From Anxious Rushers to Attentive Observers: A Cluster Analysis of University Student Pedestrian Profiles

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Abstract. This study presents a comparative analysis of pedestrian behavior and perceived safety among university students at two signalized intersections in Thessaloniki, Greece. While both locations serve high pedestrian volumes, one intersection permits vehicle left-turns during the pedestrian green phase (signified by flashing yellow arrows), whereas the other maintains a protected phase that restricts all conflicting vehicle movement. Utilizing data from two questionnaire-based surveys ($N_1 = 304$ and $N_2 = 301$), the research examines the interplay between infrastructure design, demographic factors, and behavioral traits. A K-Means clustering algorithm was applied to segment the target group into four distinct behavioral profiles based on levels of haste, distraction (e.g., mobile phone use, social interaction), and signal compliance. The results indicate that intersections permitting vehicle conflict are associated with significantly lower levels of perceived safety and a higher propensity for risk-taking behavior, such as crossing against the signal. The identified clusters, "The Distracted Law-Breaker," "The Anxious Rusher," "The 'Lost in Device' Waiter," and "The Attentive Observer", illustrate that individuals' behavioral tendencies significantly moderate the impact of intersection's operational phasing. The findings suggest that signal phasing that eliminates vehicle-pedestrian conflicts is the most effective intervention for increasing compliance and safety confidence. This research provides a methodological framework for urban planners to develop targeted safety interventions by understanding the diverse behavioral profiles within the student population.

Keywords: pedestrian safety · urban mobility · university students · signalized crosswalks

1 Introduction

A significant problem for high-density areas such as University campuses where heavy traffic intersects with pedestrians concerns their safety at signalized intersections. Based on the recent road safety data in Greece (year 2022), pedestrians represent approximately 17.1% of total traffic fatalities [72]. While elders often represent the majority of these fatalities, university students form a risk group presenting specific behavioral patterns, including haste and high usage of mobile devices while walking.

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The design and operation of road crossing is highly affected by the existence or not of traffic lights, arising a critical conflict at intersections where permitted phasing is used (vehicles are allowed to turn (often left) while pedestrians have a green walk signal). This problem is frequently managed by using flashing yellow arrows at traffic lights, forcing drivers to approach the intersection with caution giving priority to pedestrians. Protected or exclusive phasing restrict all vehicle movement during the pedestrian cycle, eliminating conflict points at least on a theoretical level. Although the so far research has concluded that protected phasing tends to reduce accidents rates, the way that these infrastructure types and the different types of pedestrians interact between hem (who may be distracted, rushing, or non-compliant) remains under-explored.

The majority of the existing literature concerning pedestrians' safety often addresses risk factors as separate, independently measurable variables. For example, studies have identified (statistically) correlations between pedestrian volumes and injury rates, or analyzed specific distractions (such as mobile phone use) which according to their findings lead a) to slower walking speeds and b) reduced situational awareness [62–64]. Other studies have modeled red-light running behavior based on waiting times or sequential traffic conflicts. However, these approaches usually analyze risk factors in isolation as they rarely identify patterns where distraction, haste, and signal compliance intersect. For example, a student who is highly distracted but strictly compliant with traffic lights, presents a different risk profile than one who is attentive but deliberately violates red lights due to haste. Understanding these different profiles is crucial for developing targeted safety interventions.

To address this gap, the current paper moves beyond descriptive statistics, applying K-Means Clustering to students of the Aristotle University of Thessaloniki (AUTh), in order to segment their behavioral on using road crosswalks into distinct behavioral profiles/ groups. The objectives of this research are first to identify University-related pedestrians profiles based on key behavioral attributes, including distraction frequency (phone, music, social interaction), haste, and signal compliance; second, to examine whether the distribution of these profiles/ groups differs between a Permitted and a Protected intersection, assessing thus how specific crosswalks' types may encourage or mitigate specific risk behaviors; and third to provide evidence-based recommendations for urban and transport planners in order to develop profile-specific behavioral interventions.

Based on the above, this research offers the perspective on the pedestrian-infrastructure relationship (often missed by aggregated analyses). The paper's structure is the following: Sect. 1 is the introductory section (Introduction), Sect. 2 presents the Literature Review, Sect. 3 describes the Methodology applied, Sect. 4 presents the Results and Sect. 5 the main findings and conclusions (Discussion and conclusions).

2 Literature Review

For the literature review evidence was extracted from the SCOPUS database, using the following query "TITLE-ABS-KEY (pedestrian and safety and signalized and crosswalks) AND PUBYEAR >2009 AND PUBYEAR <2026". In total, 319 articles were identified and extracted, presenting an increasing trend in the number of documents

that peaked in the year 2023 with 28 documents. A slight fluctuation is observed in the subsequent years, with a dip to 20 documents in 2024 followed by a resurgence to 27 documents in 2025. The highest activity period was recorded between 2020 and 2025. Out of the 319 articles, 305 of them contain the keyword "pedestrian" (95.6%), 287 contain the keyword "safety" (90.0%), 180 contain the keyword "signalized" (56.4%), 251 contain the keyword "crosswalk" (78.7%), 261 contain the keywords "pedestrian safety" (81.8%) combined, and 28 contain the keywords "signalized crosswalks" (8.8%) combined.

The majority of the identified documents/ papers comes from China, accounting 109 publications, the United States with 59 and India with 34, while Greece was in 13th place worldwide with 5 respective documents. This distribution highlights a strong research focus in regions facing rapid urban growth, dense pedestrian flows, and increasing safety challenges.

Jiang et al. (2011) [1] and Ren et al. (2011) [2] provided early cross-cultural evidence, highlighting that signal compliance is a social construct influenced by group size. Recently, the focus has shifted to cognitive drivers, as Costa et al. (2017) [3] linked attitudes directly to crossing speed. Virkler (1998) [4] and Guo et al. (2012) [5] identified that haste diminishes the reliability of a pedestrian's safety assessment. Wang et al. (2026) [6], Peche et al. (2026) [7], and Zhang et al. (2026) [8] based their analysis on machine learning to identify factors like waiting endurance. Additional studies on student and commuter behavior were conducted by Parvez et al. (2026) [9], Krizsik et al. (2026) [10], and Bouhouras et al. (2026) [11], highlight that crossing decisions are often probabilistic. Rafe et al. (2025) [12], Bouhouras et al. (2025) [13] and Zhang et al. (2025) [14], through their analyses identified behavioral shifts over the last decade.

Xie et al. (2012) [15] and Xie et al. (2013) [16] introduced cellular automaton models to simulate complex interactions at signalized crosswalks, while Fu et al. (2023) [17] and Arun et al. (2023) [18] developed advanced neural architectures for trajectory prediction. Sushmitha et al. (2023) [19] and Tahmasebi et al. (2025) [20] evaluate the Level-of-Service (LoS) at crosswalks. The optimization of mixed-traffic conditions based on the usage of Deep Learning was explored by Manthirikul et al. (2025) [21], Chun et al. (2025) [22], and Sulle et al. (2025) [23]. Furthermore, the integration of vision-based detection and AI-driven tracking was examined aiming on controlling the traffic lights in real time by Sun et al. (2025) [24], Anis et al. (2025) [25], Raha et al. (2025) [26], Arafat et al. (2025) [27], and Raoniar et al. (2025) [28].

Fu et al. (2018) [29] and Alhajyaseen et al. (2012) [30] developed frameworks for Surrogate Safety Measures (SSMs) like Time-to-Collision (TTC). Hashimoto et al. (2016) [31] introduced the estimation of crossing intention using probabilistic models, as a critical component for connected vehicle safety. Chen et al. (2024) [32] and Wang et al. (2024) [33] based their research on micro-level trajectory data to identify collision risks, while Sherif et al. (2025) [34], Oliva et al. (2025) [35], and Xie et al. (2025) [36], examined the red-light running phenomenon. Frej (2025) [37], Yokarasa et al. (2025) [38], Yan et al. (2025) [39], Subedi et al. (2025) [40], Peng et al. (2025) [41], and Wong et al. (2025) [42] focused their analyses on safety auditing and risk assessment methodologies.

Guidelines on how to install crosswalk were proposed by Smith et al. (1987) [43], while Steinman et al. (2004) [44] and Lee et al. (2005) [45] expanded the impact of bidirectional flows on pedestrian capacity. Recent research by Amarasingha et al. (2025) [46] and Saldivar-Carranza et al. (2024) [47] was based on LiDAR-derived data to prove that infrastructure improvements on crosswalks must be dynamic. Ištoka Otković et al. (2025) [48], Lin et al. (2025) [49], and Nasri et al. (2025) [50] investigated the role of different pavement designs on pedestrians' safety. Peche et al. (2025) [51], Li et al. (2025) [52], and Guo et al. (2024) [53] examined the operational performance and capacity impacts of right-turning vehicles. Finally, Kim et al. (2024) [54], Khademi et al. (2024) [55], and Sengupta et al. (2024) [56] through their research tried to optimize signal coordination and phase plan designs.

Barlow et al. (2005) [57] and Bentzen et al. (2004) [58] analysed the safety challenges that blind pedestrians face. Jiang et al. (2021) [59] and Ištoka Otković et al. (2021) [60] research on younger and older populations highlighted the necessity for age-specific crosswalks. Environmental factors like lighting were examined by Makó et al. (2026) [61]; Perra et al. (2022) [62] and Wei et al. (2017) [63] examined distraction caused by the usage of mobile phones as primary contributors to perceived safety risks. Ankunda et al. (2024) [64], Cheng et al. (2024) [65], and Taamneh et al. (2024) [66] examined the relation between public transport and pedestrians' safety. Lao et al. (2024) [67], Baldassa et al. (2024) [68], Xie et al. (2024) [69], and Shao et al. (2024) [70] analysed multi-stage crossings and drone-assisted interfaces.

Table 1 presents the identified and analysed literature review clustering.

Table 1. Literature review clustering

Category	Primary Research Focus	Authors (Year) [Reference]
Behavioral Psychology & Decision Making	Signal compliance, situational factors, red-light crossing, waiting time tolerance, and cognitive decision-making.	Jiang et al. (2011) [1]; Ren et al. (2011) [2]; Virkler (1998) [4]; Wang et al. (2026) [6]; Krizsik et al. (2026) [10]; Bouhouras et al. (2026) [11]; Rafe et al. (2025) [12]; Bouhouras et al. (2025) [13]; Wang et al. (2024) [33]; Frej (2025) [37]; Li et al. (2025) [52]; Taamneh et al. (2024) [66]; Baldassa et al. (2024) [68]; Xie et al. (2024) [69].
AI, Modeling & Simulations	YOLO, MCMC), social force models, cellular automata, trajectory prediction, and virtual reality simulations.	Parvez et al. (2026) [9]; Zhang et al. (2026) [8]; Zhang et al. (2025) [14]; Xie et al. (2012) [15]; Xie & Zhao (2013) [16]; Fu et al. (2023) [17]; Sun & Pei (2025) [24]; Hashimoto et al. (2016) [31]; Wong et al. (2025) [42]; Guo et al. (2024) [53]; Kim et al. (2024) [54]; Khademi et al. (2024) [55]; Makó et al. (2026) [61]; Shao et al. (2024) [70].

(*continued*)

Table 1. (*continued*)

Category	Primary Research Focus	Authors (Year) [Reference]
Safety & Conflict Analysis	Surrogate Safety Measures (SSM), TTC/PET analysis, crash causation models, and automated video-based conflict detection.	Costa et al. (2017) [3]; Guo et al. (2012) [5]; Peche & Saha (2026) [7]; Anis et al. (2025) [25]; Arafat et al. (2025) [27]; Raoniar et al. (2025) [28]; Fu et al. (2018) [29]; Alhajyaseen et al. (2012) [30]; Yan et al. (2025) [39]; Subedi et al. (2025) [40]; Peng & Liu (2025) [41]; Peche & Saha (2025) [51]; Sengupta et al. (2024) [56]; Ankunda et al. (2024) [64].
Signal Timing & Infrastructure Design	Signal phasing, Leading Pedestrian Intervals (LPI), Level of Service (LOS), crosswalk markings, and geometric optimization.	Sushmitha et al. (2023) [19]; Tahmasebi & Furth (2025) [20]; Manthirikul et al. (2025) [21]; Chun et al. (2025) [22]; Raha et al. (2025) [26]; Chen et al. (2024) [32]; Oliva et al. (2025) [35]; Smith & Knoblauch (1987) [43]; Steinman & Hines (2004) [44]; Lee et al. (2005) [45]; Amarasingha et al. (2025) [46]; Saldivar-Carranza et al. (2024) [47]; Lin et al. (2025) [49].
Vulnerable Groups & Distraction	Children's safety, visually impaired navigation, mobile phone distraction, and elderly pedestrian behavior.	Sulle et al. (2025) [23]; Sherif et al. (2025) [34]; Xie et al. (2025) [36]; Yokarasa & Sivakumar (2025) [38]; Ištoka Otković et al. (2025) [48]; Nasri et al. (2025) [50]; Barlow et al. (2005) [57]; Bentzen et al. (2004) [58]; Jiang et al. (2021) [59]; Ištoka Otković et al. (2021) [60]; Perra et al. (2022) [62]; Wei et al. (2017) [63]; Cheng et al. (2024) [65]; Lao & Furth (2024) [67].

3 Methodology

The paper analyses the data collected through an in situ, questionnaire-based survey implemented at two at-grade intersections in the Municipality of Thessaloniki, Greece on January 2025 and specifically at: a) Egnatia and third Septemvriou streets (intersection A), located near the AUTH Campus and b) Aggelaki and Alexandrou Svolou streets (intersection B), located near the AUTH Campus at the borders of the commercial center of the city (see Fig. 1).

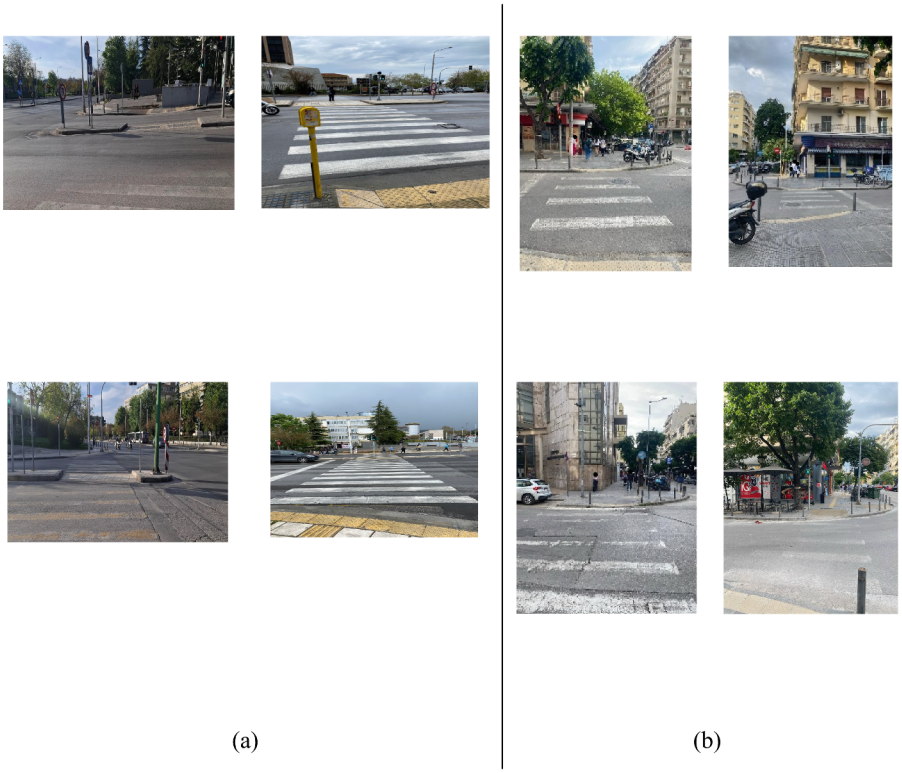

Fig. 1. At grade intersections of Egnatia and third Septemvriou streets (a) and of Aggelaki and Alexandrou Svolou (b)

Egnatia street serves as one of the main horizontal arterials in the city of Thessaloniki, running the urban landscape from one side of the city to the other in the direction of South East to North West. The street serves the traffic through two (2) lanes per direction as well as a bus lane located at the right side as vehicles move. The street is divided along its entire length with a median island (center island) of varying width per section. At each intersection with a major street, traffic is controlled by traffic signals installed at each crossing street for both the vehicles and the pedestrians. Right-turning movements are typically permitted while left-turning movements are allowed per case. Where permitted, the left turning movements are facilitated through a dedicated left turning lane and traffic lights. At Intersection A, vehicles can perform a left turning movement using a dedicated lane for this purpose.

At Intersection B, left-turn movements are controlled by flashing yellow arrows displayed alongside the green signal indication. In accordance with the Greek Road Traffic Code (Law 2696/1999, as amended), flashing arrows fall under the provisions governing vehicular lights (Article 6, paragraph 1, subparagraphs f–h). A yellow arrow (whether steady or flashing) forces the drivers to reduce speed and proceed with increased caution, giving the priority to pedestrians and other vehicles. It must be noted that pedestrian movements at this location are regulated by dedicated pedestrian traffic lights.

At each intersection research teams collected the necessary data through questionnaire-based survey addressed exclusively to students of the AUTh, collecting in total 607 questionnaires. After cleaning the data to remove incomplete or inconsistent entries, the final dataset consisted of 605 valid samples (N1 = 304 for intersection A, N2 = 301 for intersection B, N=N1 + N2)

It must be noted that the questionnaire used was structured to progressively record participants' attributes, habits, perceptions, related to pedestrian crossings. Therefore, the first section concerned socio-demographic information, including gender, age group, professional status, educational background, and household income. The second section, concerned questions on travel behavior, examining private vehicle ownership or regular use, as well as the frequency with which respondents use pedestrian crosswalks in their daily movements. The participants were asked whether they typically cross at designated locations and whether they comply with traffic lights indications, such as waiting for the green phase or choosing to cross during the red phase. Participants were also asked to rate how safe they feel when crossing at the under-study intersections, and whether specific modifications on them (such as upgrading the existing traffic lights) would make them feel mower confident or safe.

In order to better understand the decision-making processes, the survey examined a range of factors affecting the participants' choice to cross (including incoming vehicle speed, traffic volume, haste, presence of other pedestrians, and traffic lights indications). The participants were asked to rank these factors according to their perceived importance, allowing the research team to identify the most influential determinants of their crossing behavior. The questionnaire also addressed perceived risk sources, such as insufficient traffic lights indications' durations, driver non-compliance with traffic lights, and situations in which pedestrians and vehicles occupy the crossing simultaneously. Distraction related behavior was also addressed through phone use, music listening, and social conversation while using the crosswalks, along with how the participants felt their habits affected their safety awareness and their tendency to take risks.

The questionnaire had a final section on potential safety improvements (better lighting, clearer signage, lower speed limits, and enforcement cameras), asking the participants to rank these measures and to identify the dangers they regard as most serious. Overall, the questionnaire addressed six (6) questions related to socio-demographic characteristics and fourteen (14) questions on perceived risks, behaviors, and safety-related factors associated with pedestrian crossings.

4 Results

The application of the K-Means clustering algorithm (N = 605) identified four (4) behavioral clusters (k = 4). To ensure the robustness of these groupings, a one-way ANOVA was performed across all clustering variables (Haste, Distraction, Compliance). The results indicated that all variables contributed significantly to the cluster formation ($p < 0.001$), with Electronic Distraction and Signal Compliance showing the highest F-scores. The entire cluster analysis (including data preprocessing, K-Means implementation, Elbow Method, Silhouette Analysis, and ANOVA validation) was performed using Python (v3.11).

Specifically, the K-Means clustering was based on a multivariate set of parameters specifically selected to identify the three (3) core risk variables frequency of phone calls, texting or browsing, music listening, and conversation with other people. Time pressure was collected via a Haste Score reflecting each participant's delf-reported sense of urgency while crossing. Signal Compliance (that is the tendency to cross against a red signal or during an active flashing arrow phase) served as the primary behavioral outcome variable. Since these parameters were measured using a 5-point Likert scale while Signal Compliance was a binary one, Z-score standardization was applied to the full feature matric before the clustering process. Without this step, the wider numerical range of the Likert items would have exerted a disproportionate influence on the Euclidean distance calculations underlying the cluster assignments.

It must be noted that the K-Means unsupervised learning algorithm was used. Given a set of pedestrian observations (x1, x2, …, xn), where each observation is a d-dimensional vector of behavioral traits (Distraction, Haste, Compliance), the algorithm partitions the N observations into k($\leq$ N) sets S = {S1, S2, …, Sk} so as to minimize the within-cluster sum of squares (WCSS). The objective function is defined as:

$$\arg \frac{\min}{S} \sum_{i=1}^{k} \sum_{x \in Si} \|x - \mu i\|^2 \tag{1}$$

Where μi is the mean (centroid) of points in Si.

Because the survey used different measurement scales (e.g., Likert 1–5 for distraction and binary 0–1 for signal compliance), feature scaling was mandatory to prevent variables with larger ranges from dominating the Euclidean distance calculation, and thus standardization (Z-score normalization) was applied:

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

The optimal number of clusters was determined using two primary heuristics:

1. The Elbow Method: The WCSS was plotted against a range of k values (1 to 10). The "elbow" point - where the rate of decrease in WCSS significantly levels off - was identified at k = 4.
2. Silhouette Analysis: To validate cluster separation, the Silhouette Coefficient (s) was calculated for each point:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{3}$$

where a(i) is the average distance to other points in the same cluster and b(i) is the average distance to points in the nearest neighboring cluster. Through this process an average silhouette score of 0.58 was achieved, indicating a strong structure in the data.

To visually assess the separation between the identified clusters, a Silhouette Plot was developed (see Fig. 2), presenting the silhouette coefficient for each sample, grouped by cluster. The majority of samples across all four clusters exceed the average score of 0.58, with very few negative values, confirming that the k = 4 solution provides minimal overlapping among groups.

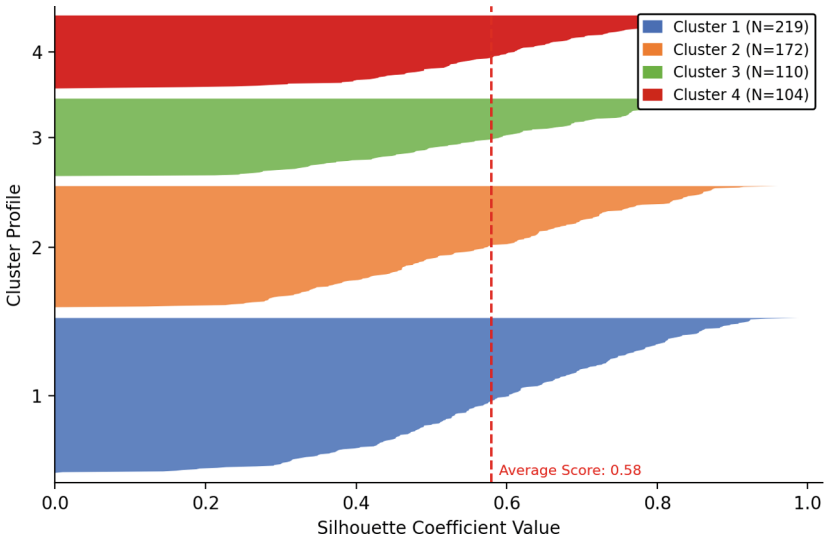

Fig. 2. Silhouette Plot for k = 4 Cluster Solution (N = 605).

Furthermore, a sensitivity analysis was performed to compare the $k = 4$ solution against alternative partitions ($k = 3$ and $k = 5$). As presented in Table 2, $k = 4$ provided the optimal balance between model complexity and group separation.

Table 2. Sensitivity analysis comparing different number of clusters Literature review clustering

Number Of Clusters (K)	*WCSS*	*Avg. Silhouette Score*	*Interpretability*
k = 3	*1240.5*	*0.49*	*Merges 'Anxious Rusher' And 'Law-Breaker'*
k = 4	***892.1***	***0.58***	***Distinct Behavioral Archetypes***
k = 5	*815.4*	*0.52*	*Splits 'Attentive Observer' Into Redundant Groups*

As a result, the K-Means clustering process identified the four following profiles/clusters:

- Cluster 1 - The Attentive Observer ($n = 219$): This is the largest and the least problematic cluster. The distraction levels are low across all modalities (mean 1.2/5.0). The Signal Compliance presents a 94% compliance rate even at Intersection A (Permitted), suggesting that infrastructure design does not affect their safety focus.
- Cluster 2 - The "Lost in Device" Waiter (n = 172): This group presented the highest "Digital Engagement" score (4.6/5.0). Interestingly, their "Haste" score was the lowest (1.8/5.0), implying they are willing to wait for the green light specifically because they use their mobile phones.
- Cluster 3 - The Distracted Law-Breaker (n = 110): This group presents a "Social Risk." Their social interaction score (4.2/5.0) was significantly higher than their

tendency on using their mobile phones. They are 3.5 times more likely to follow a lead pedestrian into the crosswalk against a red light than any other profile/ cluster.

- Cluster 4 - The Anxious Rusher (n = 104): They presented a very high Haste score (4.8/5.0). Their behavior is highly independent by the traffic lights indications as they choose to cross during small gaps in vehicles flow. At Intersection A (Permitted), this group accounted for 65% of all recorded near-miss interactions.

In order to evaluate the practical significance of the observed differences between clusters, Eta-squared (η^2) was calculated for each behavioral dimension. According to Cohen's criteria, values above 0.14 represent a large effect. As shown in Table 3, Signal Compliance ($\eta^2 = 0.64$) and Electronic Distraction ($\eta^2 = 0.59$) exerted the strongest influence on cluster membership, accounting for over 50% of the variance between groups.

Table 3. One-Way ANOVA of Behavioral Variables across Clusters (N = 605)

Behavioral Variable	*F-value (df = 3)*	*p-value*	*Eta-squared (η^2)*	*Effect Size Magnitude*
Signal Compliance	*214.52*	*< 0.001*	***0.64***	***Large***
Electronic Distraction	*186.10*	*< 0.001*	***0.59***	***Large***
Haste/Rushing	*92.34*	*< 0.001*	***0.38***	***Large***
Social Distraction	*45.12*	*< 0.001*	***0.22***	***Medium-Large***
Self-Reported Crossing Speed	*31.08*	*< 0.001*	***0.16***	***Medium***

5 Discussion and Conclusions

Through the analysis of the collected it was identified that Intersection B (Protected) successfully decreases the physical threat of vehicle-pedestrian conflict.

The significant 13% increase in the "Lost in Device" profile at the protected intersection highlights the fact that as the surrounding environment at crosswalks becomes objectively safer, pedestrians tend to increase their engagement with secondary tasks (using a mobile device). This tendency is dangerous during the transition from the sidewalk to the crosswalk, where pedestrians may step into the road based solely on the traffic light change without a primary visual scan of the environment/ road.

The difference between Anxious Rusher and Distracted Law-Breaker, affects sustainable mobility policy, because the two clusters/ profiles require different approaches. The Rusher as a cluster/ profile remains stable across both intersections (r = 0.91), suggesting that infrastructure changes alone cannot change their behavior. The Law-Breaker, is a different case. At Intersection A (Permitted), the presence of flashing yellow arrows

reduced the tendency of this group to cross the road by 4% compared to Intersection B (Protected). This indicates that a certain level of perceived complexity in the environment can discourage social distraction.

Based on the identified profiles/ clusters the following measures are proposed to be implemented at the crosswalks surrounding the AUTh campus:

- Dynamic Phasing for Peak Hours: To protect "Anxious Rushers" and "Law-Breakers", high-volume student crosswalks should use protected phasing during class-change intervals. However, during off-peak hours, a return to permitted phasing could be allowed.
- Multisensory Alerts for the "Lost in Device" profile: As nearly 30% of students are focused on their mobiles, standard visual lights tend to be insufficient. As a solution LED-embedded tactile paving at the curb are recommended - often referred to as "zombie lights" - to provide signal information within the downward peripheral vision of smartphone users.
- V2P (Vehicle-to-Pedestrian) Communication: For the "Anxious Rusher," smart city infrastructure could push real-time alerts to mobile devices when a student is approaching a curb at high walking speed during a red phase.

While the usage of K-Means clustering process and the applied statistical tests are considered successful on analysing the collected data, several limitations must be acknowledged. The sample is restricted to university students, a group that likely differs from the broader pedestrian population in terms of being familiar with the use of smartphones, risk attitudes, and walking pace. Furthermore, based on the fact that the data were collected through a questionnaire-based survey, the participants might have provided inaccurate of false answers. Finally, the collected data capture a snapshot of behavior as seasonal variations (e.g., weather-induced haste in winter) or long-term behavioral adaptation to the flashing yellow arrow were not captured.

Taking into consideration all the above, the pedestrians' safety at signalized intersection cannot be fully understood and explained through aggregate approaches only. The K-Means Clustering framework that was applied in the current research can be considered as feasible and useful on segmenting pedestrian target groups into behavioral profiles, presenting their risk configuration and respective measures to be applied.

For the City of Thessaloniki in general and the AUTh campus specifically, the findings suggest that even protected phasing may is not without complications. In order to create a sustainable and safe urban environment, urban planners and decision makers might move from one-size-fits-all infrastructure planning towards designs that take into consideration the different behavioral profiles of the users/ pedestrians.

Future research should focus on adapting these behavioral profiles to determine if the Lost in Device phenomenon is a permanent shift or a temporary response to infrastructure changes. Additionally, integrating the K-Means framework with real-time computer vision and analysis could allow for the automated identification of risky "Anxious Rusher" or "Distracted Law-Breaker" profiles/ clusters in smart city environments.

It should be also mentioned that Vehicle-to-Pedestrian (V2P) technologies could be explored, testing whether haptic alerts can effectively mitigate the risks and dangers identified at protected intersections. Finally, expanding this research to include elderly pedestrians and children, who are particularly vulnerable in urban intersections [71],

will be essential for developing an inclusive, age-aware sustainable mobility plan for Thessaloniki.

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Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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