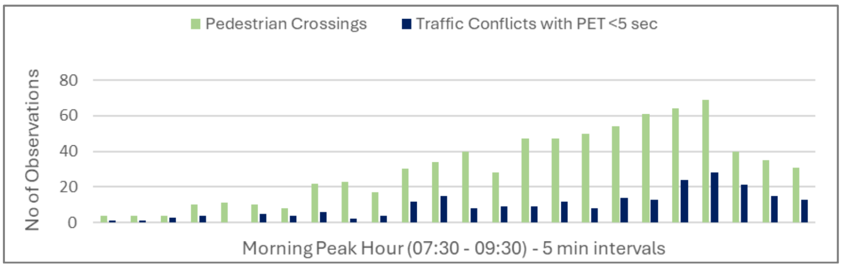

Figure 6. The share of observed traffic conflict events relative to the total number of pedestrian crossings during morning peak hour

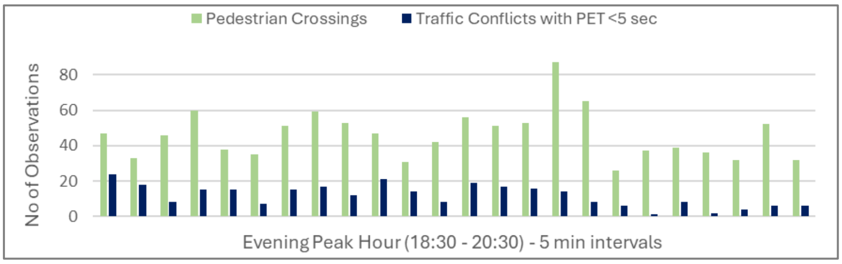

Figure 7. The share of observed traffic conflict events relative to the total number of pedestrian crossings during evening peak hour

It can be claimed that reduced visibility conditions contribute to increased hesitation among pedestrians when approaching crossings, potentially leading to more cautious behavior unless the right of way is clearly perceived. However, it is noted that this observation remains descriptive and further statistical analysis is necessary to substantiate any definitive conclusions. Studies have highlighted the influence of nighttime conditions on the severity of accidents compared to those occurring during daytime hours (Alogaili and Mannering, 2022). In this context, it should be noted that even if less conflicts can be observed during night-time, pedestrians may be exposed to higher risks due to speeding and other parameters typically amplified during night hours, such as distraction (Hasanpour *et al.*, 2025).

Table 5. Distribution of PET indices for the various turning movements

Time of Day / Turning Movement	[T]		[R]		[L]	
	Morning	Evening	Morning	Evening	Morning	Evening
Vehicle yields to pedestrians (%)	52.4%	46.7%	72.8%	65.3%	40.5%	47.8%
Average pedestrian age (*)	28.2	26.5	28.3	26.7	28.3	29.5
Male-to-female (*) conflict ratio	2.00	1.31	1.00	0.96	1.10	1.46
Average PET	2.835	2.742	2.843	2.473	2.782	2.748
Minimum PET	1.001	0.220	1.010	1.060	1.010	0.970
Maximum PET	5.110	4.970	5.190	4.810	4.820	5.101
Curb nearest distance	3,51	3,01	3,44	2,97	3,39	3,03

(*) estimated

The average lateral distance from the curb at which the recorded events occurred was approximately 3.2 meters, indicating that the majority of incidents took place closer to the northern curb of the crossing as the width of the crossing is approximately 8.5 meters.

Notably, 84 traffic conflicts were identified outside the designated pedestrian crossing area. This implies that approximately 16% of pedestrians exposed to hazardous conditions did not cross cautiously or as intended within the marked crossing. Instead, their trajectories deviated from the expected path that drivers would typically anticipate.

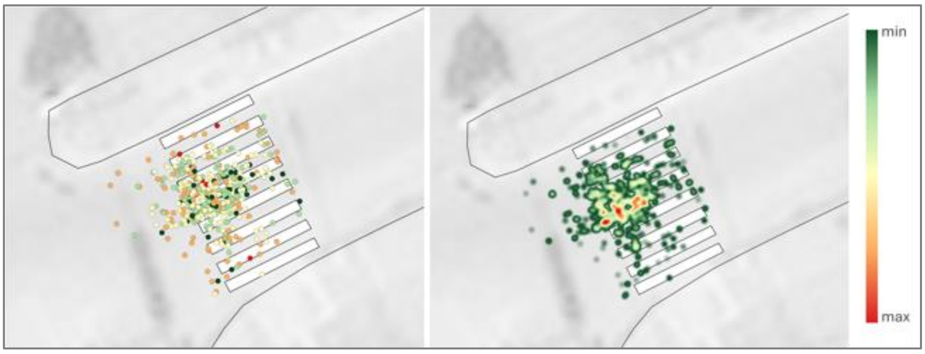

Figure 8. The spatial distribution of the examined traffic conflicts

The figure above highlights the spatial distribution of the identified conflict events, categorizing them by severity. The right panel of the figure presents the density of events across the crossing area. The density of the identified traffic conflicts confirms that most traffic conflicts were concentrated in the central and northern sections of the crossing.

5. Conclusions

This study demonstrates the efficacy of employing AI-based technologies concurrently with semi-automatic techniques to utilize road user trajectory data and analyze surrogate safety measures, to assess pedestrian safety at a signalized intersection with high pedestrian volumes and frequent vehicle-pedestrian interactions.

The lack of accurate and reliable historical crash statistical data on specific road intersections can contribute to difficult evaluations of the traffic safety, while the process of collecting crash statistics can be time-consuming. Therefore, in this study, through the integration of AI-driven video analytics and semi-automated GIS-based methodologies, 513 conflict events were identified, categorized, and spatially mapped to evaluate the severity and spatial distribution of pedestrian-vehicle interactions.

The quantitative analysis's findings highlight the need for signal control systems that better accommodate pedestrian safety by showing that right-turning vehicle movements that coincided with pedestrian green phases were the main source of conflict. Furthermore, the identification of 53 major and high-risk conflicts underscores the substantial exposure to hazardous situations, especially for younger pedestrians, who represented the largest user group in the research area.

The spatial concentration of conflicts near the northern edge of the crossing and the occurrence of 16% of conflicts outside the designated pedestrian paths further indicate systemic issues related to both infrastructure design and user behavior. Furthermore, based on descriptive statistics of the analysis and literature review, it is suggested that reduced visibility conditions during evening hours may influence pedestrian crossing behavior and potentially exacerbate conflict severity.

The findings reinforce the utility of PET as a proactive, time-efficient metric for identifying safety concerns prior to the occurrence of collisions, thereby facilitating the development of targeted interventions either in the geometry of the intersection or the operation of the road network.

Overall, this research contributes to the growing body of literature advocating for the integration of SSMs and AI-based trajectory analysis in pedestrian safety evaluations. It supports the advancement of data-driven decision-making frameworks for urban intersection design and traffic signal optimization.

A notable limitation of this study is its focus on data collected exclusively during peak traffic hours. While peak periods typically involve a higher number of vehicular movements, this may not correspond proportionally to (i) pedestrian volumes, (ii) the number of conflicts, or (iii) the severity of those conflicts. During such times, vehicle speeds are generally lower, and movement is often constrained by traffic congestion and vehicle-following behavior, which may reduce the likelihood or criticality of certain conflict types. As a result, the temporal scope of the analysis may not fully capture the variability in pedestrian-vehicle interactions that occur under different traffic flow conditions. To provide a more comprehensive assessment of safety dynamics, future research should incorporate data from multiple time periods, including off-peak and nighttime hours. This would enable a more nuanced understanding of how temporal factors influence conflict frequency, typology, and severity, ultimately supporting more effective, context-sensitive interventions for pedestrian safety.

Future research will expand upon these findings by incorporating longitudinal data, additional behavioral variables (such as speed, vehicles maneuvers, etc.), and simulation-based testing of mitigation scenarios to further inform pedestrian safety strategies in complex urban environments. The completion of STREET21 project will be based on a comprehensive geospatial database encompassing various types of intersections. This will facilitate comparative analyses across multiple urban contexts and contribute to the formulation of generalized design and policy recommendations aimed at enhancing pedestrian safety in complex traffic environments.

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Declaration of Generative AI and AI-assisted technologies in the writing process:

- During the preparation of this manuscript the author(s) did not used Generative AI and AI-assisted technologies and take(s) full responsibility for this declaration.

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