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Drone-Enabled Behavioral Mapping of Pedestrian-Vehicle interactions on Zebra Crossings near Schools

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Abstract

As the emphasis on active mobility grows, ensuring pedestrian safety has become increasingly important. Understanding how road users behave during interactions between pedestrians and vehicles is essential for establishing effective road safety measures. AI coupled with drone technology can significantly enhance the detection and analysis of these interactions and behaviors. While traditional microsimulation methods can simulate road user behavior and potential risks, they are prone to inaccuracies since the environment is manually calibrated, and the calibration parameters may not fully represent the real-world environment. Modeling real-world trajectories and environments directly could facilitate the identification of potential risks at a micro-scale and help understand how different road users respond to soft modes and the associated infrastructure. This paper presents an innovative solution that uses drones and an AI-driven workflow to detect pedestrian-vehicle interactions and analyze vehicle behavior in high-density pedestrian areas. The system automates the detection of these interactions based on predetermined spatial and temporal conditions. Once these interactions are detected, a baseline of vehicle behavior is established by plotting the dominant speed profiles as vehicles approach zebra crossings. This baseline behavior is then used to estimate deviations for each vehicle at each movement at an unsignalized three-legged intersection. The workflow helps pinpoint behavioral anomalies' location, cause, and temporal signature, enabling automation across extensively recorded video data. The findings highlight the potential of these disruptive technologies to assist policymakers, urban planners, and mobility experts to be aware of current traffic situations and aid in making informed decisions to enhance road safety and improve driving conditions.

Keywords: Road Safety; Pedestrian-vehicle Interaction; UAV; AI

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1. Introduction

For a substantial amount of time, researchers working in the area of road safety have been exploring the use of behavioral data for a better understanding of the underlying causes of road accidents. Several factors shape a driver's behavior including distraction, vehicle maneuvers, violations, brake response time, and involvement in pedestrian-vehicle interaction as discussed in the past literature by Hancock et al. (2003); Luo et al. (2023); Rosenbloom and Perlman (2016), and Wood and Troutbeck (1994). In the recent past, researchers have extensively investigated the profile ratings of drivers using naturalistic driving data – for example Beusen et al. (2009) used data obtained from onboard logging devices, Ellison et al. (2015) analyzed GNSS-based trajectories to determine the smoothness of maneuvers and Papadimitriou et al. (2019) utilized cellular data for driver categorization and estimation of crash risk probability. These already established measures are great at determining naturalistic driving behavior but pose certain limitations. For instance, installing expensive onboard devices on vehicles poses certain operational and legal constraints limiting the adequate sample size representative of an area's population. Similarly, GNSS-based methods are somewhat unreliable due to positional inaccuracies and clocking issues as the receiving device tends to face delays in transmission.

Microsimulation platforms like PTV VISSIM, PARAMICS, and AIMSUM are widely used to model current traffic environments and quantify the impact of an intervention in terms of driving behavior and road safety. Mahmud et al. (2019) reviewed several studies that utilized these microsimulation platforms and their applicability in modeling real-world traffic environments and naturalistic driving conditions. The authors acknowledged the limitations of these platforms as they are highly data-dependent, and often, real-life conditions cannot be entirely replicable within a probabilistic microsimulation. For example, it is challenging to model non-lane-based heterogeneous traffic environments. Similarly, active or vulnerable users like pedestrians and cyclists may not always follow their designated walkways or lanes, impacting the behavior of approaching vehicles. Although these violations are often perceived as non-threatening, they still have some implications.

Recent advancements in computer vision and image processing systems offer reliable alternatives to conventional data collection and analysis mechanisms. Saunier and Sayed (2007) demonstrated that these technologies offer the potential to develop automated solutions for generalized and specialized traffic scenarios. With the advent of AI-enabled Unmanned Aerial Vehicle (UAV) technology or recently coined so-called YOLO-based-UAV technology (YBUT), road traffic analysis has been revolutionized, as discussed in a study by Chen et al. (2023). Butilă and Boboc (2022) systematically reviewed the use of UAVs in urban traffic monitoring and concluded that these intelligent technologies offer a strong alternative to the conventional road traffic data collection and analysis due to the enhanced coverage and aerial perspective that is otherwise not offered by conventional means, thereby enabling a holistic view of road traffic with minimal blind spot risks. Aerial footage combined with AI technology can also help uncover patterns that may go unnoticed but are consistently impacting the driving behavior. Avola et al. (2022), for instance, proposed a novel two-branch Generative Adversarial Network (GAN)-based method for low-altitude RGB aerial video to identify and localize anomalies. They define anomalous situations as encounters with interactions with foreign objects like gas bottles, boxes, and suitcases, representing a danger to attention.

With the growing emphasis on active or soft mobility, it is important to identify the interaction behavior of soft modes with motorized transport to foster a safer shared environment, as discussed by Che et al. (2021). Sullman et al. (2012) similarly emphasized that this understanding becomes extremely critical in high-density pedestrian environments such as school districts, where the presence of vulnerable road users is significantly high. While surrogate safety indicators like time-to-collision and post-encroachment time are commonly used to identify potential risk zones, Renard et al. (2022) utilized UAV footage combined with an AI-based platform called Datafromsky to evaluate safety for active road users, i.e., school children. Although surrogate safety indicators can be used to identify near-miss incidents and conflicts, behavioral profiling can enable a holistic analysis, and the insights can even help mitigate the cause of the near-miss incidents. Moreover, post-intervention studies could help model and determine the efficacy of soft-mobility infrastructure and its impact on regular traffic. Vehicle trajectories from AI-enabled drone technology can help map the naturalistic traffic behavior in these areas and identify unsafe road crossings and resultant anomalous vehicle behavior in response.

This paper presents an approach to determining and analyzing traffic behavior in high-density pedestrian areas using AI-based drone technology. The proposed method establishes a baseline behavior of vehicles interacting with pedestrians at a three-legged intersection within a school district. The method extracts the real-world traffic directly, enabling the ability to model the traffic behavior at a foundational level; therefore, the chances of calibration errors are non-existent. This leads to the development of a workflow that reflects reality, in contrast to microsimulation methods that depend on user expertise and may overlook deviant user behaviors that are often caused by the built environment itself. The findings uncover anomalous patterns in vehicle-pedestrian interactions resulting from infrastructural intervention. These patterns often remain undetectable by conventional methods; therefore, the study's results offer insights for policy adjustments at a micro-level to ensure the safety of vulnerable road users.

2. Data and Methods

2.1. Study location and experimental setup

The experimental design consists of a DJI mini pro 3 flying at a height of 60 meters at 14:15 local time under all-clear sky conditions over a three-legged intersection at ElfdeLiniestraat in Hasselt, Belgium (see Fig. 1). This particular location was selected due to the high density of vulnerable road users because of the nearby schools. Considering the intersection's design, six gates are placed across each vehicle movement. The approaching gates 1, 3, and 6 were placed at 20 meters since the higher distance could help capture the speed profile more accurately, whereas departure gates 4, 2, and 5 were placed at 5, 8, and 8 meters, respectively, based on the dimensions of the intersection. This helps retain the records that are critical for determining the vehicle-pedestrian interaction and discard the unnecessary records. Additionally, this setup is tailored for the built environment of the selected location.

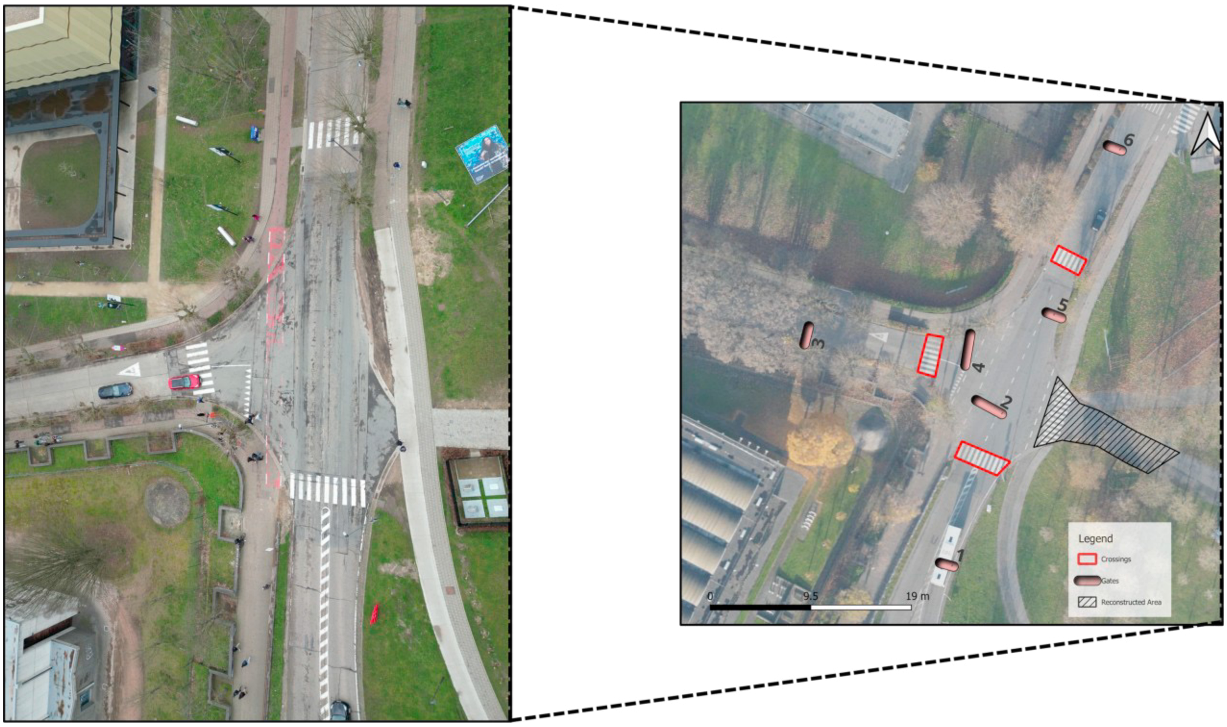

Fig. 1. The location of the experiment and gate assignment at ElfdeLiniestraat in Hasselt, Belgium. [Left: drone image; right: annotated satellite view].

The workflow consists of drone footage (see Fig. 2) processed by DataFromSky, a platform which performs road user object detection on the recorded footage and extracts the trajectories that are used to calculate road user parameters as previously demonstrated by Adamec et al. (2020). To enable a spatially consistent output, a spatial reference system UTM 31N is defined by manually defined ground control points (GCPs). Subsequently, the data undergoes a transformation process, and critical information like vehicle track IDs, type, speed, positions, and time stamps are structured into a database for analysis.

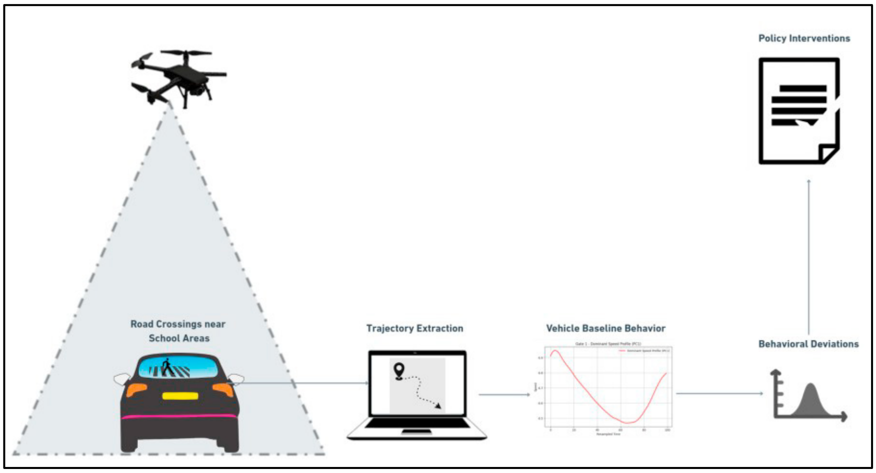

Fig. 2. Illustration of the methodological framework of the study.

2.2. Defining vehicle-pedestrian interaction

Due to the large data volume, it was essential to develop a method to retain the relevant information only. In a 45-minute long traffic footage, there were approximately 1,259 unique road user trajectories, of which 76% are active road users—specifically pedestrians (66%) and cyclists (10%) —while 24% are vehicles (20.49% cars, 0.95% medium vehicles, 0.05% heavy vehicles, 0.74% motorcycles and 1.43% buses). For the experiment, it was crucial to establish criteria for detecting pedestrian-vehicle interactions at road crossings. For each vehicle trajectory passing through a crosswalk the interaction with pedestrian was detected by spatial and temporal conditions, similar to Hu et al. (2022). We define the interaction criteria by equations (1) and (2), respectively.

a) Spatial condition: pedestrian within a crossing:
A pedestrian p at time t is considered to be inside a crossing C_k.

$$p_t \in C_k \Rightarrow pedestrian\ inside\ crossing \quad (1)$$

Where $p_t = (x_{p,t}, y_{p,t})$ is the pedestrian's location at time t, $C_k$is the k_{th}crossing polygon due to the presence of multiple polygons and a pedestrian may cross multiple polygons within a footage.

b) Temporal condition: time matching:
For an interaction, a pedestrian must be present at the crossing at a time t_p close to the vehicle's time t_v within a time tolerance Δt.

$$|t_p - t_v| \leq \Delta t \quad (2)$$

Where $\Delta t = 3\ seconds$ based on reasonable crossing speed assumption. The Δt helps capture a vehicle's behavior upon approaching a pedestrian. Both conditions ensure that an event is logged as a co-occurrence in both space and time.

2.3. Determining the baseline behavior and deviation from normality

After enforcing spatial and temporal criteria, 468 unique interactions were identified. Speed profile geometry of vehicles upon interaction was plotted, and then Principal Component Analysis (PCA) was applied to reduce the dimensionality, estimating the cumulative behavior and thereby determining a dominant speed profile with respect to the distance to respective crossing from each gate. Given the dataset $X = \mathbb{R}^{n \times p}$, where n is the number of filtered interactions in the form of trajectories crossing through a gate, and p represents the number of features or dimensions in each observation as outlined in the reference guide by Kurita (2019). PCA is applied to the gate-specific matrix after data standardization as described by equation (3).

$$X_{scaled} = \frac{X - u}{\sigma} \tag{3}$$

and calculating the covariance matrix C in equation (4):

$$C = \frac{1}{n} X_{Scaled}^{\mathrm{T}} X_{scaled} \,. \tag{4}$$

Next we perform eigenvalue decomposition to extract the principal components, as shown in equation (5):

$$C_v = \lambda v \tag{5}$$

C_v is simply λ, i.e., the corresponding eigenvalue times v. This shows that v is the direction or pattern in the speed profile space along which the variance (i.e., the differences in vehicle speeds as they approach the crossing) is maximized. The pattern, captured by the first principal component (PC1), captures the most common trend in vehicle speeds at that gate while a pedestrian is moving through the nearest road crossing (illustrated in Fig. 3).

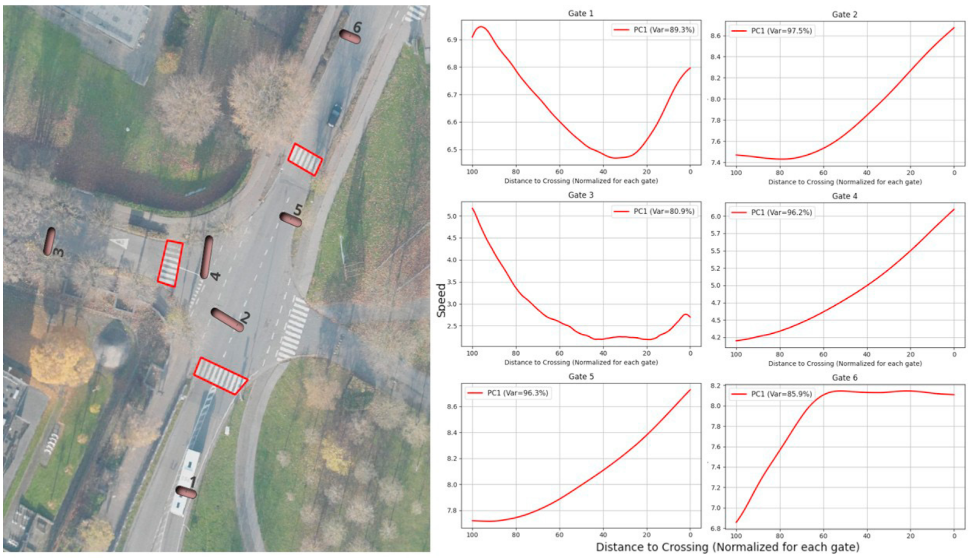

Fig. 3. Dominant speed profiles (PC1) for vehicle trajectories across gates, showing the relationship between speed and distance to crossing (normalized for each gate). Each gate has a different percentage of variance retained, i.e., Gate 1 (89.3), Gate 2 (97.5), Gate 3 (80.9), Gate 4 (96.2), Gate 5 (96.3), and Gate 6 (85.9).

While the vehicles are moving at different speeds, the overall speed-profile geometry upon pedestrian-vehicle interaction would be comparable; therefore, the cosine similarity was used to capture the deviant behavior. Cosine similarity is defined as similarity between two vectors of an inner product space as described by Han et al. (2012). It is estimated by the cosine of angle between the two vectors and determined whether they are oriented in a similar direction , as defined in equation (6).

$$Cosine\ Similarity\left|S_i, S_{pc1}\right| = \frac{S_i, \cdot S_{pc1}}{\|S_i\| \left\|S_{pc1}\right\|} \quad (6)$$

Where:

$S_i, \cdot S_{pc1}$ is the dot product between the individual trajectory and PC_1. $\|S_i\|$ and $\left\|S_{pc1}\right\|$ are Euclidean norms of the vectors. Since cosine similarity ranges from -1 (completely opposite) to 1 (identical), we define deviation (d) as equation (7):

$$d = 1 - Cosine\ Similarity(S_i, S_{pc1}) \quad (7)$$

If the deviation is 0, it suggests that the vehicle's speed follows the baseline geometry, whereas a deviation > 0 suggests unusual behavioral deviations upon interaction. This similarity measure helps identify if the driver had to take an abrupt action due to the interaction with a pedestrian as its speed vector would be significantly deviate from the baseline. All of the vectors representing vehicle speeds during interaction were compared with the baseline and statistically evaluated (further discussed in table 1).

3. Results and Discussion

The deviations were estimated upon analyzing the 468 unique interactions at different gates. Fig. 4 and Table 1 depict the deviation values across different gates, showing how individual vehicle trajectories differ from the baseline behavior at each gate. The y-axis represents the deviation in each vehicle's speed profile compared to the baseline, with higher values indicating greater divergence from the typical speed pattern at its respective gate. The results reveal that Gate 3 exhibited the highest variability and deviations, demonstrated by a wide interquartile range (IQR), and confidence interval ranging from 0.15 to 0.21. This indicates that vehicle behavior at Gate 3 is significantly inconsistent compared to the other gates. This issue was later investigated, and the root cause was identified (see Fig. 5).

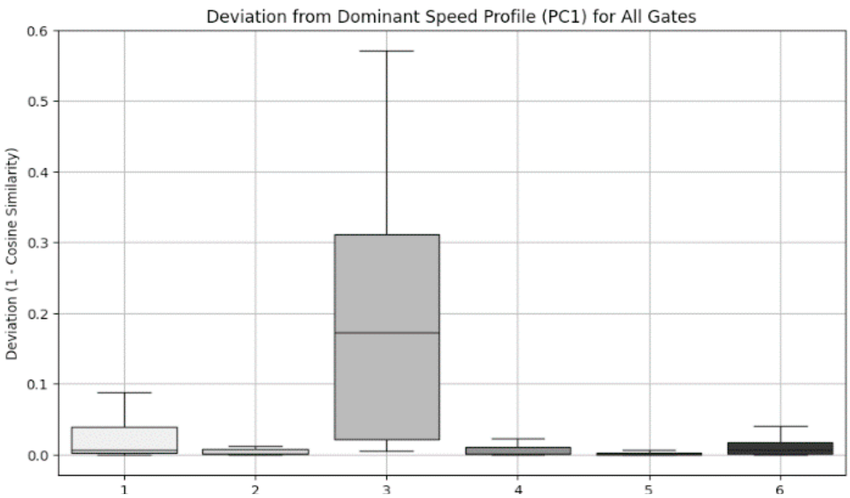

Fig. 4. Boxplot of deviation values (1 - cosine similarity) from the dominant speed profile (PC1) across different gates. The high variability of Gate 3 corresponds to infrastructure-induced risk.

In contrast, Gates 1, 2, 4, 5, and 6 showed relatively lower deviations, as evidenced by their narrower IQRs and lower median deviation values. This suggests more stable and uniform speed behaviors at these locations. However, the presence of a few outliers was linked to a few instances of deviations like acceleration or deceleration, while a larger spread indicates a deeper problem associated with the existing infrastructure.

Table 1. Summary statistics of deviation values by gate, including mean deviation, standard deviation (SD), and 95% confidence interval (CI) lower (L) and upper (U) bounds.

Gate ID	Mean	SD	CI (L)	CI (U)
1	0.05	0.09	0.03	0.06
2	0.02	0.06	0.01	0.04
3	0.18	0.17	0.15	0.21
4	0.04	0.10	0.02	0.07
5	0.02	0.06	0.01	0.03
6	0.03	0.06	0.01	0.04

After further investigation, the root cause of the unusual behavior at gate 3 was identified. The issue originates from the introduction of a bicycle path in close proximity to the gate. This biking path, intended for bicycles, is used by pedestrians as a crossing point due to its convenience as the shortest path (highlighted in Fig. 5). This behavior resulted in a high frequency of abnormal speed profiles, resulting from abrupt braking and deceleration of vehicles. This situation depicts confusion among drivers when a pedestrian unexpectedly enters the cycling lane. The situation seems to be an unintended consequence of the biking infrastructure, and relocating the bike path to align with the existing zebra crossing could help alleviate this issue.

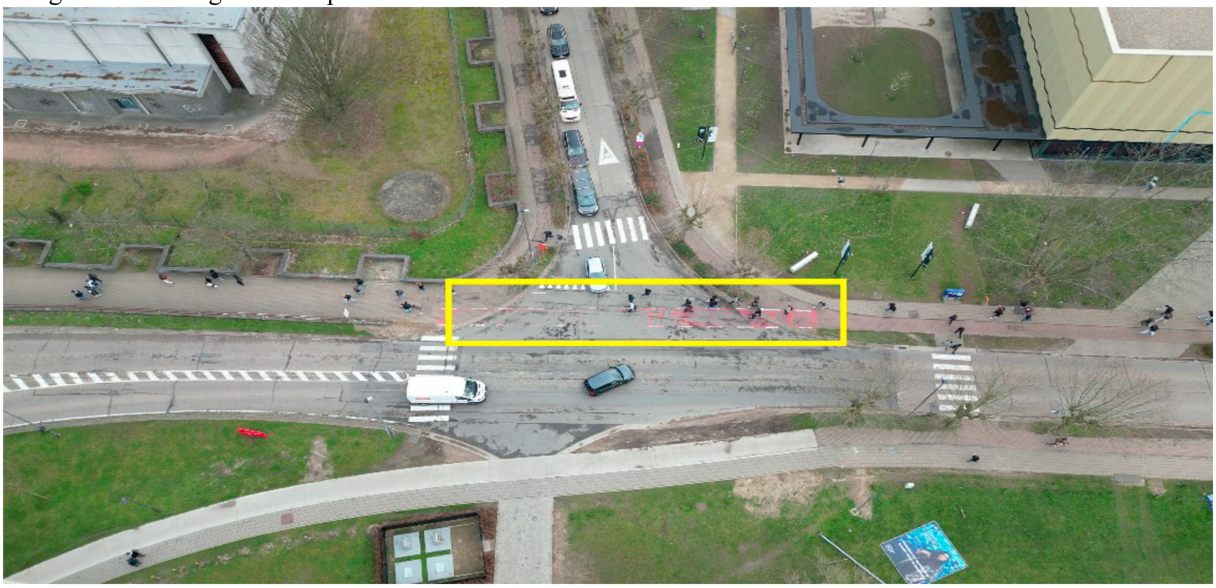

Fig. 5. The cyclist lane occupied by pedestrians leading to extreme deviations in speed profile at gate 3.

The study demonstrated the unparalleled potential of AI, combined with the aerial perspective of UAVs, for the detection of behavioral anomalies in road traffic. The proposed workflow can be tailored to fit the geometry of the study area, as the placement of monitoring gates can be customized. Additionally, this workflow necessitates the establishment of a baseline that represents normal behavior in a localized area. Anomalies are then detected by comparing current behavior against this baseline. These features make the proposed solution highly customizable and scalable. Furthermore, the workflow relies on high-quality data; therefore, having extensive data, such as hours or days of footage, can significantly enhance the robustness of user behavior modeling. However, a limitation of this study is the quality of the data. While DataFromSky was utilized for this experiment, which is known for providing reliable and high-quality vehicle trajectories, noisy data can adversely affect the results. Therefore, it is essential to perform quality checks on the experimental data before implementation.

4. Conclusion

This study represents one of the initial efforts to combine UAV and AI technologies for quantifying pedestrian-vehicle risks at actual sites through unsupervised behavior profiling. The proposed approach first establishes a baseline behavior and then recognizes deviations from aerial footage of road traffic. In this case study, the observations revealed that deviant behavior was primarily caused by a bike path, originally intended for bicycles, being used by pedestrians as a convenient crossing point due to its shorter route. These unusual behaviors are often challenging to capture through conventional methods, leading to frequent underreporting of potential hazards. The findings strongly advocate for the application of these disruptive technologies in real-world environments, thereby promoting a robust integration of AI in road traffic monitoring.

In conclusion, the proposed method facilitates a micro-level analysis of real-world traffic behavior in densely populated pedestrian areas, a capability not offered by current microsimulation platforms. This analysis allows users to pinpoint the location, causes, and timing of anomalies identified in traffic footage. This method is adaptable to different urban contexts with varying geometries and behaviors. Combining it with microsimulation frameworks to model and evaluate the impacts of different inventions, it can assist policymakers in making informed decisions backed by data. Future research will explore locations with differing built environments to analyze behavioral aspects of road users and to identify both local and global behavioral patterns.

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