Multilevel crash risk assessment under autonomous vehicle integration: From partial to full autonomy through urban traffic simulation

By

Maria G. Oikonomou

Thesis submitted for the degree of Doctor of Philosophy

Advisory Committee:

Prof. George Yannis (Supervisor)
Prof. Eleni Vlahogianni
Asst. Prof. Konstantinos Gkiotsalitis

Submitted in January 2026

Executive summary

Technological advances in the automotive industry are expected to fundamentally reshape traffic systems. **Autonomous Vehicles** (AVs) are projected to increase road capacity while reducing travel time, emissions and crashes by limiting human error. However, as AVs begin to interact with Human-Driven Vehicles (HDVs) and Vulnerable Road Users (VRUs), ensuring their **safety remains a crucial challenge**. Safety evaluation will therefore be essential throughout all future stages of automation.

Due to the absence of historical and generalizable crash data for high levels of automation and future Market Penetration Rates (MPRs), **microscopic traffic simulation** is a promising approach. Microscopic simulation models individual vehicles and their interactions, making it increasingly suitable for road safety research through Surrogate Safety Measures (SSMs). As simulated traffic is “crash-free,” SSMs such as Time-to-Collision (TTC) or traffic conflicts provide an indirect yet practical means to estimate crash likelihood and severity, supporting safety assessment where real crash data are limited or unavailable. Surrogate safety analysis is particularly valuable for emerging AV deployment because large-scale, reliable crash datasets are difficult to obtain even for HDVs. Moreover, merging multiple data sources can introduce bias, and no extensive crash history exists for AVs at higher automation levels.

Despite its advantages, safety assessment of AVs through simulation also presents several challenges. Key issues include:

- Limited background knowledge on **AV modelling parameters**, and variations across simulation platforms and behaviour models.
- Lack of **established simulation methods** for crash representation, since existing models are designed to avoid collisions.
- Difficulty in reproducing **real-world complexity**, including human behaviour and unpredictable events, requiring validation against empirical crash data.
- Need to evaluate safety across **different SAE automation levels** and driving scenarios to ensure reliable AV performance.

These challenges motivate this thesis, which aims to address and resolve these issues related to the crash risk of AVs across various levels of autonomy, ranging from partial to full automation, in urban areas. To achieve this, the thesis has established the following **objectives**:

- Undertake a systematic review of existing literature to consolidate past research and define **parameters utilized in modelling AVs within traffic simulation**.
- Emphasize the **applications of traffic simulation on road safety assessment** by synthesizing past research findings through a systematic literature review.
- Establish **a solid safety evaluation approach for estimating crash risk through microsimulation** in future AV deployment scenarios.

- **Validate the evaluation approach** for estimating crash risk through microsimulation by conducting a comprehensive comparative analysis of traffic safety metrics derived from simulated and field crash data to identify safety patterns.
- Conduct **a multilevel safety assessment of AV deployment** using an integrated simulation-Machine Learning (ML)-spatial framework to evaluate, rank and understand crash risk dynamics across multiple scales and automation levels, establishing a robust understanding of safety performance under automation.

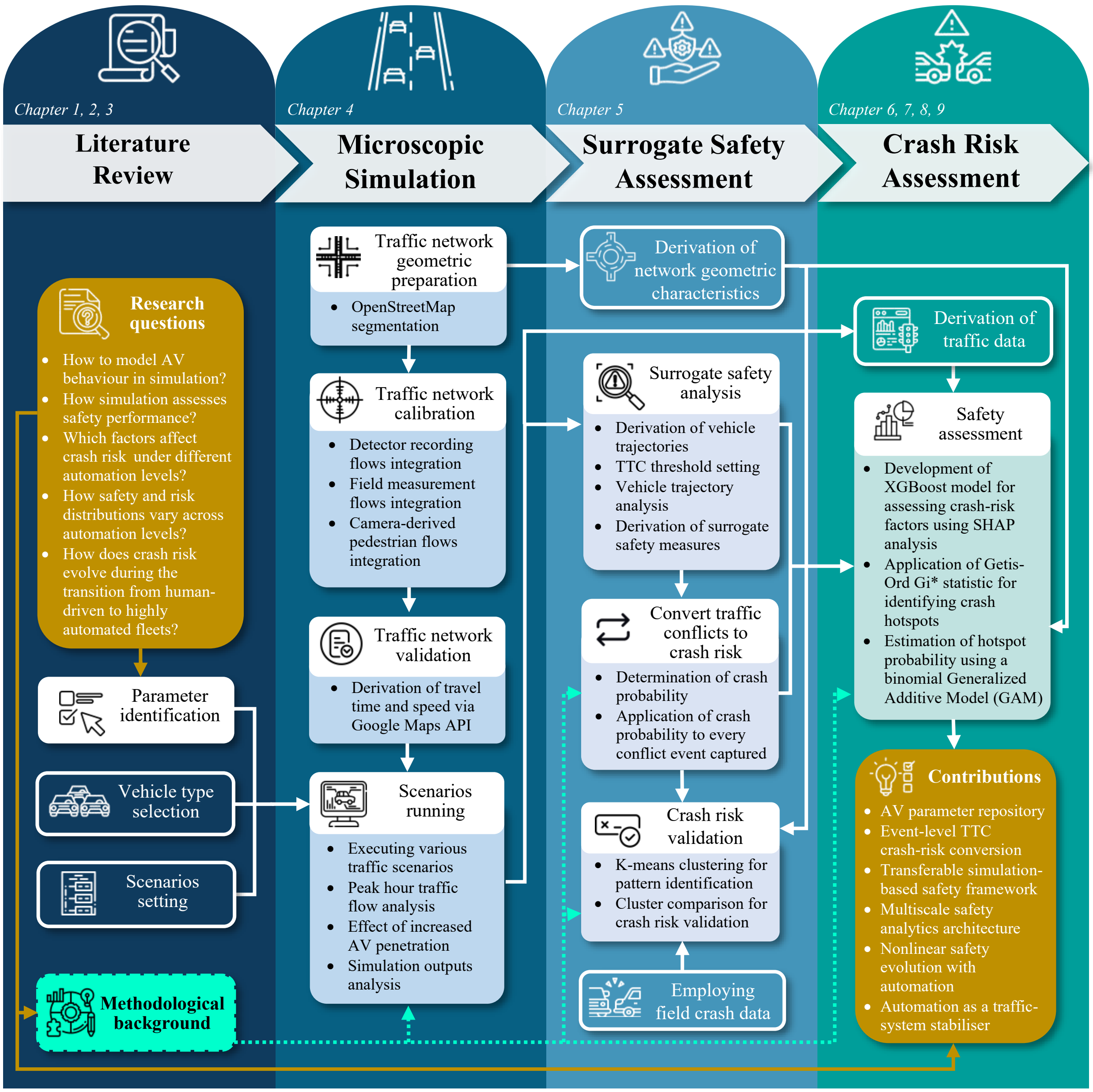


Figure 1: PhD thesis process flowchart

In Figure 1, a visual representation **of the methodological framework employed** in this thesis is illustrated. The thesis flowchart outlines the key components and their interconnections, showing how each aspect contributes to the overall research process aimed at assessing the crash risk of AVs across varying levels of autonomy. Following this framework, the thesis is structured around **four foundational pillars** that reinforce the research. Each pillar represents a critical aspect of the study, addressing specific components. The following sections provide a detailed examination of each pillar.

Literature Review

This pillar serves as a foundational element of this thesis, addressing critical research gaps in the crash risk assessment of AVs. It begins with the **Research Questions**, which frame the key investigations into AV modelling, safety assessment through microsimulation, and the evaluation of crash risk across automation levels and urban scales. **Parameter identification** highlights specific parameters that differentiate AVs from HDVs, offering insights crucial for accurate modelling in simulations. This exploration is complemented by the **Vehicle type selection** component, where various SAE automation levels are examined to understand their implications for road safety. Additionally, the **Scenarios setting** integrates these insights by developing diverse AV deployment scenarios to evaluate crash risk effectively. Finally, the **Methodological background**, guided by existing literature, outlines the appropriate approaches adopted throughout the thesis.

Research questions

The present thesis aims to address the aforementioned research gaps related to crash risk assessment of AVs. To achieve this, the following **Research Questions (RQs)** are formulated:

- **RQ1**: Effectively incorporating AVs into traffic simulations often require adjusting parameters within existing behavioural models. However, the reliability of such simulations heavily depends on both the accuracy of parameter adjustments and the assumptions regarding AV behaviour and interactions with HDVs. *Which parameters can represent and model the behaviour of autonomous vehicles within traffic microsimulation frameworks?*
- **RQ2**: In road environments characterized by large AV fleets and higher SAE automation levels, reliable crash data are often unavailable, making direct safety assessment infeasible. In such cases, traffic simulation offers a valuable alternative for evaluating safety. *How can traffic microsimulation be effectively used to assess road safety performance?*
- **RQ3**: While AVs aim to reduce human error, the primary cause of road crashes, their overall safety performance depends on complex interactions between traffic, infrastructure and automation characteristics. *Which design, traffic, and automation-related factors most critically affect road safety outcomes across different automation levels and market penetration rates in urban traffic systems?*
- **RQ4**: As automation levels and fleet compositions evolve, spatial variations in safety performance may emerge across urban networks. *How do safety patterns and risk distributions change across different fleets of automation, and at multiple scales within urban road networks?*

- **RQ5**: The shift from human-driven traffic to highly automated fleets is gradual and involves multiple stages of mixed traffic, each with distinct behavioural and safety implications. Understanding how crash risk changes throughout this transition is essential for anticipating system-level impacts. *How does crash risk evolve during the transition from human-driven traffic to highly automated fleets?*

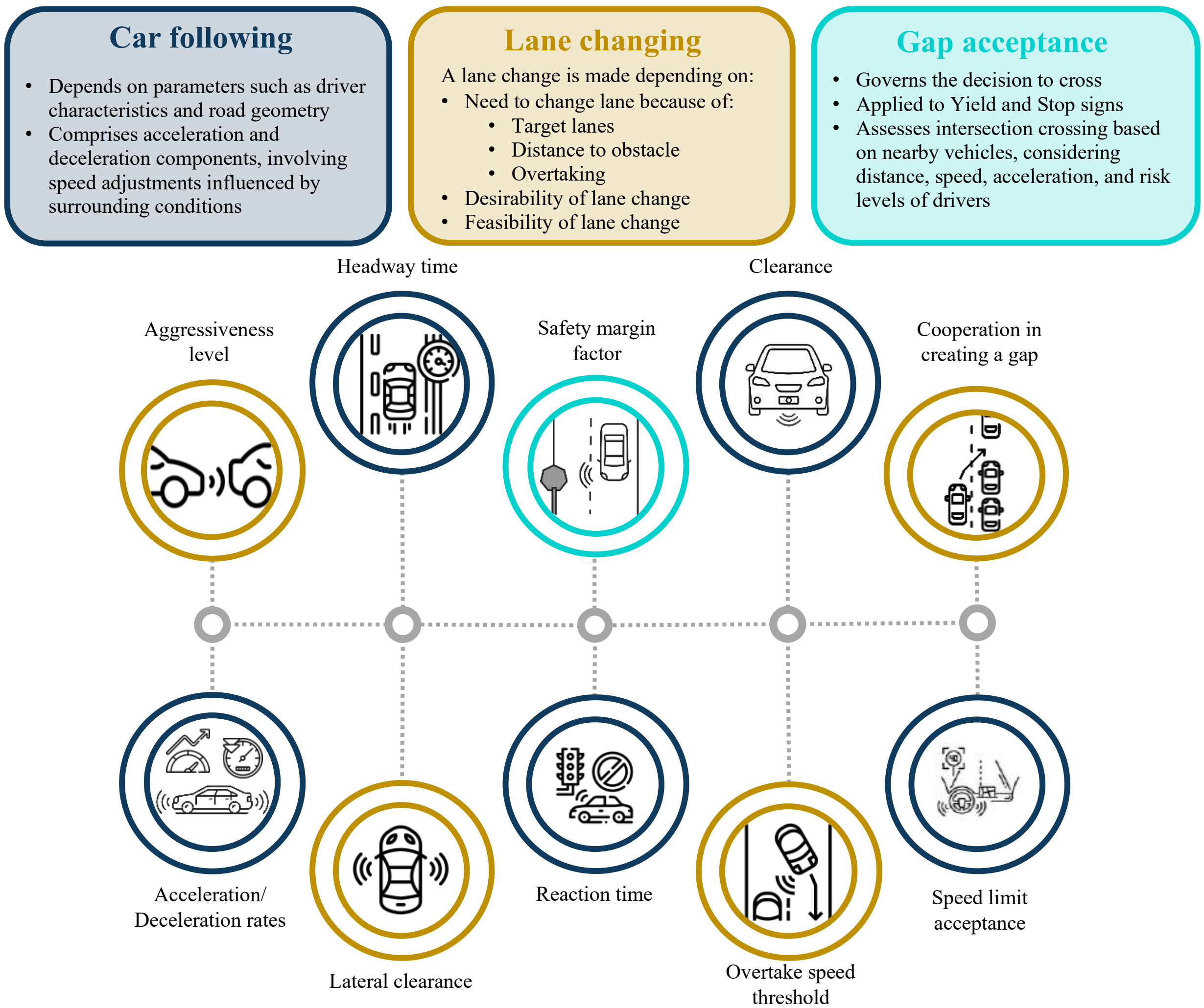


Figure 2: Differentiated parameters for modelling autonomous vehicles in Aimsun Next software

Vehicle type selection

Through a systematic review, this thesis constitutes an effort to fill the research gap of **parameter definition in microscopic simulations of AVs**, all along while benchmarking them against HDVs. To that end, 934 candidate studies were identified initially, and after thorough screening, 54 studies with suitable parameters were reviewed overall. By comparing these identified parameters with those relevant to HDVs, valuable insights pivotal for advancing traffic simulation are provided, including parameter-specific numerical averages, which will simplify the parameter specification process of future researchers and free related cost and effort resources.

In addition, the present thesis attempts to review the existing literature findings systematically and to further identify **road safety assessment aspects in which traffic simulation is applicable**. Through a systemic review, the schemes of safety evaluation that traffic simulation can be applied were identified.

Based on literature review, several parameters are identified while it can be noticed that many **vehicle types of AVs** have been investigated. These differ in SAE automation level, connectivity or behaviour such as aggressiveness, inserted, etc. For the present thesis, efforts are focused on including as much of future technologies namely all levels of automation. Specifically, vehicle types representing each two SAE levels are selected to investigate namely, SAE level 0-1 that represents a manual mode, SAE level 2-3 that represents a partial automation mode, SAE level 4-5 that represents a full automation mode and SAE level 4-5 with an aggressive mode that represents performance automation.

Parameter identification

For each of the selected vehicle types described above, the **corresponding parameters** were identified based on findings from the literature review. Specifically, the average values of these parameters, applicable to the same vehicle types in Aimsun Next software (used in this thesis), were calculated to facilitate modelling and integration into simulations. The parameters that differ in the case of AVs compared to HDVs are illustrated in Figure 2, along with the related behaviour models, including car following, lane changing and gap acceptance models.

Scenarios setting

For integrating AVs to simulations, **scenarios representing potential future implementation** should be selected for crash risk of their conditions to be assessed. For the present thesis fifteen scenarios are selected in order multiple possible AV deployment scenarios to be investigated while including all four selected vehicle types. These are illustrated in Figure 3.

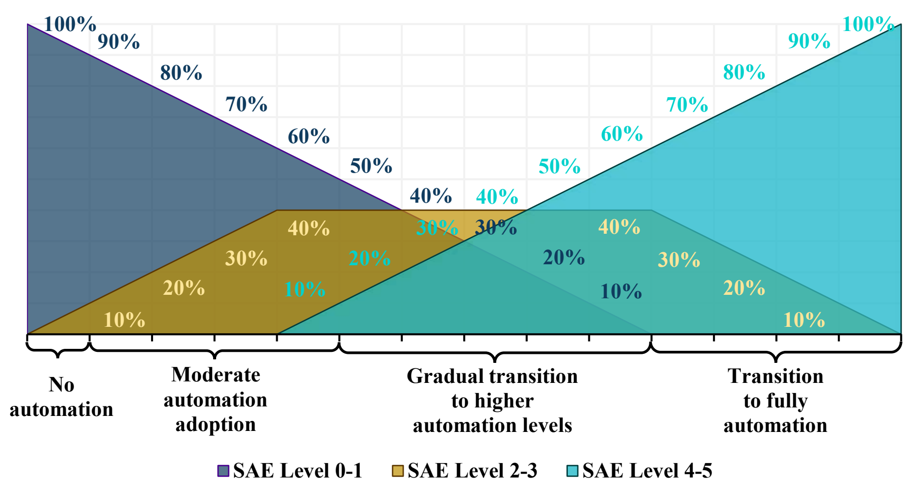


Figure 3: Simulated AV deployment scenarios

Methodological background

The research draws upon a broad methodological background encompassing **simulation-based modelling, statistical and ML approaches, and spatial analytical techniques**. These foundations informed every stage of the workflow, from the calibration and validation of microsimulation outputs to the estimation, modelling, and spatial interpretation of crash risk. The selected methods, including conflict-to-crash risk formulation, regression-based and ML, and spatial statistics, were derived from established practices in transportation safety analysis and adapted to the specific context of AV evaluation. By integrating these methodological principles, the thesis ensures that all subsequent analyses are grounded in robust, transparent and scientifically validated techniques, supporting the development of a reliable multiscale framework for assessing crash risk under varying levels of automation.

Microscopic Simulation

This pillar is essential to this thesis, including a detailed analysis of traffic dynamics within various AV deployment scenarios in the urban context of Athens, Greece. This pillar begins with the **Traffic network geometric preparation**, where the city centre complex traffic network is modelled using data from the OpenStreetMap platform, ensuring that the geometric and functional characteristics of each road segment and node are well-represented. Following this, the **Traffic network calibration** utilizes comprehensive traffic and pedestrian data, including measurements from the Athens Traffic Management Centre and manual observations, to refine the simulation model and ensure it accurately reflects real-world conditions. The **Traffic network validation** process further strengthens the model by comparing estimated travel times with actual data, demonstrating the simulation predictive capability. Finally, the **Scenarios running** component details the execution of fifteen distinct AV deployment scenarios, each assessed through multiple replications to evaluate crash risk and vehicle interactions under varying conditions.

Traffic network geometric preparation

The **study area** selected for the present thesis is the city centre of Athens, Greece, a critical urban zone characterized by dense motorized traffic and frequent congestion. This area also experiences the highest levels of motorbike traffic and pedestrian activity in the entire Athens metropolitan region. Additionally, the city centre is a hub for public transportation, offering a wide array of mode choices including buses, trolleys, trams and metro services for urban travel. Figure 4 illustrates a map of Greece, with the Attica region road network highlighted in blue, and a red line marking the study network within the city centre of Athens. The selected area is considered as an ideal network for investigating the integration of autonomous urban mobility. It provides valuable insights into urban environments with high density and diverse transportation modes and users, presenting complex and under-explored conditions.

The **geometry of the study network** was derived from the OpenStreetMap digital map platform and integrated into the Aimsun Next simulation software. Its accuracy was verified through random sample comparisons with additional maps. The model includes detailed geometric and functional characteristics for each road segment, such as length, width, number of lanes, direction, public transport lanes, free flow speed, speed limit and capacity. Similarly, each node attributes, such as allowed movements, number of lanes per movement, priority, traffic signs, traffic light control plans, free speed flow and capacity, were accurately represented.

The **simulated network** covered approximately 3.2 square kilometres and included 192 nodes and 434 road segments, with a total length of 47 kilometres, as shown in Figure 5. The Origin-Destination (OD) matrices for this network consist of 102 centroids. Additionally, the model incorporates public transport lines, including 43 bus lines and 14 trolley lines, along with their 129 stops, frequencies and waiting times derived from the Athens Urban Transport Organisation.

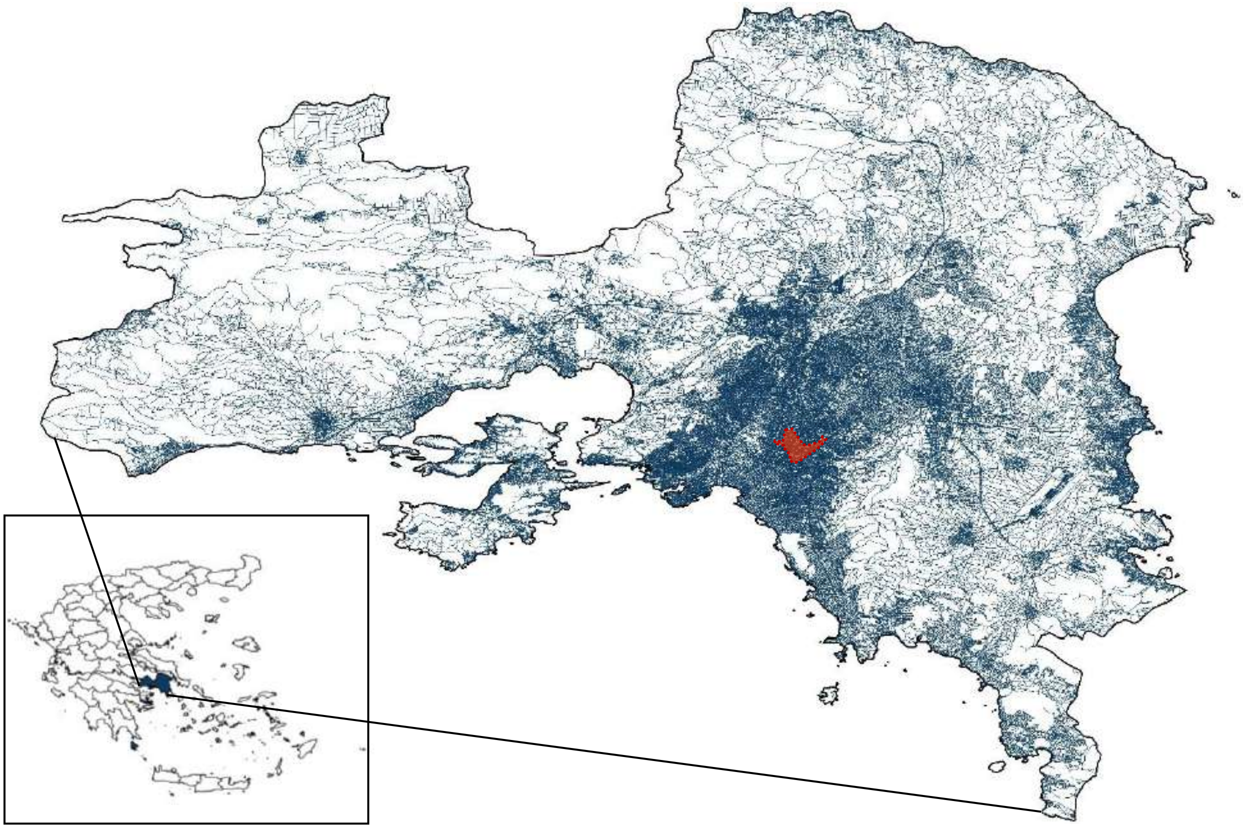
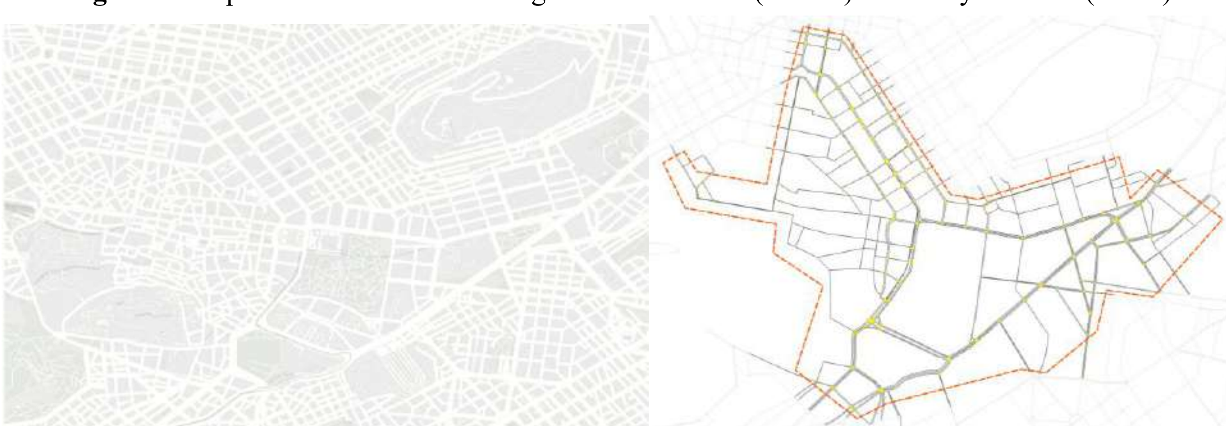


Figure 4: Map of Greece with Attica region road network (in blue) and study network (in red)



(a) (b)

Figure 5: (a) Study area and (b) simulated road network of the Athens city centre

Traffic network calibration

In the model **pedestrian flows** were also integrated. Pedestrian measurements were conducted manually by analysing videos from strategically placed cameras. The integration of pedestrian areas into the model was based on the availability and coverage of these cameras. The measurements were taken from videos recorded on June 11, 2020, between 8:00-9:00 a.m., ensuring that every visible pedestrian crossing was included in the analysis. From these manual measurements, a total of 6,912 pedestrians were counted during the simulated period.

Focusing on **motorized vehicle data integration**, traffic data for the morning peak hour (8:00-9:00 a.m.) were collected from the Athens Traffic Management Centre (ATMC) for Tuesdays and Thursdays in May 2019. Data were sourced from 19 detectors (cameras that record traffic volume). Following data collection, the measurements were verified to ensure there were no significant deviations, and the average of these measurements was calculated and used for model calibration.

Additional data from **field measurements** were also considered to account for fleet composition. These measurements were conducted over a one-week period from Monday, November 30, 2019, to Friday, December 3, 2019, between 7:30-9:30 a.m. Organized by the National Technical University of Athens, the field measurements were performed at critical nodes within the study area. At each node, the number of vehicles exiting in each direction was recorded for fifteen-minute intervals. The vehicle categories measured included: (a) motorbikes, (b) heavy goods vehicles, and (c) passenger cars, light goods vehicles and taxis.

In the present model, the **Geoffrey E. Havers (GEH) index confirmed successful calibration**, with 85.2% (46 out of 54) of the cases having a GEH value lower than 5, and 100% (54 out of 54) of the cases having a GEH value lower than 10. This calibration process ensures that the model accurately represents real-world traffic conditions, enhancing the reliability and validity of the simulation results. In addition, the R^2 coefficient of this simulation model is 0.9837 based on a simple linear model, indicating an excellent model fit. This finding indicates that 98.37% or more of the variance in observed traffic volumes is explained by the simulation.

The calibration procedure resulted in **adjusted OD matrices** comprising the 102 network centroids for each mode. Specifically, during the morning peak hour (08:00-09:00 a.m.), the simulation model accounted for a total of approximately 20,987 trips. Of these, 7,850 trips corresponded to passenger cars, representing 37% of the total traffic. Motorbikes accounted for 6,522 trips, or 31% of the total traffic, while taxis contributed 5,853 trips, equating to 28% of the total traffic. Additionally, trucks were responsible for 762 trips, making up 4% of the total traffic.

Traffic network validation

To validate traffic of the microscopic model, particularly regarding estimated **average travel times**, data from main roads in the study area were utilized. This data was collected over one week, from Monday, November 30, 2019, to Friday, December 3, 2019, between 8:00-9:00 a.m. Travel times were recorded at ten-minute intervals using the Google Maps Application Programming Interface (API) application. The observed travel times were compared with the corresponding travel times produced by the simulation model and showed small deviations, confirming the acceptable accuracy of the model.

Scenarios running

In this thesis, the **fifteen simulation scenarios** (Figure 3) were executed to investigate multiple possible AV deployment situations, incorporating all four selected vehicle types. For each scenario, **ten replications** were conducted using different random seeds to ensure a robust analysis of the results.

Surrogate Safety Assessment

This pillar serves as the bridge between microsimulation outputs and quantitative safety evaluation by transforming vehicle interactions into crash-equivalent measures and validating their accuracy against real-world observations. This pillar begins with the **Derivation of network geometric characteristics**, where the detailed geometric and operational attributes of the simulated Athens city network are extracted and aligned with real-world information. Following this, the **Surrogate safety analysis** stage processes vehicle trajectories from microsimulation using the Surrogate Safety Assessment Model (SSAM) to identify traffic conflicts. Subsequently, the **Conversion of traffic conflicts to crash risk** transforms these identified conflicts into crash-equivalent measures by applying a conflict-to-crash risk formulation that integrates both conflict frequency and severity. The **Crash risk validation** stage then evaluates the predictive accuracy of these simulation-derived risks through clustering and discriminant analysis, confirming strong correspondence between simulated and observed safety outcomes. Finally, the **Employment of field crash data** enables the validation of the proposed framework.

Derivation of network geometric characteristics

To capture the impact of network geometry and control diversity, **road capacity, number of lanes, traffic control type and the presence of public transport lines** were incorporated as structural attributes, derived and verified through OpenStreetMap data.

Surrogate safety analysis

The **vehicle trajectories** were extracted from microsimulation per 0.1 seconds, equal to the simulation time step and were analyzed using the **SSAM software**. The software processed the vehicle trajectory data and identified conflicts. A conflict is identified when the TTC and Post-Encroachment Time (PET) are lower than preset thresholds. The default values are 1.5 and 5.0 seconds for TTC and PET, respectively. These thresholds were adapted to reflect the behaviour of both human-driven and AVs across different SAE automation levels, ensuring consistency between simulated driving behaviour and safety event detection. Conflicts were categorized into three maneuver types, rear-end, lane-change, and crossing and georeferenced within the urban network. The resulting dataset contained detailed information for each conflict, including vehicle type, identifiers, coordinates, segment location and multiple surrogate safety metrics such as speed, heading and deceleration.

Convert traffic conflicts to crash risk

In the absence of reliable crash records, particularly under emerging automation conditions, direct safety evaluation becomes challenging. In such cases, traffic simulation serves as an effective alternative, providing surrogate indicators of safety performance derived from vehicle interactions rather than observed crashes. Since microsimulation represents crash-free traffic flow, it enables the estimation of safety only through surrogate safety measures, such as those obtained from the SSAM analysis described previously. To overcome this limitation, the present thesis **developed and applied a conflict-to-crash risk formulation** that systematically links the characteristics of identified conflicts to the expected probability of crash occurrence.

Crash risk validation

The validity and predictive capability of the proposed conflict-to-crash risk formulation framework were evaluated by comparing simulation-derived crash risk estimates with corresponding field crash data for 122 urban roads. Both datasets were normalized using Min-Max scaling to ensure comparability and subsequently analyzed through k-means clustering to identify groups of roads exhibiting similar safety characteristics. The Elbow method was applied to determine the optimal number of clusters, while Linear Discriminant Analysis (LDA) was used to assess the distinctness and stability of the identified risk groups. The analysis produced two consistent clusters, representing low and high crash risk roads, which were found to align closely between simulated and observed data. This strong correspondence confirms the framework ability to accurately reproduce real-world crash risk patterns. The model achieved a classification accuracy of 87.7%, indicating **high predictive reliability and validating the robustness of the simulation-based approach**.

Employing field crash data

Validation relied on crash data obtained from **ELSTAT for the years 2017-2019**, encompassing variables such as number of severely injured individuals, involved vehicles and crashes, some geometric data were also used to enhance the categorization of clustering, including speed limits and lengths of roads. These data were carefully matched with simulated road segments to ensure spatial and temporal alignment. Visual and statistical comparisons between simulated and observed results showed consistent spatial distributions of crash risk across the network. Minor discrepancies were primarily associated with **roads lacking sufficient calibration data**, emphasizing the critical importance of high-quality input data in model development. Overall, this validation process confirmed that the combined microsimulation-surrogate safety approach provides a reliable and transferable framework for estimating crash risk in scenarios where empirical crash data are limited, such as under AV traffic conditions.

Crash Risk Assessment

This pillar extends the safety evaluation to a multilevel framework that investigates crash risk from both macroscopic and microscopic perspectives, providing an integrated understanding of how automation influences safety at the network and local levels. This pillar begins with the **Derivation of traffic data**, where detailed traffic performance measures are extracted from Aimsun Next simulations for each AV deployment scenario. Following this, the **Safety assessment** integrates machine learning and spatial statistical modelling to quantify crash risk across different levels of automation. Finally, the **Contributions** of this pillar lie in demonstrating a validated simulation-based safety framework, an integrated simulation-ML-spatial approach, and a multiscale understanding of crash risk evolution under automation.

Derivation of traffic data

To capture the operational dynamics of the network under varying automation conditions, detailed traffic performance measures were extracted from the Aimsun Next microsimulation model for all links and nodes and separately for each automation scenario. Specifically, the collected traffic data included **flow, speed, density, delay time, queue length, number of lane changes, and number of stops**. These measures were aggregated at the road level to ensure consistency across scenarios and to enable meaningful comparisons. In parallel, the extraction process was complemented by structural network attributes and automation-related indicators, including the **MPRs of SAE Level 2-3, SAE Level 4-5, and SAE Level 4-5 (aggressive mode)** vehicles, which were integrated as scenario-level parameters to reflect the evolving composition and behavioural characteristics of the traffic stream.

Safety assessment

The safety assessment was performed through a **multilevel analytical framework** encompassing both road-level crash risk estimation and conflict-level spatial hotspot analysis, enabling a holistic evaluation of automation-related safety impacts.

At the road level, crash risk analysis was conducted using a dataset comprising 1,812 aggregated roads, derived from microsimulation outputs and network geometry data. Crash risk was estimated through the conflict-to-crash formulation framework applied to SSAM results, followed by a machine-learning-based factor analysis. A **tuned XGBoost model** predicted crash risk based on traffic, geometric and automation-related variables, while SHAP values provided interpretable insights into each factor influence.

The analysis showed that traditional traffic and geometric conditions, notably traffic density, queue length, lane-changing activity and control type, are the dominant predictors of crash risk across all scenarios (Figure 6). **Automation variables**, although less influential, demonstrated consistent trends: increasing shares of SAE Level 2-3 vehicles slightly raised crash risk due to behavioural heterogeneity in mixed traffic; in contrast, higher penetration of SAE Level 4-5 vehicles produced a progressive decline in risk, indicating smoother and more predictable operations. The aggressive SAE 4-5 profile had minimal impact, showing only a modest protective effect under high AV market penetration.

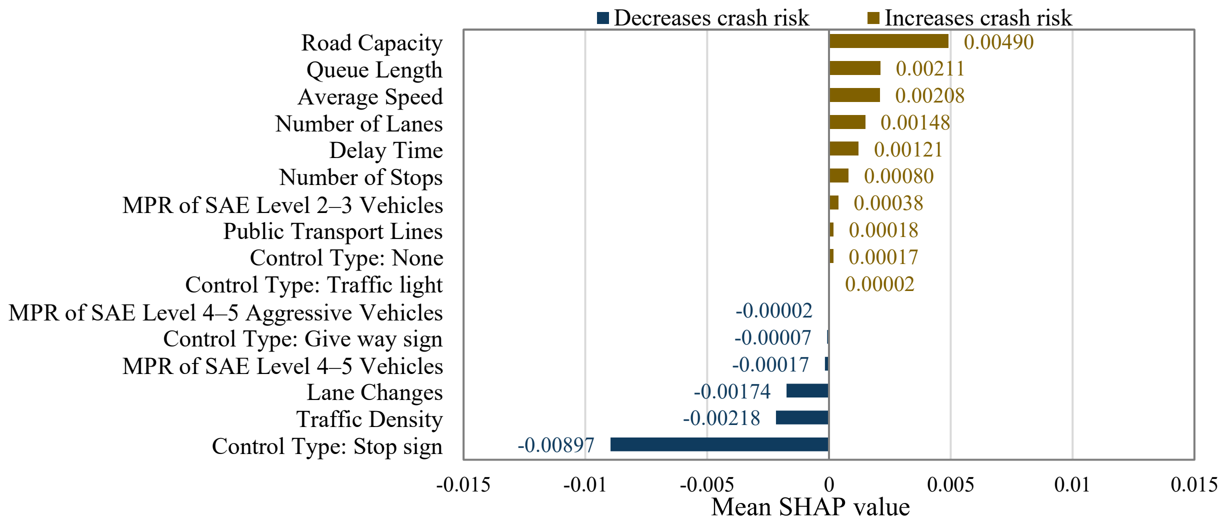


Figure 6: Directional impact of features on crash risk based on mean SHAP values

At the conflict level, safety was assessed using 883,603 simulated conflict events, mapped onto a 30 m × 30 m grid and analysed with the **Getis-Ord Gi* statistic**. A **binomial Generalized Additive Model (GAM)** quantified how road context, conflict type, vehicle pairing and automation scenario influence the likelihood that conflicts form spatial crash hotspots. The model showed that hotspot clustering is driven mainly by intersections, crossing-type conflicts and uncontrolled locations, all of which significantly increase collision exposure.

A key outcome is the identification of **a nonlinear, stage-dependent relationship between automation and hotspot occurrence**. Mixed Manual-AV interactions had the highest hotspot probability, while AV-AV elevated risk only during transitional phases. Scenario effects followed a U-shaped pattern: early and moderate automation increased hotspot probability, whereas high automation scenarios produced a strong and consistent decline as behavioural variability reduced. Spatial hotspot maps (Figure 7) showed a clear evolution: dispersed hotspots under early automation, consolidation during intermediate stages and substantial risk contraction once AVs dominated.

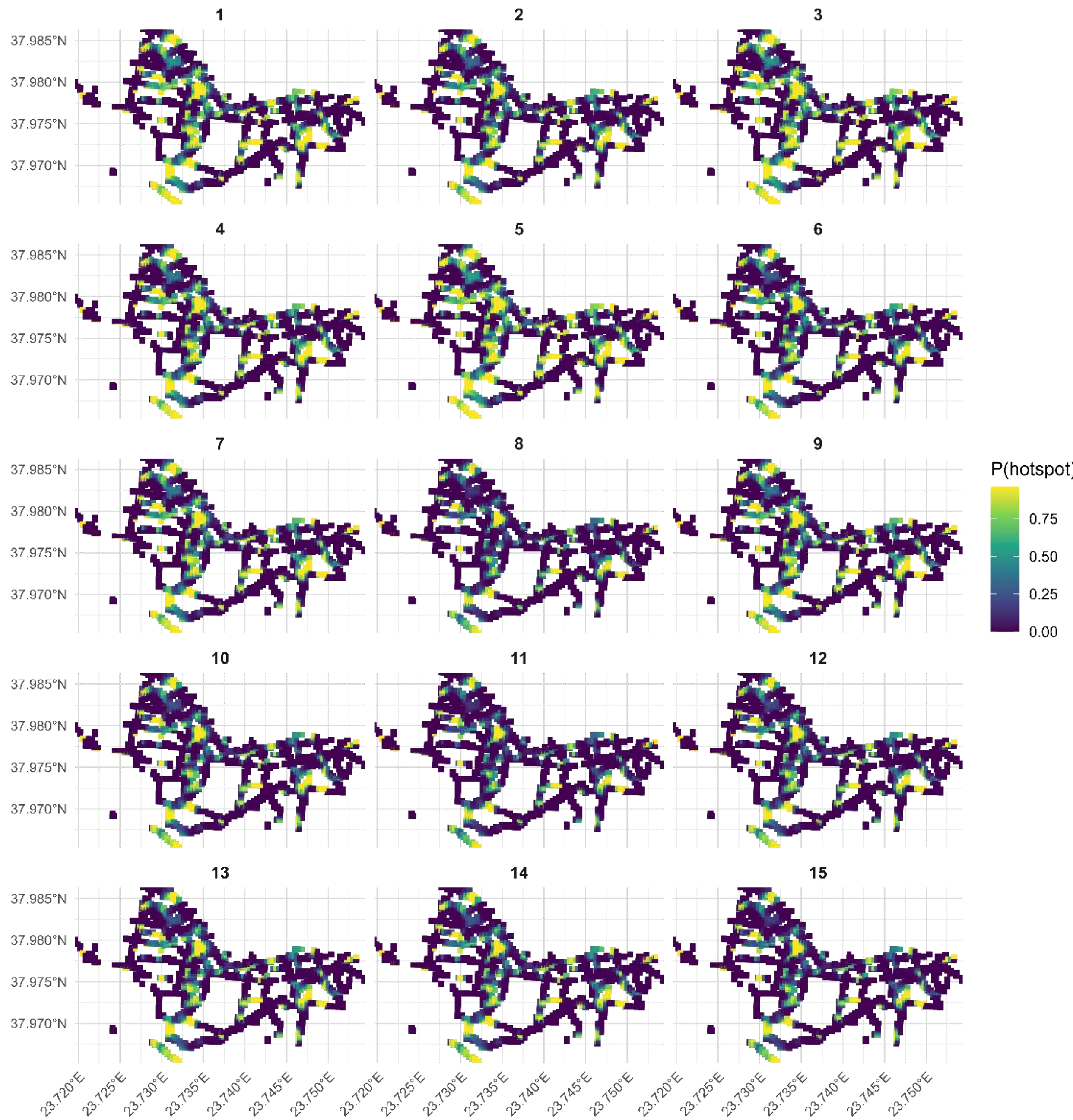


Figure 7: Predicted probability of crash hotspots across AV scenarios

Contributions

Finally, the thesis introduces **six methodological and conceptual innovations** for AV safety assessment (Figure 8), including:

1. **A systematic repository of AV behavioural parameters**, derived from an extensive literature review, enabling realistic, consistent and reproducible AV modelling in microscopic simulation.
2. **A novel TTC-based event-level crash-risk conversion framework**, allowing individual simulated conflicts to be translated into crash-equivalent probabilities across automation levels.
3. **A transferable methodology for safety assessment in emerging mobility environments**, integrating microsimulation, surrogate safety indicators, crash-risk conversion and empirical validation, suitable for contexts with limited crash data.
4. **A multiscale safety assessment approach**, combining machine learning and spatial-statistical modelling to evaluate crash risk both at road-segment and conflict-level spatial resolutions.
5. Evidence of **nonlinear crash-risk evolution across automation levels**, with risk peaking under mixed traffic and declining as high automation stabilises network behaviour.
6. Insights that **automation acts as a system stabiliser**, reducing behavioural variability and hotspot clustering rather than acting as a direct, isolated safety factor.

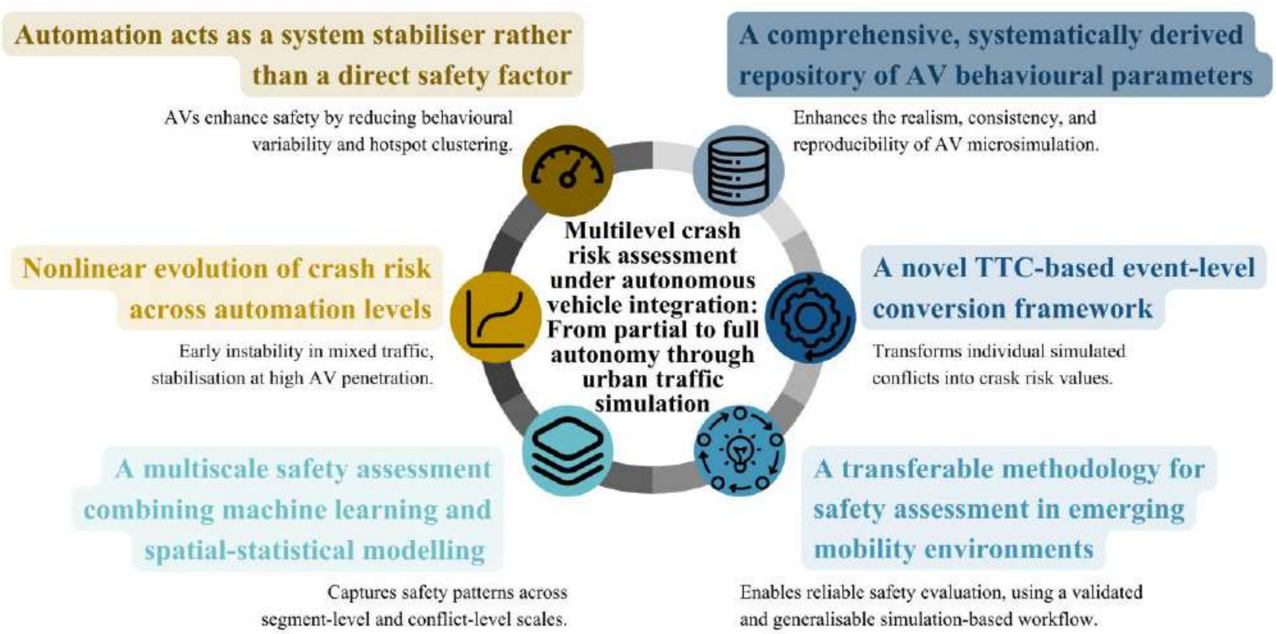


Figure 8: Innovative contributions of the thesis