Integrating Telematics and Video-Based Recognition for Vehicle Behavior Analysis in Athens

Stella Roussou[1], Apostolos Ziakopoulos [1], Roberto Ventura [2], Dimitris Oikonomopoulos [3], Haris Sideris [3], George Yannis [1]

[1]Department of Transportation Planning and Engineering, National Technical University of Athens, 5 Heroon Polytechniou Str., s_roussou@mail.ntua,gr
[1]Department of Transportation Planning and Engineering, National Technical University of Athens, 5 Heroon Polytechniou Str., apziak@central.ntua.gr
[2]Department of Civil, Environmental, Architectural Engineering and Mathematics (DICATAM), University of Brescia - Via Branze, 43 – 25123 Brescia (Italy, roberto.ventura@unibs.it
[3]OSeven Single Member Private Company, Greece, hsideris@oseven.io
[3]OSeven Single Member Private Company, Greece, doikonomopoulos@oseven.io
[1]Department of Transportation Planning and Engineering, National Technical University of Athens, 5 Heroon Polytechniou Str., geyannis@central.ntua.gr

Abstract

Introduction

Understanding how vehicles behave in complex urban environments is fundamental for developing effective road safety and mobility strategies. Telematics and computer vision have made very important progress. This has made it possible to collect driving data all the time, which gives researchers a chance to study driver behavior on both a small and large scale. Telematics combines real-time data, GPS, and wireless communication to let people keep an eye on speed, acceleration, and route changes on a large scale (Siami et al., 2021; Kirushanth & Kabaso, 2018; Ziakopoulos et al., 2022). Artificial Intelligence and deep learning algorithms can analyze video in real time to find, classify, and track road users. They can also be used to detect events such as red-light violations, near misses, and harsh braking (Taccari et al., 2018; Olszewski et al., 2016).

Despite their complementary advantages, these two data sources have rarely been integrated systematically. Telematics provide extensive spatiotemporal coverage but mostly specific transport mode (e.g. private vehicle car, motorbikes, etc.) details and without covering all road user aspects, while video offers high spatial detail but short observation periods with size-intensive datasets. Recent studies emphasize the transformative potential of combining these complementary data streams for proactive safety management (Nikolaou et al., 2025; Bhalla et al., 2025). The present research was conducted under the PHOEBE (Predictive Approaches for Safer Urban Mobility) project, focusing on the city center of Athens in Greece, a dense urban environment. It addresses the aforementioned gap by developing and applying a fusion framework that analyzes both telematics and video sources for the Athens metropolitan area (PHOEBE, 2023). The analysis focuses on three representative sites, the road of Vasilissis Amalias (for the specific study, it will be mentioned as Spot 3), Vasilissis Sofias (Spot 5), and Panepistimiou Street (Spot 8), all characterized by heavy traffic volumes and frequent signal-controlled interactions.

The objective of this study is twofold: (a) to compare and interpret vehicle speed patterns derived from telematics and video-based data, and (b) to explore how these datasets can jointly support the identification of high-risk driving behaviors. Ultimately, this work contributes to the design of proactive safety indicators that go beyond traditional crash-based approaches. These methods allow for a more holistic understanding of how drivers interact with their surroundings and how risky situations emerge in real-world traffic (Tarko et al., 2018).

[1] * Stella Roussou. Tel.: +30 210.7721575;
E-mail address: s_roussou@mail.ntua.gr

Methodology

The integration methodology involved four key stages: (i) data collection, (ii) preprocessing, (iii) harmonization between the two different datasets, and (iv) comparative analysis.

Data collection involved two complementary streams. The first one, the Telematics data, provided by OSeven Telematics (https://oseven.io/), was collected from 2019 to 2023 using mobile-based monitoring algorithms that capture surrogate safety measures such as speeding, harsh acceleration and braking, headway, and mobile phone usage. These data were obtained for selected segments in the center of Athens and aggregated under GDPR compliance, ensuring anonymity and privacy. Similar telematics-driven frameworks have been effectively applied in international contexts to evaluate policy impacts and driver risk profiles (Bhalla et al., 2025; Ziakopoulos et al., 2022).

Regarding the second stream, comprising the video dataset, footage recordings were undertaken using smartphone cameras mounted on tripods in June 2024 at the three representative intersections mentioned above in Vas. Amalias, Vas. Sofias and Panepistimiou (Figure 1 below). Afterwards, the video recordings were processed and analyzed using a custom AI Video Detection algorithm to track the objects and the environment's details in an automated manner, extensively outlined in previous research (Ventura et. al, 2025). Each video dataset corresponds to a single intersection (Titled Spot 3, 5, or 8 from previous involvement in the PHOEBE project) and includes frame-by-frame measurements of vehicle positions, speeds by vehicle id, and the Time-To-Collision (TTC) metric.

Figure 1: Locations Map (source: Map-KDK_allMeasurementPoints by George Yannis)

The video data were inserted into the custom video detection algorithm, which includes the component of the color segmentation of the traffic light. The algorithm is based on the neural network of YOLO-v8, including Kalman Filtering, Re-identification featuring, the Hungarian algorithm, and the Homography transformation in order to convert the video coordinates into the real-world coordinates, and also capture frame by frame each different transport mode. The area was defined by drawing the Region-of-Interest (ROI) by setting specific coordinates.

Both datasets were preprocessed, harmonized, and jointly analyzed to identify behavioral trends, focusing on speed and Time-to-Collision (TTC) based surrogate measures of safety. Preprocessing and harmonization were essential to ensure comparability between sources. All speeds were converted to kilometers per hour (km/h) and filtered to retain values between 5 and 60 km/h, removing unrealistic or stationary conditions of outliers, which could have a negative effect. For each dataset, trimmed means were computed by excluding the top and bottom 10% of values to minimize the impact of noise or extreme events. For TTC analysis, critical events were defined as instances where TTC < 1.5 s, aggregated into 10 second windows with a minimum exposure threshold of 10 samples.

It is important to note that setting the Region of Interest (ROI) at the intersection and the pedestrian crossing at the traffic light might influence the results, as that ROI is where vehicles typically decelerate. In contrast, telematics records cover entire trips that include both free-flow and congested segments. This difference was carefully considered in the comparative phase to ensure valid interpretation. Table 1 summarizes a sample of the telematics dataset, while Table 2 presents an excerpt from the video data.

Table 1. Sample of Telematics Data (Spot 3 - From 2019 to 2023)

Timestamp	spot_number	Average_speed (km/h)	speeding_rate
2019-06-01 17:00:00	Vas.Amalias-Panepistimiou-MS376	32.637	0.295
2019-06-01 18:00:00	Vas.Amalias-Panepistimiou-MS376	35.775	0.297
2019-06-02 17:00:00	Vas.Amalias-Panepistimiou-MS376	41.669	0.238

Table 2. Sample of Video-Based Data (Spot 3 - June 2024)

Timestamp	spot_number	Average_speed (km/h)	median_speed_mps
2024-06-01 17:00:00	Vas.Amalias-Panepistimiou-MS376	24.144	6,744
2024-06-01 18:00:00	Vas.Amalias-Panepistimiou-MS376	33.869	9.70
2024-06-02 17:00:00	Vas.Amalias-Panepistimiou-MS376	30.371	8.478

Results

Table 3. Comparison of Mean Speeds

Recording location	Mean (km/h)	Telematics Mean (km/h)	Δ (Video − Telematics)	Description
Spot #3	24.8	31.6	-6.8	Intersection approach near Vas. Amalias
Spot #5	13.8	22.8	-8.9	Moderate flow on Vas. Sofias
Spot #8	13.8	29.0	-15.1	Dense intersection at Panepistimiou

Average telematics speeds were consistently higher than those derived from video analysis. This discrepancy reflects not only the shorter temporal span of video observations but also the spatial localization of the cameras near intersections, where vehicles decelerate in response to traffic signals. Scatter plots and mean-with-standard-deviation graphs confirmed this pattern: video-based speeds cluster at the lower end of the distribution (typically 10–25 km/h), while telematics exhibit wider variability, up to 50–60 km/h.

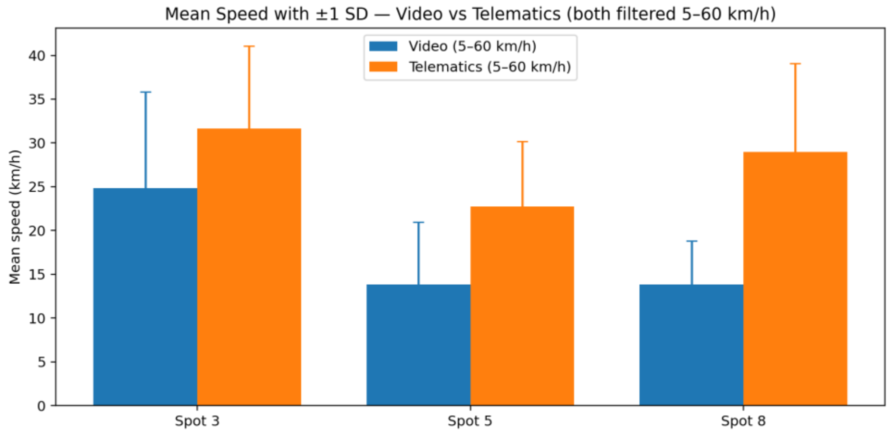

Figure 2: Telematics and Video-recognition extracted speeds

The analysis of critical Time-to-Collision (TTC) events, defined as instances where TTC < 1.5 seconds, revealed distinct spatial and temporal safety patterns across the three monitored sites. When aggregated in 10-second intervals, the mean critical TTC rate was estimated at approximately 2.9 per 1000 observations for Spot 3, 0.4 per 1000 for Spot 5, and almost 0 for Spot 8. These results position Spot 3 (Vasilissis Amalias) as the most conflict-prone location based on descriptive statistics, characterized by recurrent short-term near-collision events. In contrast, Spot 8 (Panepistimiou) serves as a low-risk baseline with minimal micro-conflicts.

The dispersion of TTC rates further underlines the variability in traffic interactions between sites. Spot 3 exhibited notably wider confidence intervals, indicating temporal instability in conflict occurrence, suggesting that high-risk moments appear in short, intense bursts rather than being evenly distributed over time. In contrast, the narrow distribution observed at Spot 8 suggests stable and homogeneous flow conditions, consistent with limited pedestrian interference and more coordinated signal timing.

A rolling 60-second window analysis provided deeper temporal resolution. At Spot 3, a pronounced conflict surge was detected around the 10-12 second mark, peaking at roughly 50 critical events per 1000 observations. This short-lived spike likely corresponds to the signal transition phase, when vehicles approach the intersection at reduced headways or during amber-light crossings. Spot 5 exhibited a smaller, isolated rise near the 30-second mark (~15 per 1000), whereas Spot 8 displayed no meaningful peaks throughout the observation period.

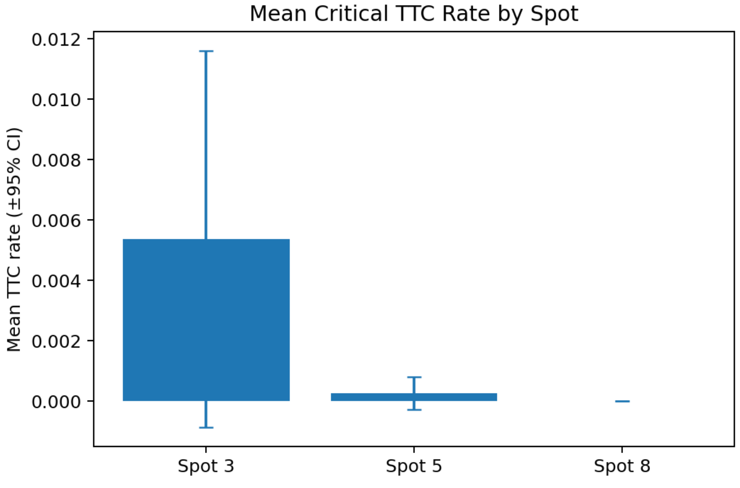

Figure 3: Mean TTC rate per spot

These short bursts are signs of temporary high-risk situations, such as when speed changes quickly, vehicles are too close together, or pedestrians enter the road too late. The Spearman correlation between mean speed and critical TTC rate was negative ($\rho = -0.25$, $p > 0.05$), indicating that the association was not statistically significant. This suggests that higher mean speeds do not necessarily correspond to higher short-term conflict risk. Instead, the main determinants of micro-conflict formation appear to be speed variability, sudden deceleration, and interaction density. Additionally, the correlation between mean speeds derived from telematics and video analysis was positive and strong ($\rho = 0.95$, $p < 0.05$), confirming that while video-derived speeds were systematically lower due to their spatial localization near intersections, both datasets reflected similar directional variations across sites.

The TTC-based analysis demonstrates that urban traffic conflicts are highly dynamic, emerging or disappearing rapidly over short time intervals. It also shows the difference between persistent stability and episodic instability in different places. By separating these micro-temporal risk patterns, the method exhibits a sensitive response to the operational characteristics of each intersection. This sensitivity allows for proactive safety evaluations and targeted changes to signals or infrastructure. The observed spikes occur in instances of high traffic or pedestrian flows. The timing of the peaks suggests that safety risks at Spot 3 are not always evident, but may be related to signal phases or late-pedestrian entries.

The results showed that the average speeds recorded in videos were consistently lower than speeds recorded by telematics. This is because the Region of Interest (ROI) near intersections includes areas where cars slow down before stopping. The TTC analysis demonstrated that there was a lot of spatial variability, with Spot 3 being the most conflict-prone area and Spot 8 staying mostly stable and free of micro-conflicts.

These results show that combining long-term telematics data with high-resolution video analytics provides a complete picture of driving behavior, risk over time, and safety performance in specific areas. The suggested method helps with proactive safety monitoring and provides information for evidence-based interventions for smart mobility planning in cities.

Discussion and Conclusion

The examination of significant TTC events validated distinct spatial variations in short-term conflict intensity. Spot 3 had the highest number of near-collision situations, with a mean critical TTC rate of about 3 per 1000 observations and a 95% confidence interval that was wider than those of other sites. Spot 5 had some isolated risk events, but Spot 8 stayed mostly free of conflict. These patterns match older traffic observations, which suggest that higher pedestrian flows and mixed-phase operation at Vas. Amalias lead to an increased amount of near-conflicts.

The integration of video-based TTC analysis and telematics data provided complementary insights into driving behavior and safety dynamics. While the Spearman correlation between mean speed and critical TTC rate was negative but not statistically significant, this suggests that higher mean speeds do not inherently increase near-conflict risk. Instead, the main contributors to short-term conflicts appear to be speed variability, abrupt deceleration, and dense vehicle-pedestrian interactions. These findings are consistent with previous research emphasizing that localized instability, rather than average traffic speed, better explains momentary risk fluctuations (Nikolaou et al., 2025; Bhalla et al., 2025).

The results also show that TTC-based indicators can find small changes in safety at very high temporal resolution (10-second intervals). This level of detail helps find short, high-risk moments that traditional minute-based analyses often miss. Combining TTC measures with telematics-derived indicators like harsh braking frequency and acceleration variance can help understand the causes of the driving behavior.

In conclusion, the present comparative framework developed within the PHOEBE project shows that using computer vision and telematics together makes a strong base for proactive safety assessment in cities. Future work will build on this integration by using temporal forecasting and hotspot analysis to improve signal control, timing of pedestrian phases, and targeted enforcement strategies. This will support the transition of Athens towards smarter and safer mobility.

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Keywords: Telematics, Video-based recognition, Driving behavior, Road safety, Artificial intelligence, PHOEBE project, Athens

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