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When the Lights Go Out: Observing Pedestrian and Driver Behavior During a Traffic Signal Failure in Central Athens

Stella Roussou[a], Apostolos Ziakopoulos[a], Roberto Ventura[b], George Yannis[a]

[a]*Department of Transportation Planning and Engineering National Technical University of Athens, Athens, Greece, GR15773*

[b]*Department of Civil, Environmental, Architectural Engineering and Mathematics (DICATAM), University of Brescia - Via Branze, 43 – 25123 Brescia*

Abstract

This paper examines how urban road users behave when a traffic light stops working. The study use data derived from a one-hour video recording from a central intersection in Athens, where both pedestrians and drivers had to use the street without any signal control. When the signal failed, traffic flow did not stop, but it was pedestrians who hesitated or waited for long periods before attempting to cross and taking opportunities only when traffic slowed or a small gap appeared. Vehicle phases were generally longer and more irregular, while pedestrian crossings were shorter. Groups that included elderly individuals waited longer and crossed more cautiously, whereas younger groups tended to move faster and accept smaller time gaps between vehicles. This reflects how people make quick safety judgments and how these decisions often emerge collectively within a group. Throughout both the observation period and the automated video analysis, behavioral patterns remained consistent. These findings demonstrate the ability of the pedestrians to manage to cross, but the situation was far from efficient or safe. Long waiting times and uncertainty highlight the need for reliable backup or adaptive systems that can take over when signals fail.

Keywords: Traffic signal failure; Pedestrian behavior; Gap acceptance; Video analysis; Urban safety; Athens

1. Introduction

Pedestrian behavior at signalized intersections has been a focal topic in transport safety and behavioral modeling, as it encapsulates the negotiation between human decision-making and traffic control systems (23; 14). Traffic signals that give priority and control movements often govern the interactions between pedestrians and vehicles at city intersections. Under normal conditions, pedestrians rely on visual and temporal cues provided by signals, but when these cues are removed, such as during signal malfunctions, as occurred during a one-hour event at Omonoia Square in central Athens, the formal system vanishes and informal behaviours emerge. Then the decision to cross becomes a function of social dynamics, perceived risk, and traffic gaps (7). In that hour, vehicles did not stop by obeying to the traffic light signal regulation, and pedestrians crossed only when group behaviours enabled safe movement. This event offers a unique "natural experiment" for observing how road users self-organise when signal control is not functional.

The city of Athens presents a dense traffic environment, combined with high pedestrian volumes, mixed mobility modes, and tourist flows. Omonoia Square lies at the intersection of major arterials, Panepistimiou and Patission Streets, and represents a complex crossing environment throughout the city. Without signal control, the dynamics shift as priority becomes visual, behavioural, and situational rather than rule-based. Studies on pedestrian-vehicle interactions indicate how signals typically reduce conflicts and delay risky behaviour (13; 9). On the other hand, unsignalized crossings depend a lot on gap acceptance and social cues (23; 17; 5). In Greece, self-reported pedestrian attitudes often diverge from actual safe crossing behaviour, indicating that informal negotiation is a key element of interactions within the road environment, especially in cases such as the city of Athens (12).

Another important dimension of these interactions is cultural and perceptual. Social norms, impatience, and trust strongly affect decisions to yield or to cross (19). In cities with mixed local and tourist populations, such as Athens, varying familiarity with traffic conventions can further intensify uncertainty. Visitors often interpret signals or driver intentions differently, which can heighten the complexity of shared decision-making at crossings. In this sense, a temporary signal outage does not simply expose risky behaviour but also reveals how people interpret social cues, eye contact, and movement anticipation when institutional guidance is absent.

Shared-space research emphasises that reducing formal control invites more cautious behaviour through uncertainty (8; 10). In the case of Athens, vehicles are a big part of life, as also in the bigger part of the Mediterranean cities, and road users don't always obey to the rules. This makes it less likely that informal spaces will lead to safer interactions between users. Instead, pedestrians tend to act opportunistically, often initiating crossings when a critical mass forms or when a single individual takes the lead. Drivers, meanwhile, preserve dominance through momentum and confidence in their perceived right of way. Additionally, most of the European countries have in their road safety culture, the tendency of stopping at pedestrian crossings, which is something is not included in the drivers in the city of Athens as a driving habit. Recent findings (17) highlight that in Athens, the frequency of pedestrian violations is strongly influenced by surrounding urban form, pedestrian density, and prevailing traffic conditions, suggesting that crossing behaviour is highly context-dependent.

Methodologically, video-based observation enables the direct study of how pedestrians and drivers interact in real time. Using object detection and trajectory tracking, indicators such as Time-To-Collision (TTC), Post Encroachment Time (PET), and movement speeds can be extracted (1; 18;21). Research in central Athens (15) has shown that walking behaviour is highly sensitive to spatial context, particularly to urban environments, road design, and traffic pressure. Previous studies highlight that crossing speed and compliance depend on demographic characteristics such as age and gender (13), and contextual factors such as group size (4; 6) and vehicle flow intensity (11). In particular, the presence of elderly pedestrians significantly reduces average crossing speeds due to physical and cognitive constraints, while younger pedestrians often display opportunistic behavior (2).

The current analysis extends these findings by observing naturalistic pedestrian and vehicular interactions during a full signal failure, where no explicit priority cues are available. Methodologically, the study combines the interpretability of classical models (e.g., ANOVA, correlation) with the adaptability of non-parametric learning techniques (Random Forest), following hybrid data-driven approaches applied in previous intelligent transport behavior studies (24; 3). The final stage employs unsupervised learning (Ward's hierarchical clustering) to reveal latent behavioral patterns.

Understanding how users adapt during signal failure has both theoretical and practical importance. Theoretically, it elucidates the manner in which human agents navigate risk and prioritize in ambiguous urban environments. Practically, it informs contingency planning, adaptive signal logic and pedestrian safety management for old infrastructure. This paper examines pedestrian and vehicle behaviour during a one-hour traffic light outage at Omonoia Square, Athens. Using smartphone-cameras ,mounted on tripods, video recording was implemented and with this data, movement patterns, interaction frequencies and surrogate safety metrics are analyzed under the specific traffic condition. Specific focus is placed on how pedestrian groups initiate crossing, how vehicle drivers respond under varying densities, and how these behaviours compare to control periods. The remainder of the paper is structured as follows: Section 2 details the data collection methodology including pedestrian and vehicle counts, TTC, PET, speed distributions and group behaviour; Section 3 presents the analysis approach; Section 4 demonstrates the results and discussion; Section 5 and 6 conclude with policy implications for urban traffic resilience and pedestrian safety.

2. The data selection

The data originate from a one-hour video recording captured by using smartphone cameras mounted on tripods of a signal malfunction at Omonoia Square, a central Athens intersection, conducted under regular daylight conditions. The malfunction produced a unique natural experiment, revealing coordination between vehicles and pedestrians when signal control was absent.

Each crossing cycle was defined as a complete phase in which one user group (either pedestrians or vehicles) exclusively occupied the intersection. A total of 38 original cycles (19 pedestrian and 19 vehicle) were extracted from a 60-minute segment of the malfunction. Each observation included demographic and contextual attributes summarized below.

Table 1. Data Sample from the Manual Observations.

cycle	Time (min)	time (sec)	duration (sec)	Total Ped	female	male	<35	35 - 65	>65	Total Veh	PV	MT	Taxis	PT	Other
1	Ped	0	12	12	10	5	5	1	4	5	0	0	0	0	0
	Veh	1	48	84	0	0	0	0	0	0	96	30	32	33	1
2	Ped	1	49	6	10	2	8	3	5	2	0	0	0	0	0
	Veh	1	52	106	0	0	0	0	0	0	75	37	27	11	0
3	Ped	3	8	8	15	7	8	5	4	6	0	0	0	0	0
	Veh	3	16	37	0	0	0	0	0	0	43	19	16	8	0
4	Ped	3	53	7	3	2	1	2	1	0	0	0	0	0	0
	Veh	4	1	9	0	0	0	0	0	0	12	7	2	3	0

The video data were processed using an automated recognition and tracking pipeline designed for detailed motion analysis, as demonstrated and analyzed in the work of Ventura (21; 18). Object detection was performed on every video frame (approximately 30 frames per second) using a deep learning model trained to identify and classify moving objects such as vehicles and pedestrians. Once detected, object positions were tracked continuously through trajectory estimation algorithms, allowing for the calculation of kinematic variables such as horizontal and vertical velocity components (vx, vy) and corresponding speeds. Pedestrian and vehicle trajectories were then exported as frame-level datasets in CSV format.

To synchronise time across all observations, each frame was converted into a continuous time index expressed in seconds and minutes, with 30 frames corresponding to one second. This enabled aggregation of TTC, PET, and speed values into one-second and one-minute intervals, matching the manual observational structure used for cross-validation. The TTC metric represents the estimated time remaining before a potential collision if the observed trajectories continued unchanged, whereas PET measures the temporal gap between a vehicle and a pedestrian occupying the same spatial zone in succession. Both indicators were automatically computed using relative position and velocity data derived from the trajectory files.

Separate datasets were produced for vehicles, pedestrians, and their respective gate-crossing events. Each dataset contained spatial coordinates, instantaneous velocities, and derived safety indicators. Data were cleaned by removing extreme or physically implausible values (e.g., TTC $\leqslant$ 0 s, PET > 10 s), ensuring robust statistical representation. The resulting database combines over 100,000 frames, equivalent to one continuous hour of real-world interaction.

3. Methods

3.1. Statistical Analysis

The analytical framework of this study combines statistical inference, time-based modeling, and machine learning to investigate pedestrian and vehicle dynamics during a traffic light malfunction. The goal was to quantify how behavioral, demographic, and contextual variables influence the total cycle duration, the time each user group occupies the crosswalk.

The analysis employs both parametric and non-parametric methods, reflecting the structure of the dataset (mixed continuous and binary variables, moderate sample size, and potentially non-linear interactions). The methodological components are summarized further below. Descriptive statistics were computed for all continuous variables, including mean, standard deviation, quartiles, and range. Group differences were evaluated using a one-way ANOVA and independent-sample t-tests. The ANOVA tested whether mean durations differed between pedestrian and vehicle cycles:

$$F = \frac{\frac{SSB}{(k-1)}}{\frac{SSW}{(N-k)}} \tag{1}$$

where SSB and SSW represent the between- and within-group sums of squares, respectively. To assess the effect of elderly presence, group means were compared using the Welch-corrected t-test, robust to unequal variances. Linear relationships between continuous variables, e.g., cycle duration (y) and traffic flow (x), were analyzed via the Pearson correlation coefficient:

$$t = \frac{\overline{x1}-\overline{x2}}{\sqrt{\frac{s1^2}{n1}+\frac{s2^2}{n2}}} \tag{2}$$

allowing identification of proportional dependencies between flow intensity and total crossing time. Finally, an unsupervised learning approach was applied to classify cycles into behavioral regimes. Hierarchical agglomerative clustering using Ward's minimum variance method groups observations based on their Euclidean distance in the standardized feature space. This approach is robust to small datasets and reveals latent behavioral typologies without requiring prior assumptions about group structure.

Together, these methods offer complementary perspectives regarding statistical inference quantifies the strength and significance of differences, regression and correlation capture linear dependencies, random Forests uncover non-linear relationships, and clustering reveals emergent behavioral regimes.

The data accumulated in the context of the Phoebe Project (16) included a large number of hours of videos captured in specific locations in the city center of Athens, Greece. These videos were processed by creating an algorithm transferable to all the locations of the videos, which was based on specific computer vision tools.

3.2. Object Detection and Feature Extraction

The first stage of processing involves detecting objects within the video frames. For this task, the YOLOv8 model is used, which formulates object detection as a single regression problem. Given an input image extracted as a frame from the video, YOLOv8 (20) outputs a set of bounding boxes B=$(B1, B2, \ldots, B_n)$, where each bounding box B_i is defined by:

$$B_i = (x_i, y_i, w_i, h_{i,} c_i\ ) \tag{3}$$

Where (x_i, y_i) are the coordinates of the center of the box, $w_i, and\ h_i$ are the width and height of the bounding box, and c_i is the class probability score indicating whether the object in the box is a pedestrian or vehicle.

Once the objects are detected, ResNet-50 is employed for feature extraction. The feature vector F_i corresponding to each detected object B_i is extracted from the output of ResNet-50, represented as:

$$F_i = ResNet - 50(B_i) \tag{4}$$

These features are then used for tracking and re-identification. To track pedestrians over time, the system utilizes Kalman filters (Kalman, 1960). The Kalman filter operates in two phases: Prediction and Update. Firstly, this phase predicts the state estimate at time $t \in T$ based on the estimate from time $(t - \Delta t) \in T$:

$$\hat{s}_m(t|t-\Delta t) = A \cdot s_m(t-\Delta t); \quad \forall t \in T; \ \forall m \in M(t); \tag{5}$$

Secondly, the phase predicts the error covariance matrix:

$$P_m(t|t-\Delta t) = A \cdot P_m(t-\Delta t) \cdot A^T + Q_m(t); \quad \forall t \in T; \ \forall m \in M(t); \tag{6}$$

Then, for the updating phase the Kalman Gain $K_m(t)$, is computed, which determines how much the predictions are adjusted based on the new measurements:

$$K_m(t) = P_m(t|t-\Delta t) \cdot O^T \cdot \left(O \cdot P_m(t|t-\Delta t) \cdot= O^T + R_m(t)\right)^{-1}; \quad \forall t \in T; \ \forall m \in M(t); \tag{7}$$

The Kalman Gain balances the uncertainties in the prediction and the measurement. Additionally, the Hungarian algorithm is applied for data association. This algorithm optimizes the association between the predicted object locations and new detections, minimizing the cost function for object-to-track association.

4. Results

The dataset exhibits a bimodal structure. Pedestrian cycles are shorter and less variable (mean = 12.65 s, SD = 10.22), while vehicle cycles are longer and more heterogeneous (mean = 55.79 s, SD = 43.03). Figure 1 illustrates the boxplot of cycle durations by movement type, where vehicle phases dominate the upper range. The boxplot reveals that vehicle cycles dominate the upper tail of the duration distribution, indicating extended intersection occupation and delayed clearance once vehicles enter.

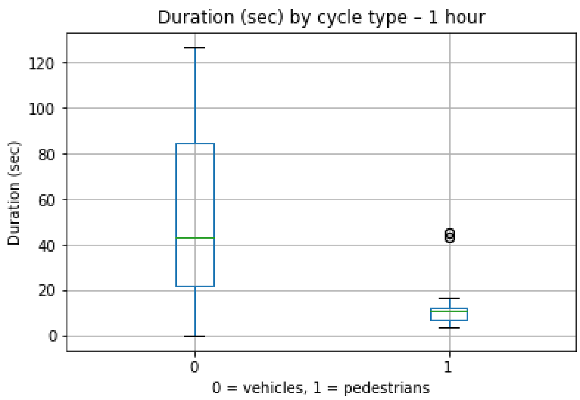

Figure 1. Boxplot of Cycle Durations by Movement Type (Pedestrian vs Vehicle)

The descriptive statistics reveal clear contrasts between pedestrian and vehicle movement patterns during the one-hour observation period. Across all recorded cycles, pedestrian movements were shorter and more uniform, with a mean duration of 12.65 s (SD = 10.22), whereas vehicle cycles were considerably longer and more variable, averaging 55.79 s (SD = 43.03). This indicates that once vehicles gained priority, they tended to occupy the intersection for extended intervals before yielding to pedestrians. Pedestrian crossings occurred more frequently but with smaller group sizes and shorter temporal spans, reflecting a cautious, opportunity-based strategy typical of unsignalized environments.

Table 2. Descriptive Statistics

	duration (sec)	number_of_ pedestrians	number_of_ vehicles	vehicle_ cycle	ped_ cycle
Mean	34.16	7.56	33.88	33.44	34.88
Std	36.79	10.12	42.82	35.64	38.27
Min	0.00	0.00	0.00	0.00	0.00

25%	8.68	0.00	0.00	9.98	8.52
50%	13.74	0.50	5.50	13.78	13.01
75%	46.34	16.00	72.50	46.49	44.61
Max	130.49	35.00	144.00	129.08	130.49

To assess the reliability of the automated video-based analysis, the time series of pedestrian and vehicle flows extracted from the computer vision system were compared with manually observed data over a one-hour period. Both datasets were aggregated at one-minute intervals and analyzed in parallel, including the distribution of pedestrians by gender and age, and vehicles by transport mode. The automated measurements exhibited a close alignment with the manually observed trends, accurately reflecting the temporal variability of pedestrian and vehicular activity at the site. Minor differences across individual minutes correspond to natural variations in crossing patterns, confirming that the algorithm successfully captures real-world movement dynamics rather than frame-level noise.

Quantitatively, the automated counts reproduced the manually observed flows with minute-level deviations below 10 pedestrians on average and around 40 vehicles per minute. The high coherence between the two data sources supports the validity of the vision-based framework as a consistent and scalable method for traffic behavior analysis in complex urban environments such as Omonoia Square.

Table 2. Descriptive Statistics

Metric	Value
Ped_MAE	7.59
Ped_MAPE	86.96
Ped_Corr	-0.22
Veh_MAE	43.36
Veh_MAPE	140.62
Veh_Corr	0.24

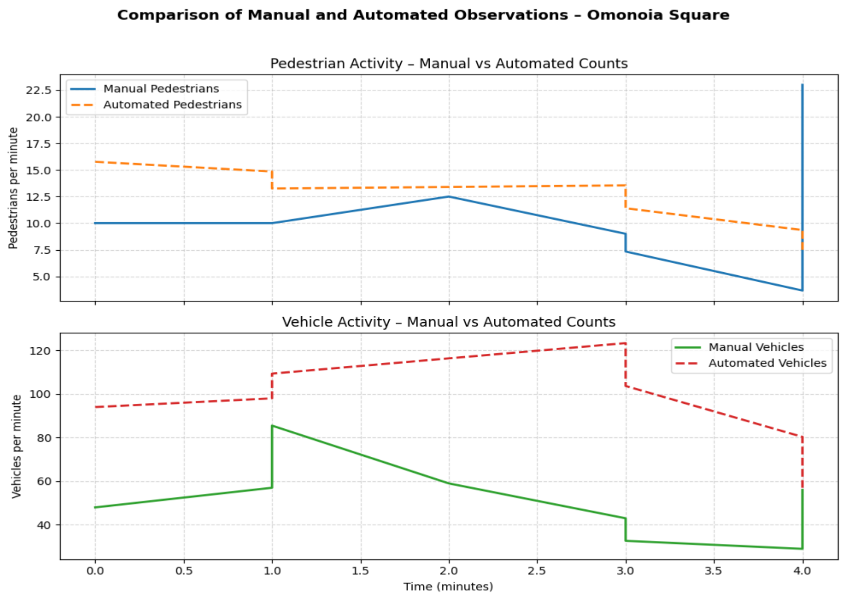

Figure 2. Comparison of Manual and Automated Observations

Complementary to the quantitative data analysis, direct observation of the recorded footage provided essential qualitative insights into the behavior of pedestrians and drivers during the traffic light malfunction. The one-hour video revealed a rich variety of spontaneous behaviors that statistical measures alone could not capture. Pedestrians often waited extended periods, frequently exceeding one minute, before attempting to cross, especially when traffic flow was heavy. In most cases, the initiation of a crossing was prompted by a single individual, whose movement acted as a social signal that encouraged others to follow. This "leader-follower" dynamic produced waves of collective crossings, often composed of six to ten pedestrians moving together. Such behavior is consistent with prior findings emphasizing the value of video-based observation for identifying spontaneous group decision-making patterns and the emergence of collective pedestrian behavior in shared spaces (1).

Several recurring interaction patterns were identified through visual examination of the footage. One common pattern was group initiative, where one person in a group did something that made everyone else in the group move almost at the same time. Another was gap hesitation, where pedestrians refrained from crossing even when the road appeared clear, waiting instead for a sufficient number of others to join before stepping forward. This shows a kind of social validation, where having peers around makes things less uncertain. A third thing noticed was that older people who were walking always waited to cross until the gap in traffic was wide enough for them to see or the flow of cars was really slow. In some cases, older people were seen waiting more than two minutes before moving, even though there were temporary safe gaps. Finally, vehicle encroachment on pedestrian spaces was a recurrent issue as several drivers were observed blocking the crosswalk during waiting periods or even using the sidewalk to bypass congestion, a behavior that compromised pedestrian safety and heightened exposure risks.

These qualitative findings reveal an important mechanism underpinning pedestrian decision-making under non-signalized conditions, such as the process of gap acceptance. Gap acceptance refers to the individual's evaluation of the time or space available between successive vehicles to determine whether it is sufficient to cross safely. Under malfunction conditions, the video data indicated that pedestrians often engaged in a form of collective gap acceptance rather than individual judgment. Groups tended to wait until a gap appeared that was deemed "safe enough" collectively, typically initiated by the most confident pedestrian. This reflects a diffusion of perceived risk, where the act of crossing as part of a group reduces personal responsibility and increases confidence. These observations align with prior empirical and theoretical work on pedestrian gap selection and safety perception, which demonstrates that age, gender, and traffic characteristics influence crossing decisions (7; 13; 19). The annotated frames from the footage visually depict these behavioral dynamics, moments of hesitation, collective decision-making, and vehicle encroachment, illustrate key behavioral types observed during the malfunction period.

Figure 3. Video Observations Figures

The Pearson correlation between vehicle count and total cycle duration was $r = 0.799$, $p < 1.49\times10^{-22}$, demonstrating a strong linear association (Figure 4). Cycles with higher vehicle flow lasted longer, suggesting congestion amplifies cycle length once vehicles take control. In contrast, pedestrian count had a weak, non-significant correlation with duration ($r = 0.22$, $p = 0.13$), indicating that pedestrian groups cross for relatively fixed times regardless of size. This asymmetry shows that vehicular flow is elastic, adjusting dynamically with density, while pedestrian flow is rigid, following stable social crossing norms.

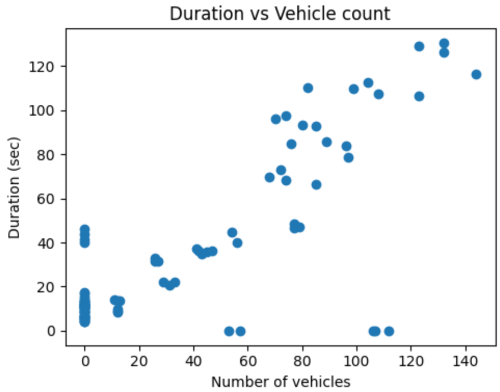

Figure 4. Scatter Plot: Vehicle Count vs Cycle Duration (r = 0.80)

Table 3. Comparison Between Quick and Slow Crossings

Speed group	duration (sec)	number_of_ pedestrians	female	male	Below 35	Above 35
Quick	7.94	10.83	5.54	5.37	2.58	3.15
Slow	61.82	3.87	1.58	2.15	0.45	1.00

Larger, older, or female-dominated groups required substantially longer crossing durations, consistent with experimental studies on pedestrian coordination and mobility (8, 9). Quick crossings typically involved small, younger groups who entered assertively, often during short gaps in traffic. These patterns emphasize social coordination costs, as group size increases, communication and alignment among pedestrians slow the overall crossing process (10).

Comparing pedestrian cycles with and without elderly participants revealed a pronounced difference. Mean durations were 13.67 s (elderly present) and 5.50 s (no elderly), yielding $t(46) = 4.68$, $p = 2.6\times10^{-5}$. This result confirms the disproportionate effect of elderly individuals on cycle duration. The extended crossing time likely reflects both slower walking speed and cautious initiation. This empirical evidence underlines the importance of incorporating age-sensitive signal design and detection technologies into adaptive systems.

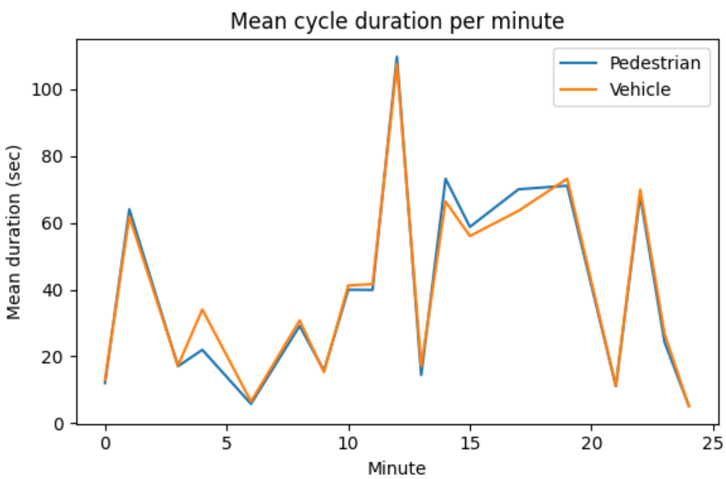

Figure 5. Mean Cycle Duration per Minute for Pedestrian and Vehicle Cycles

To explore whether crossing behavior evolved during the malfunction, mean durations were computed for each minute of observation. Linear regression produced a slope of $\beta = -0.068$ sec/min ($R^2 = 0.02$), suggesting no systematic acceleration or hesitation across time. This temporal constancy indicates that pedestrians quickly established a behavioral equilibrium, crossing consistently throughout the malfunction period without exhibiting learning or impatience effects. Such stability contrasts with driver adaptation under temporary stop-control conditions (13).

The Random Forest regression ranked predictors of crossing duration as depicted in Figure 6:

Table 4. Random Forest Feature Importances

Variable	Importance
Below 35 years	0.367
Above 65 years	0.186
Female	0.166
Number of Pedestrians	0.149
Male	0.132
Number of Vehicles	0.000
Taxis	0.000

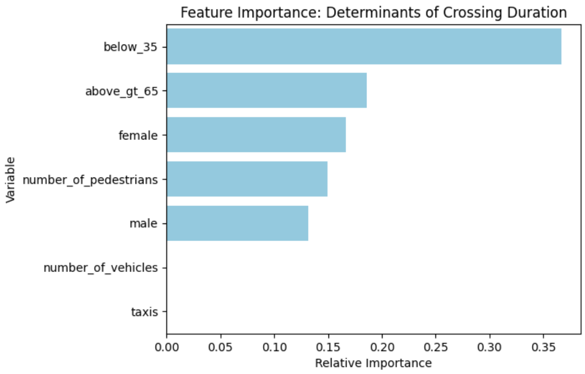

Figure 6. Random Forest Feature Importance Plot

The algorithm confirmed the primacy of age and gender composition over traffic-related factors. Once demographic structure was included, the number of vehicles contributed no predictive power, implying that pedestrian dynamics are self-determined. Hierarchical clustering using Ward's method (Figure 7) identified three distinct behavioral regimes in the 9-dimensional standardized feature space the one of vehicle-dominant cycles where what is predominant are the long durations, high vehicle counts and pedestrians small in counts. Then, the pedestrian-cautious cycles which has moderate durations, high pedestrian counts, elderly presence. Lastly, the opportunistic crossings, which is defined by short durations, small groups, often quick gap-seeking behavior.

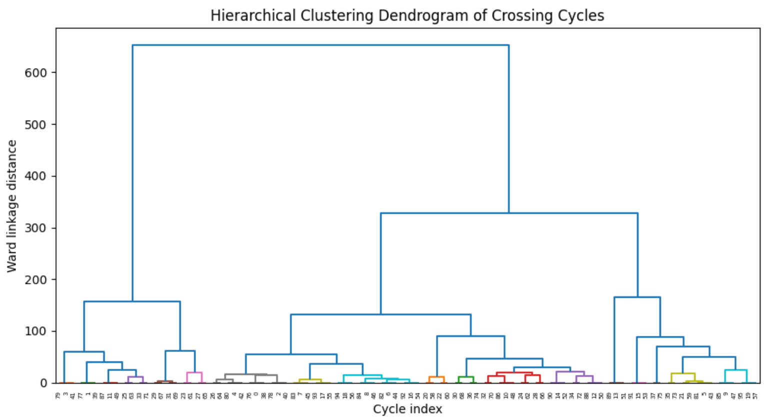

Figure 7. Dendrogram and Cluster Profiles of Crossing Cycles

These clusters illustrate emergent self-organization during malfunction conditions. Without explicit signal control, users alternate implicitly between extended vehicle dominance, cautious pedestrian assertion, and brief opportunistic phases. Across all analyses, consistent behavioral mechanisms emerge. Vehicle cycles display elasticity with flow and congestion, while pedestrian cycles remain inelastic, driven by group structure rather than external conditions. The presence of elderly pedestrians stands as the single most influential factor. Gender and age composition further modulate crossing speeds, reflecting intrinsic differences in perceived safety and assertiveness. The lack of adaptation over the observation period suggests stable social norms underpin pedestrian behavior even under control failure. Machine learning and clustering reinforce these interpretations, highlighting the dominance of human demographics over traffic volume in shaping self-organized intersection dynamics.

5. Discussion

The analysis of the one-hour video during the traffic light malfunction showcased that although there was no signal control, vehicles and pedestrians managed to coexist. Both pedestrians and drivers used informal negotiation styles. The flow of vehicles was mostly due to density and to the fact that in the Greek road culture, the drivers are not keen of the idea of having pedestrians using the pedestrian crossing. Thus, the more vehicles there were, the longer the pedestrians stayed at the intersection before letting pedestrians cross. This is in line with earlier research that shows drivers change their behavior when there are no formal signals, using informal right-of-way and eye contact to claim space (14).

On the other hand, pedestrian crossings were shorter and more stable. This shows that people don't rely as much on traffic intensity as they do on the behavior of those around them. Demographics clearly shaped pedestrian behavior. The presence of elderly individuals led to longer waiting and crossing times, confirming past findings that older pedestrians act more cautiously due to slower walking speeds and higher perceived risk (13; 11). Gender also mattered as female-dominated groups were more conservative, while younger or male pedestrians tended to cross faster and take smaller opportunities. These differences reveal how diverse perceptions of safety and confidence influence movement in shared spaces.

Much of this behavior reflects the idea of gap acceptance, the process by which pedestrians judge whether the space or time between oncoming vehicles is large enough to cross safely. In our observations, pedestrians rarely acted alone. Instead, they waited for others to initiate movement, creating a kind of collective gap acceptance. Groups seemed to share responsibility and risk, following the first mover as soon as a "safe enough" gap appearedThis is in line with earlier research that showed that people who cross in groups are more likely to accept smaller gaps and move more quickly (7; 23). The videos showed this social dynamic point of view to be true because one person's step forward often set off a chain reaction of movement, which turned doubt into confidence in the group.

Despite the unusual situation, pedestrian behavior stayed consistent throughout the one-hour period. There was no clear sign of learning or adaptation, rather, people appeared to rely on stable social norms and mutual observation. This consistency highlights how deeply rooted these coordination habits are, allowing flow to continue even without formal control. The video evidence also revealed moments of tension, such as vehicles encroaching on crossings or pedestrians hesitating at the curb, underlining the delicate balance between cooperation and competition in shared spaces (1)

6. Conclusions

The current study analyzed one hour of naturalistic traffic behavior at a signalized intersection in Athens during a total traffic light failure. The study utilized descriptive statistics, inferential tests, temporal analysis, and machine learning to investigate the self-organization of pedestrians and vehicles at crossings in the absence of formal control mechanisms. The results show that when there is no working traffic light, there is no chaos, but instead, there is an adaptive equilibrium that is maintained by social interaction and mutual observation. Vehicle cycles were much longer and more variable than pedestrian cycles. This shows that vehicle flow is more important and depends on how long the queue is. On the other hand, pedestrian crossings were shorter and more consistent, with demographics being the main factor that determined their structure, not the weather or traffic.

Elderly pedestrians and female-dominated groups were found to increase crossing duration, reflecting cautious and cooperative strategies that prioritize safety over speed. Younger or male pedestrians crossed more confidently, often using short spaces between cars. Both inferential statistics and Random Forest analysis confirmed these demographic effects, showing that age and gender were the best predictors of how long a cycle would last. Temporal modeling indicated no significant adaptation during the malfunction period, implying that behavioral patterns remained consistent and regulated by established social norms.

Cluster analysis identified three concurrent behavioral regimes, the vehicle-dominant, the pedestrian-cautious, and the opportunistic one. This demonstrates the dynamic yet organized nature of interactions in non-signalized environments. All these findings note that the during traffic light malfunction, flow intensity is not the only factors that influences the vehicle-pedestrian interaction, but also the human attributes and collective decision-making.

From an engineering and policy point of view, these insights show how important it is to include behavioral realism in the design of urban traffic control systems. Adaptive signal systems that use demographic detection or behavioral prediction could change crossing times on the fly to make them safer and more efficient for vulnerable users like the elderly. Moreover, simulation models of traffic malfunction scenarios ought to incorporate social negotiation and demographic diversity as fundamental elements of their calibration frameworks.

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