

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

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### Introduction

Understanding how vehicles behave in complex urban environments is essential for improving road safety and mobility management. Recent developments in telematics and computer vision have made it possible to **continuously collect and analyze driving data** at both large and small spatial scales.

Telematics systems provide real-time information on speed, acceleration, and vehicle trajectories across large networks, while artificial intelligence and deep learning techniques applied to **video data enable the detection, classification, and tracking of road users** and traffic events such as red-light violations, near-misses, and harsh braking.

Despite their complementary advantages, **telematics and video data have rarely been systematically integrated**. Telematics provide extensive spatiotemporal coverage but limited detail on all road users, whereas video data offer detailed behavioural information but for shorter time periods and smaller areas.

### Objectives

This research addresses this gap by developing a framework that **combines telematics and video data** to analyze vehicle speed behaviour and identify high-risk driving patterns. The study focuses on three major urban corridors in Athens and aims to **support the development of proactive road safety indicators** beyond traditional crash-based analysis.

### Study Area

The study was conducted in the city center of Athens at three signalized intersections (Vas Amalias-Spot 3, Vas. Sofias-Spot 5, and Panepistimiou-Spot 8).

Two complementary datasets were used:

- telematics data collected from 2019 to 2023 and
- video-based data collected in June 2024 using smartphone cameras and AI-based object tracking.

The telematics dataset includes speed, speeding rate, and harsh events, while the video dataset includes vehicle trajectories, speeds, and Time-to-Collision (TTC) indicators. These datasets provide both long-term network-level information and detailed local traffic behaviour at intersections.

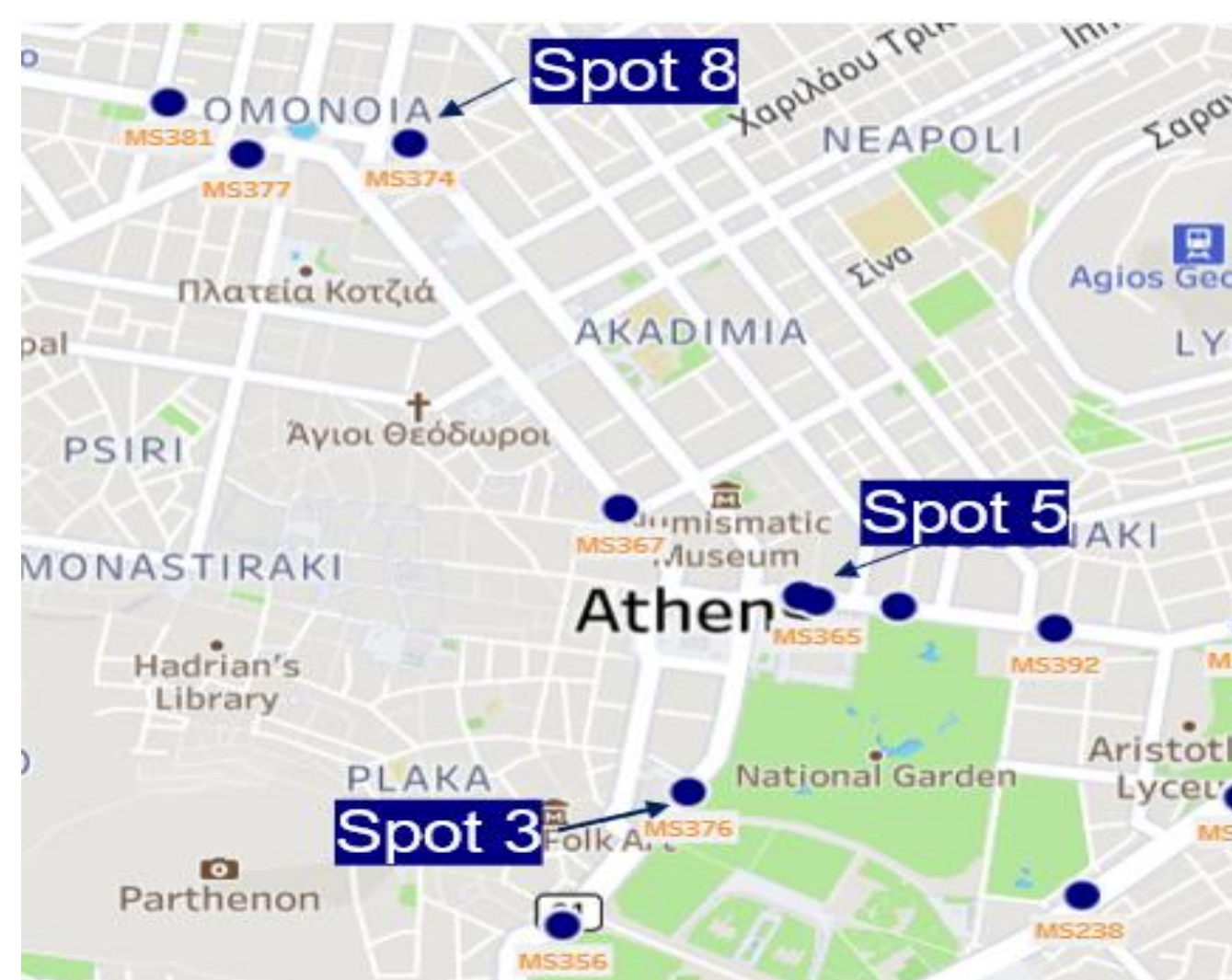


Figure 1: Locations Map (source: Map-KDK\_all MeasurementPoints by George Yannis)

### Methodology

The integration framework consisted of four main steps:

- data preprocessing,
- harmonization of telematics and video datasets,
- comparative speed analysis, and
- safety analysis using Time-to-Collision (TTC).

- Speeds were filtered between 5-60 km/h, and trimmed means were calculated to remove extreme values.
- Critical TTC events were defined as  $TTC < 1.5$  s and aggregated in 10-second intervals.

The analysis included comparison of mean speeds between datasets, spatial comparison of TTC rates across locations, rolling time-window analysis to detect short-term conflict peaks, and correlation analysis between speed and TTC indicators.

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 presents the comparison between mean speeds derived from telematics and video data for the three study locations.

- In all cases, **telematics speeds were higher than video-based speeds**.
- This difference is explained by the **spatial coverage of the datasets**, as video recordings were focused near signalized intersections where vehicles decelerate, while telematics data represent entire trips, including free-flow segments.

Despite these differences, both datasets showed consistent spatial patterns across the three locations.

Table 3: Comparison of Mean Speeds

Recording location	Mean (km/h)	Telematics Mean (km/h)	$\Delta$ (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

The comparison of speed distributions between telematics and video datasets showed that **video speeds were concentrated at lower values** (approximately 10–25 km/h), while telematics speeds presented wider variability, reaching higher values. This confirms that **telematics data capture broader driving conditions, while video data capture localized driving behaviour near intersections**.

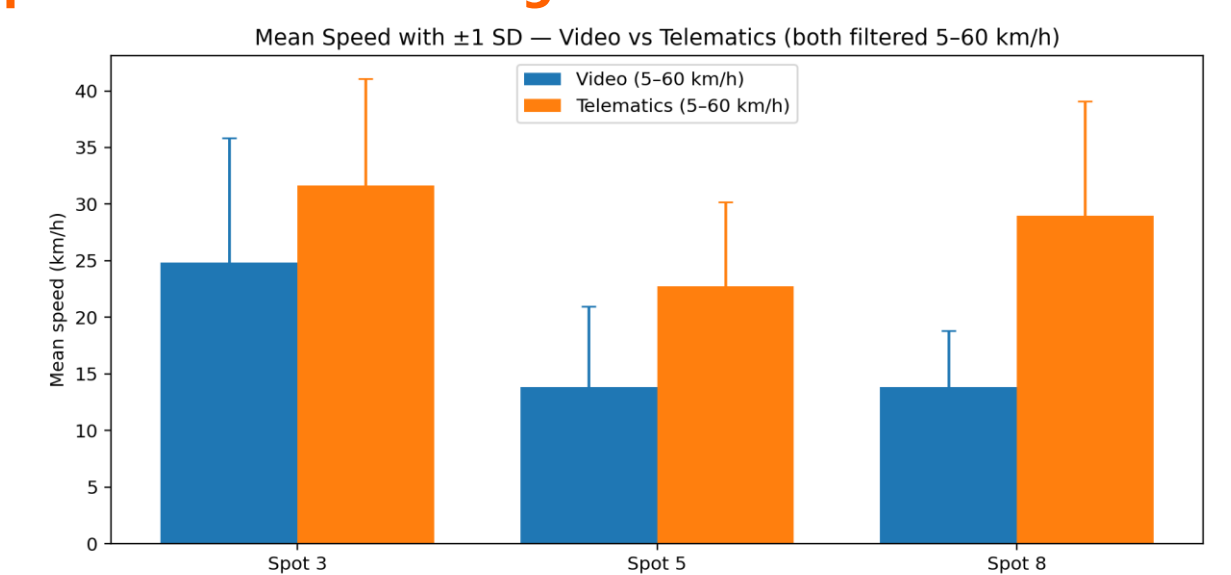


Figure 2: Telematics and Video-recognition extracted speeds

The TTC analysis revealed significant **spatial and temporal differences in traffic conflict** intensity across the three locations.

- Spot 3 showed the highest number of critical TTC events, indicating higher interaction intensity and unstable traffic conditions.
- Spot 5 showed moderate conflict levels, while
- Spot 8 remained relatively stable with very few critical events.

The temporal analysis demonstrated that

**conflicts occur in short bursts** rather than continuously, often associated with signal phase changes, pedestrian crossings, or sudden deceleration events.

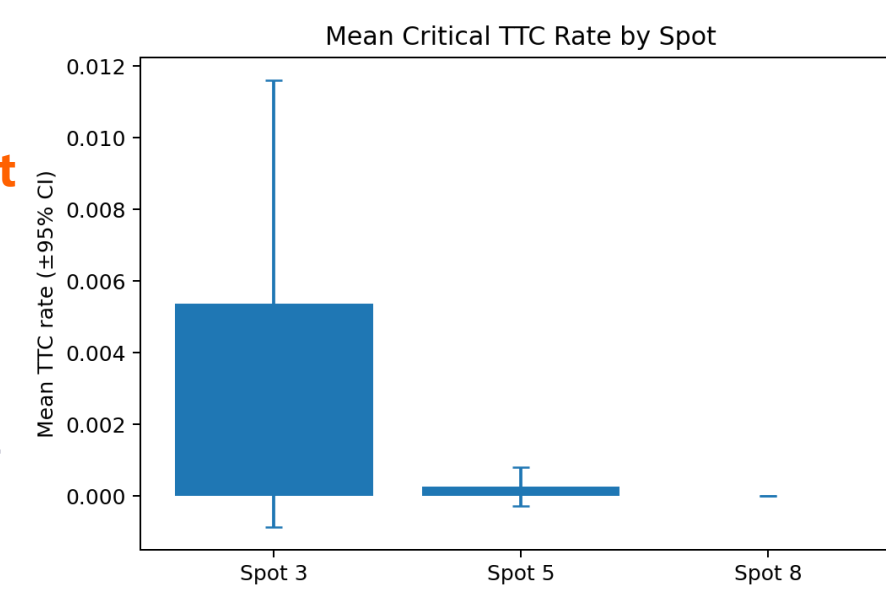


Figure 3: Mean TTC rate per spot

### Conclusions

- The comparison of telematics and video data showed that the two data sources provide **complementary information on vehicle behaviour** and traffic conditions.
- Telematics data describe speed patterns and variability at the network level, while **video data provide detailed behavioural information and interaction conditions** at specific locations.
- The results indicate that speed variability, acceleration and braking behaviour are **important indicators of risky driving behaviour**, rather than average speed alone.
- The integration of telematics and video data improves the identification of **high-risk locations and supports proactive road safety analysis**.
- The combined framework can support data-driven road safety policies, traffic management strategies, and smart urban mobility planning.
- Future work should expand the analysis to **more locations and longer time periods** and further develop integrated safety indicators.

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