A Multilevel Integrated Assessment of Safe and Green Mobility

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Outline

1. Research Motivation
2. Systematic Literature Review & Research Questions
3. Methodological Framework & Data Collection
4. Pattern Identification of Safe & Green Mobility
5. Joint Modeling of Safe & Green Driving
6. Sustainable Driving Efficiency Assessment
7. Main Research Findings
8. Innovative Contributions & Challenges

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Sustainable Mobility

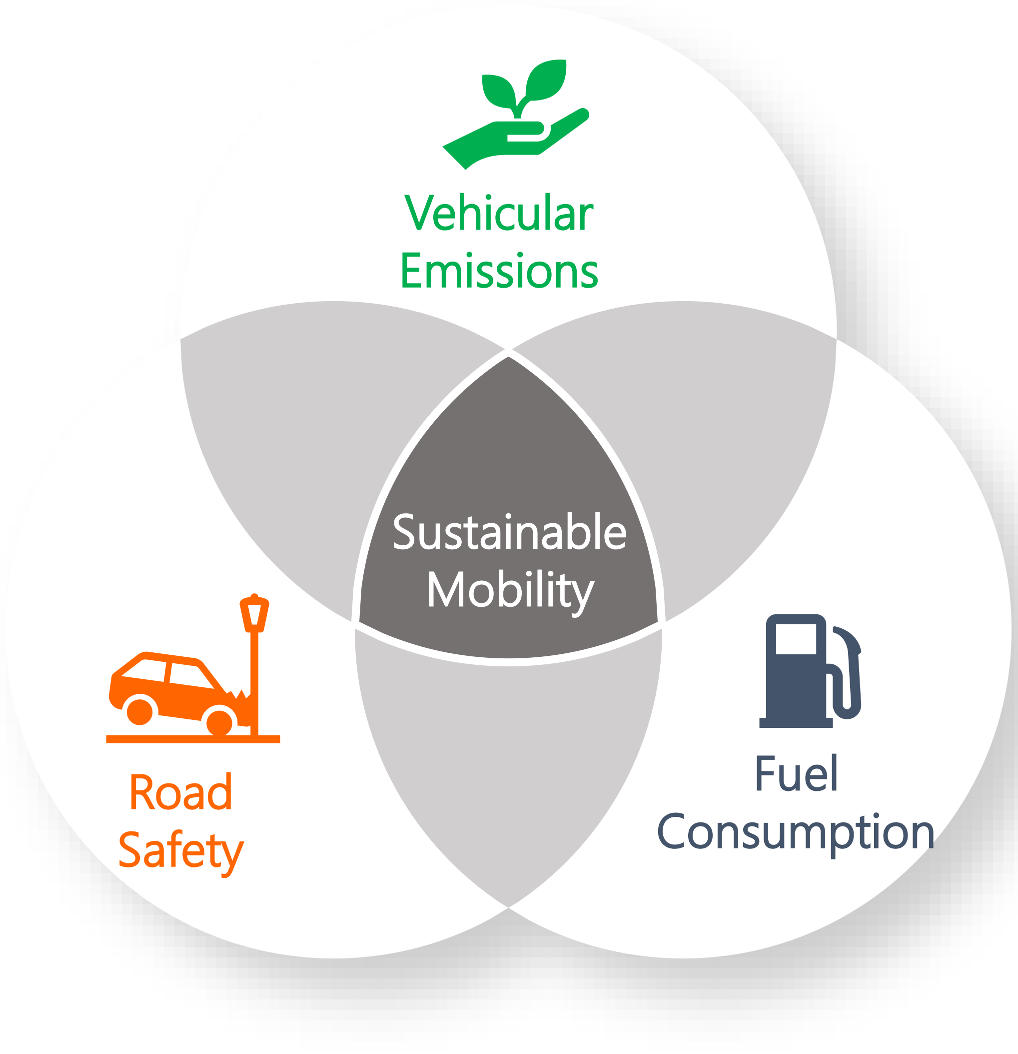
- Sustainable mobility is grounded in the broader definition of **sustainable development** (WCED, 1987)

  "Sustainable Development should meet the needs of the present without compromising the ability of future generations to meet their own needs"

- This framework identifies **three interrelated dimensions**:
  1. economic sustainability
  2. environmental sustainability
  3. social sustainability

- Both the UN and EC define **sustainable transport** as mobility with minimal greenhouse gas emissions and environmental impacts, safety, affordability, and equal access for all users

- However, most existing methodologies have attempted to address these mobility dimensions **individually**, despite the potential synergies and trade-offs that might be uncovered when addressing them jointly



Road Transport Externalities

The increasing reliance on road passenger transport, which accounts for **~ 72%** of all trips, poses significant **challenges for sustainable mobility**

Road Safety

- Road crashes constitute a major public **health issue**
- **1.19 million road fatalities** per year globally

Vehicular Emissions

- transport sector is responsible for about **25%** of the EU's total CO_2 emissions
- **72%** of which come from road transport

Fuel Consumption

- transport sector is responsible for **31%** of the EU's total energy consumption
- **74%** of which comes from road transport

Driving behavior constitutes the most critical factor

- human error responsible for 94% of crashes
- impact on energy consumption and emissions by up to 40%

Dissertation Objective

The multilevel integrated assessment of safe and green mobility

Across levels

from individual trips

to the road network

By fusing

- road infrastructure
- traffic
- weather-related data

with high-resolution naturalistic driving behavior data

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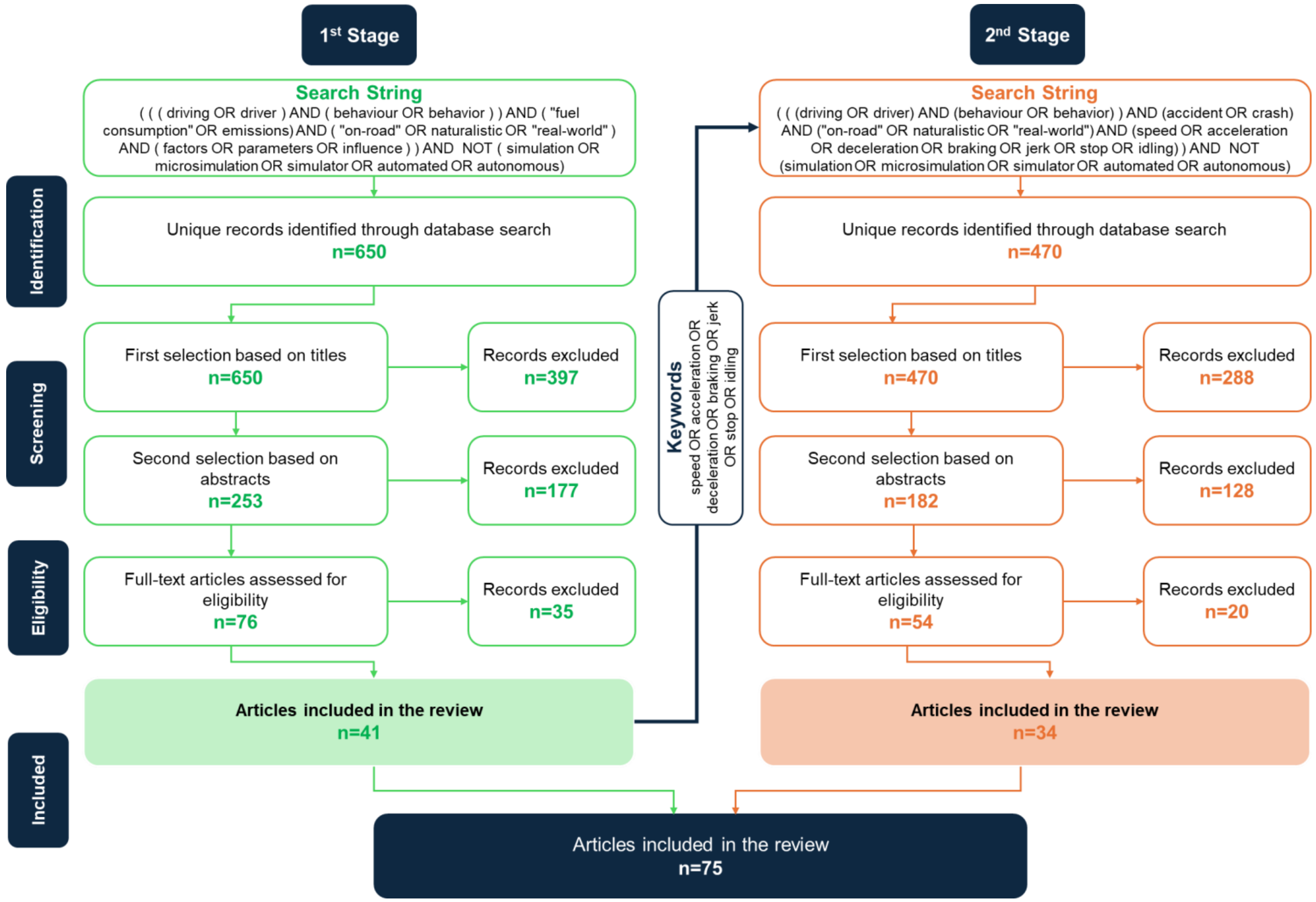
Review Objectives & Methodology

Objectives

- **Factors that simultaneously influence** safety, fuel consumption, and emissions
- **Synergies and trade-offs** between safe and fuel-efficient driving behavior

Methodology

- **PRISMA** method
- **Two-stage** search strategy:
  - **First stage** identifies driving behavior factors affecting fuel consumption and emissions
  - **Second stage** examines their impact on road safety
- **75 articles** included in the review



Common Factors

➢ **Driving behavior as the dominant mechanism**

- 32 driving behavior-related and external factors across road, traffic, and weather conditions were found to jointly influence crashes, fuel consumption, and emissions
- Driving behavior–related factors constitute the dominant determinant of both safety and environmental outcomes

➢ **Core common driving behavior factors**

Several metrics of speed, acceleration, driving volatility, and stop-go behavior consistently influence both crash risk and fuel use

➢ **Speed as a key trade-off factor**

- Moderate driving speeds optimize fuel efficiency, but do not necessarily minimize crash risk
- Lower speeds may reduce crash risk but can increase fuel inefficiency

➢ **Context dependency**

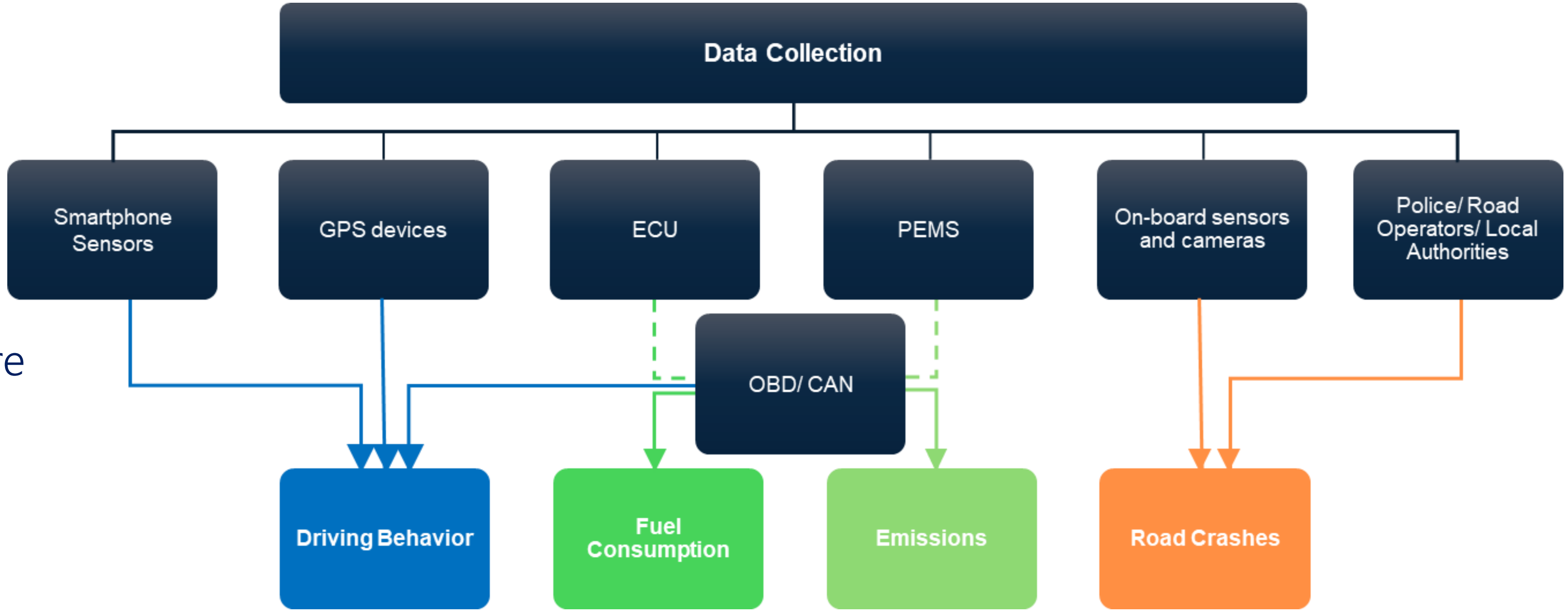
Effects vary by traffic, road type, and environment, highlighting the need for integrated and context-aware analysis

	Factor	Factor Direction	Road Crash Probability	Fuel Consumption	Emissions
Driving-related	Driving Speed	0-50 km/h ▲	- (reference)	▲	▲
		50-70 km/h ▲	▲	optimum	optimum
		>70 km/h ▲	▲	▲	▲
	Driving Volatility	▼	▼	▼	▼
	Harsh Acceleration & Deceleration	▼	▼	▼	▼
	Stopping	▼	▼	▼	▼
Context-related	Traffic Congestion	▼	▼ (▲ severity)	▼	▼
	Road Slope	▲	▲	▲	▲
	Urban areas	▲	▲	▲	▲
	Signalized intersections	▲	▲	▲	▲

Data Collection Methods

- Both safety and efficiency studies rely on GPS, OBD, and smartphone sensors **to capture driving behavior**

- Fuel, emissions, and crash data are costly and time-intensive, with high-accuracy tools (e.g., PEMS, crash records) **requiring substantial resources**



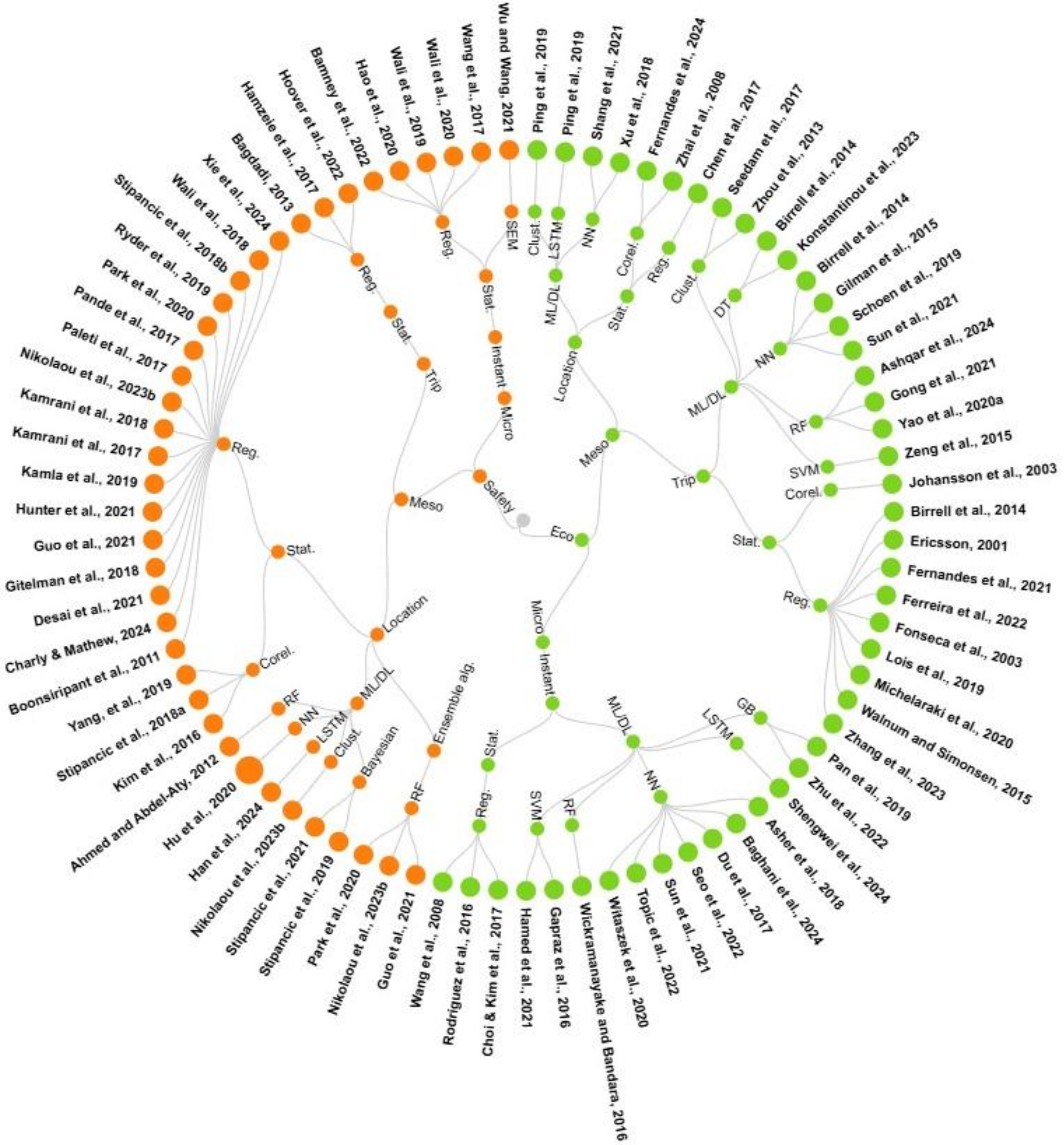
- While PEMS and ECU/OBD provide high-accuracy, vehicle-specific fuel and emissions data, **physics-based models** enable scalable and cost-efficient estimation across larger networks

- Low crash frequency leads to the use of **Surrogate Safety Measures** (SSMs), with several indicators derivable from smartphone and GPS-based driving data

- Thus, smartphone and GPS data can be leveraged to derive both fuel/emissions and surrogate safety measures, enabling large-scale, and **integrated eco-safety systems**

Modeling Approaches

- Approaches span **microscopic** (second-by-second behavior) and **mesoscopic** (trip/location-level aggregation) analyses
- **Microscopic models** capture detailed dynamics (speed, acceleration, jerk) for fuel and crash prediction, but face computational scalability limits
- **Mesoscopic models** aggregate micro-level data to assess performance across trips or networks with greater computational efficiency
- **Road safety** relies on statistical models (Poisson, NB, logistic), while eco-related studies increasingly adopt ML and DL methods



Research Questions

RQ1

How can driving behavior, road infrastructure, road crashes, traffic, and weather **datasets be fused to enable the integrated assessment** of safe and green mobility at trip and spatial levels?

RQ2

How can sustainable trip patterns be identified by integrating SSMs and fuel consumption? Is it possible to predict and explain them through behavioral and contextual features?

RQ3

How can crash risk and fuel consumption hotspot spatial patterns be systematically identified and spatially compared across road junctions?

RQ4

How can safe and green driving outcomes be jointly modeled at the trip and road segment levels? Do they share common mechanisms that explain their divergence, or co-occurrence?

RQ5

How can sustainable driving efficiency be assessed at the trip level, by integrating safety, fuel consumption, and travel time, and translated into road efficiency?

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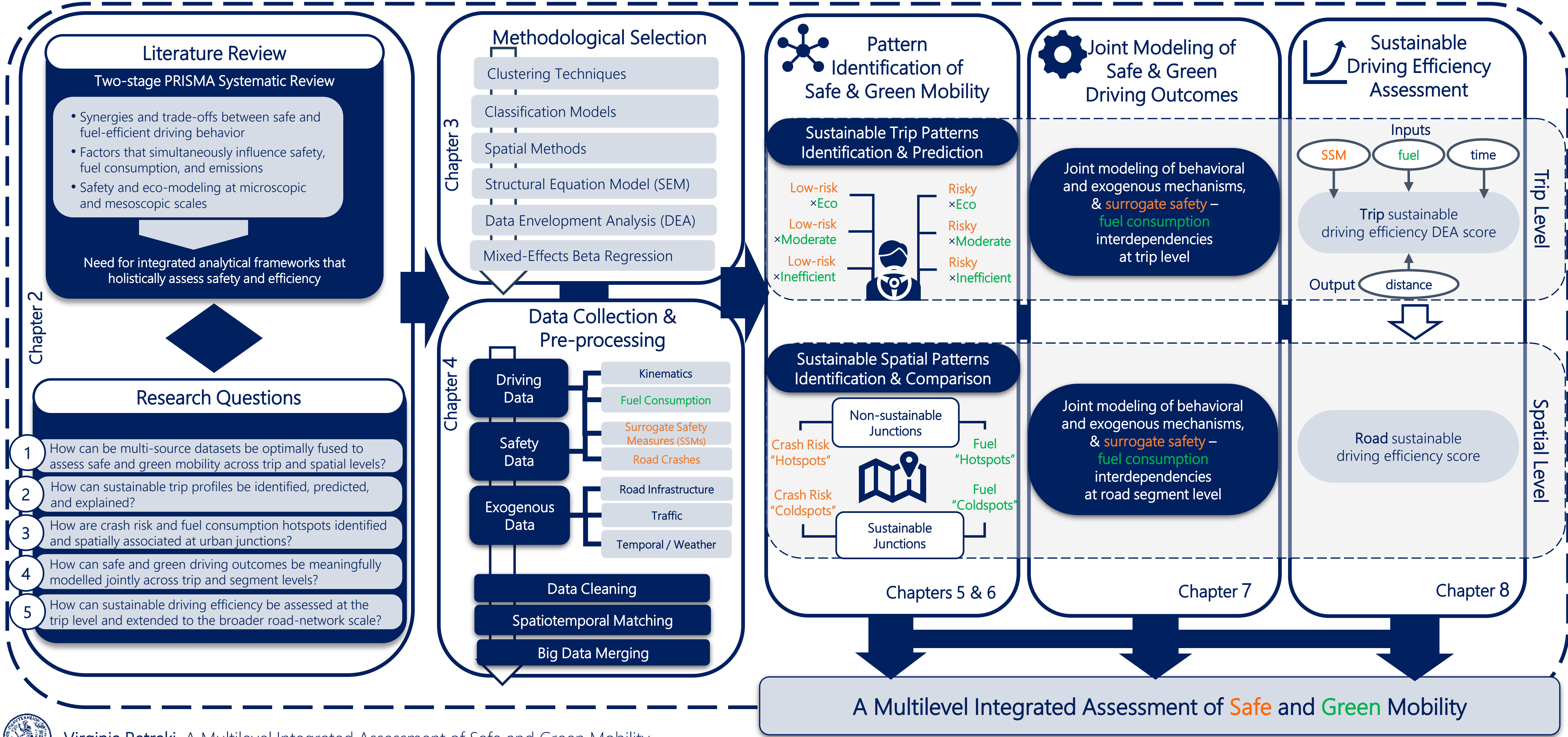
The Framework



Data Collection

Naturalistic Driving Data

- Naturalistic high-resolution driving data was obtained through an advanced system developed by **OSeven Telematics**, which collects individualized driving analytics in real time through smartphone sensors

- All data are received from OSeven in an **anonymized form** (GDPR)

- The data gathered from **March to May** during the year 2024, for the Attica Region, Greece

Number of trips	**Driving time** (seconds)	**Driving distance** (kilometers)
35,637	37,231,697	319,482

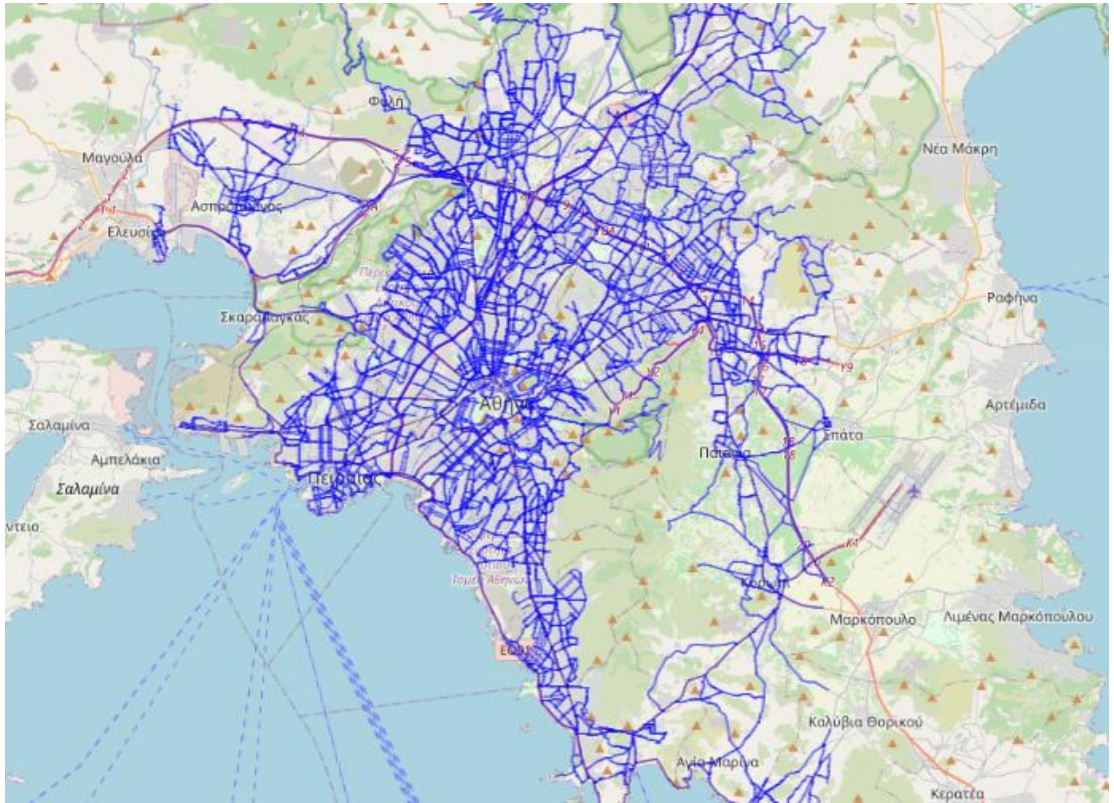
- Advanced ML and processing algorithms **detect SSMs** such as speeding, harsh events, and mobile phone use

- **New parameters are generated** based on high-resolution driving speed such as vehicular jerk, cruise speed and stops

The OSeven data flow system

Source: OSeven Telematics

The road network with driving data [Attica Region]



Fuel Consumption

- High resolution telematics kinematics data utilized to calculate fuel consumption through **Virginia Tech Comprehensive Power-Based Fuel Consumption Model** (VT-CPFM) **(Rakha et al., 2011)**

- Instantaneous fuel consumption (L/s) is computed as a quadratic function of **instantaneous power** $P(t)$**,** which is derived from vehicle resistances (aerodynamic, rolling, and grade) and speed

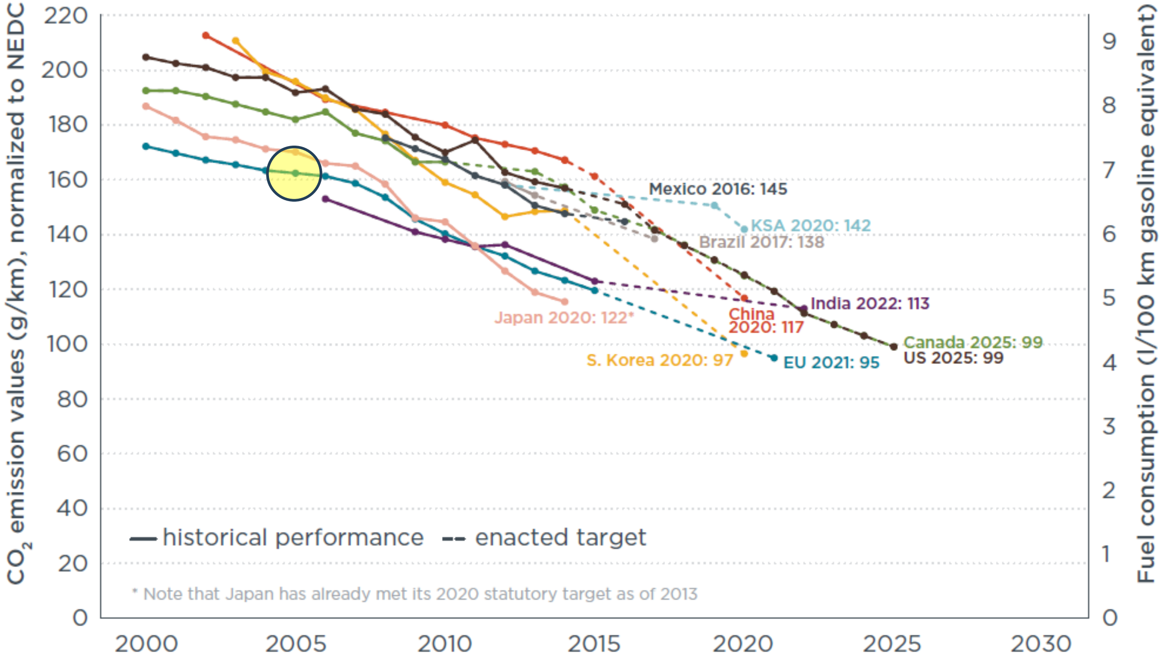
- **It was chosen**:
  - for its simplicity, and accuracy (up to 7% error),
  - for the need for the fewer vehicle-specific fields and easy calibration using publicly available data like WLTP

- **Representative vehicle**
  - Due to GDPR restrictions, driver-specific vehicle parameters were not available
  - Representative vehicle: 17-year-old gasoline passenger car in Greece **(ACEA, 2022)**
  - Fuel efficiency (WLTP): FE_city = 7.5 L/100 km
    FE_hwy = 5.5 L/100 km

$$\boldsymbol{FC(t)} = \begin{cases} \boldsymbol{a_0 + a_1 \times P(t) + a_2 \times P(t)^2, if\ P(t) \geq 0} \\ \boldsymbol{a_0\ , if\ P(t) < 0} \end{cases}$$

Instantaneous Power: $P(t) = \left(R(t) + \frac{1.04 \times m \times a(t)}{3{,}600 \times \eta_d} \times v(t) \right)$

Instantaneous Resistance: $R(t) = R_{aero}(t) + R_{roll}(t) + R_{grade}(t)$



Road Network Data

Road network characteristics and geometry at a microscopic level **derived from digital maps**

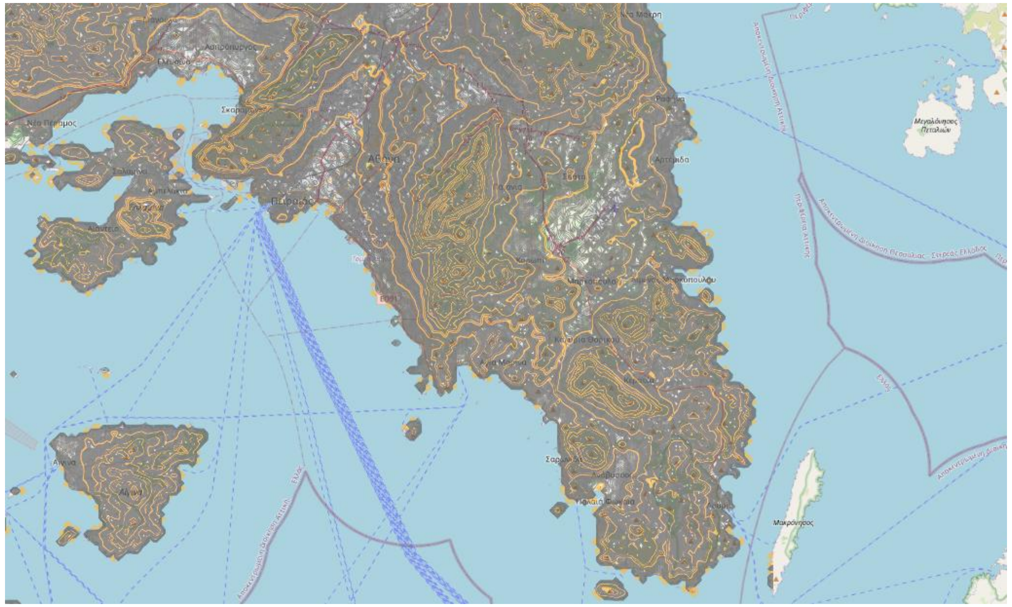
OpenStreetMap: a free, open map database

- Basic data structures: nodes → road junctions
  ways → road segments
- Dynamic **bounding box** from GPS telematics trajectories used to extract drivable road network (nodes & ways) characteristics via python library OSMnx
- Each road segment is defined by **unique identifiers**: u (origin node), v (destination node), key (edge key), and osmid (unique edge ID)

Mapzen Global Terrain: an open-source Digital Elevation Model

- Mapzen DEM is compiled **from NASA SRTM** and other open datasets
- It loaded in QGIS and resampled from 30 m to 1 m to improve surface continuity and enable finer-scale spatial analyses
- For each road segment, the road grade was calculated from the elevation difference **between its start and end nodes**

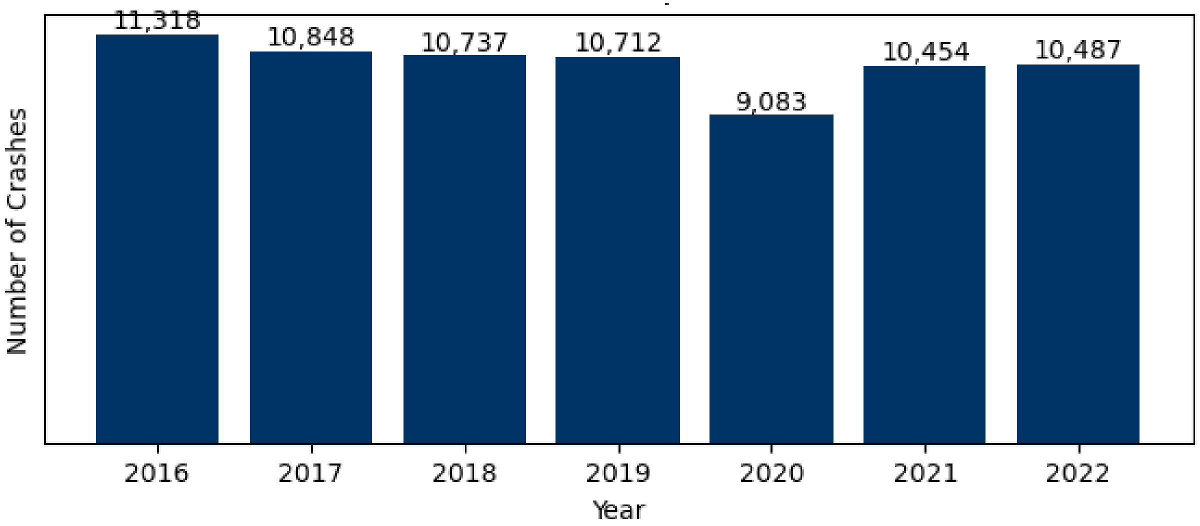
Road Class	**Number of Segments**	**Share** (%)	**Mean Length** (m)	**Oneway** (%)
residential	17,495	50.2	76	61.5
tertiary	7,751	22.2	75	63.1
secondary	5,053	14.5	86	78.2
primary	2,850	8.2	107	88.0
motorway	559	1.6	456	99.6
trunk	507	1.4	195	98.4
unclassified	610	1.7	201	33.0



Vizualization: QGIS

Road Crash Data

- Crash data exploited in this dissertation is collected from the Police and subsequently coded into the **National Road Crash Database** maintained by the Hellenic Statistical Authority
- The database records road crashes **involving at least one** injured (slightly or seriously) or fatally injured road user
- **Study area:** Attica Region
- **Study period:** 2016-2022 with 73,639 total recorded crashes
- **Unique crash identification** ensured using the year, the month and the CRASH_ID
- **Road identifiers** used to assign crashes to specific junctions
- **Segment-only crashes excluded** to avoid spatial ambiguity and ensure reliable junction-level analysis



Variable Name	Description
CRASH_ID	Five-digit crash identifier, unique within each year and month.
GEOCODE_ACC_CL	Ten-digit geographic code identifying the administrative unit of the crash location. From 2016 onward, the administrative classification follows the Kallikratis reform.
CODE_STREET_CL	Four-digit code identifying the main road where the crash occurred.
CODE_STREET_DIAST_CL	Four-digit code identifying the intersecting road at the crash location.

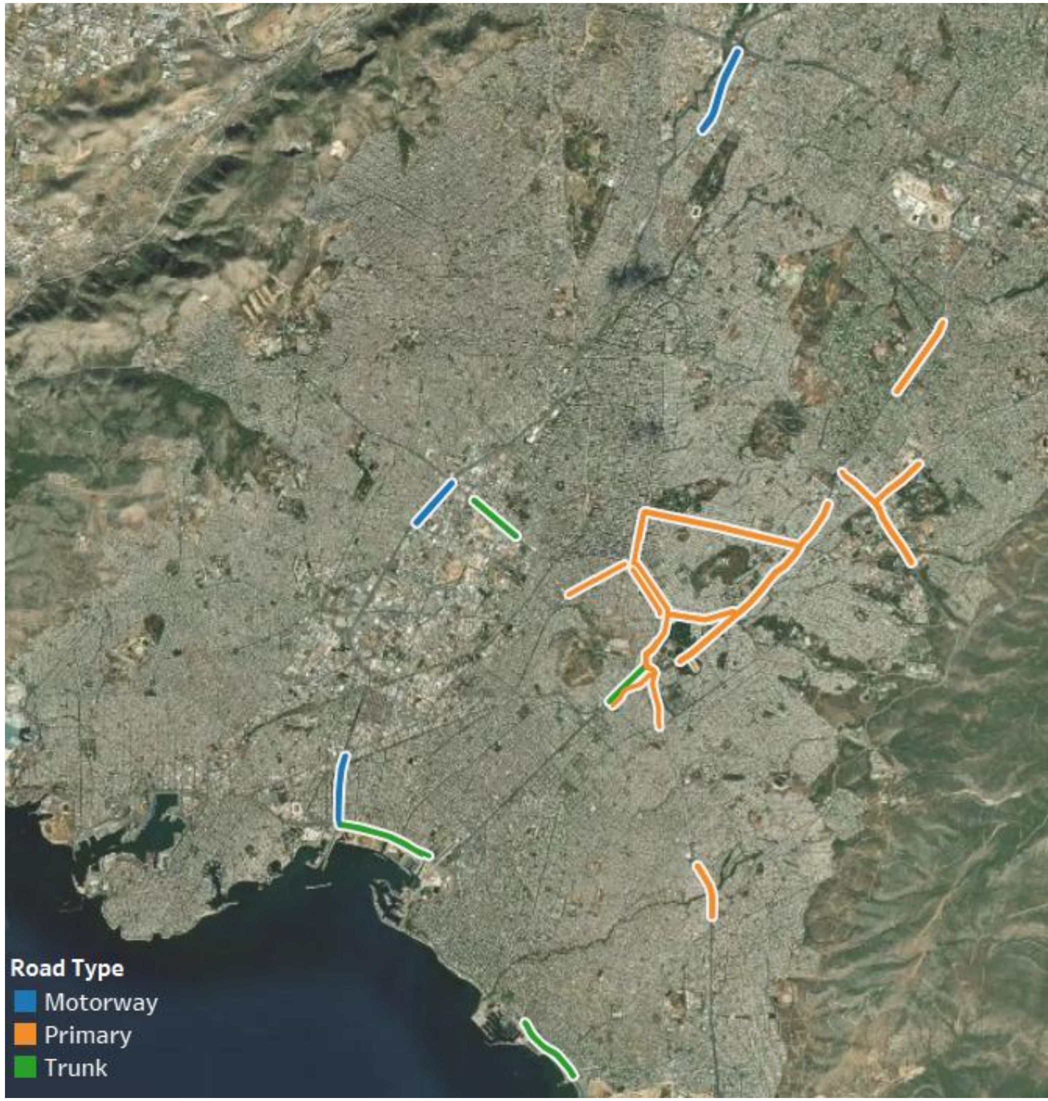
Traffic Data

- Traffic speed data collected every 20 minutes via **Google Maps Directions API** from March to May 2024
- **42 key routes in Attica** Region analyzed (central roads, entry/exit points, ring road)
- Routes categorized by OSM road class: **motorways, trunk, and primary roads**
- Data collection followed a time-of-day schedule to capture **typical travel demand patterns**
  - Weekdays: 08:00–18:40
  - Saturdays: 12:00–18:40 and 21:00–23:40
  - Sundays: 12:00–18:40
- **Congestion index** calculated based on deviation from reference speed (95th percentile)

$$congestion\_index = 1 - \frac{v}{v_{95}} \quad , \text{if } v < v_{95}$$

$$congestion\_index = 0 \quad , \text{if } v > v_{95}$$

Index ranges from 0 (low congestion) to 1 (high congestion)



Vizualization: Tableau

Weather Data

- **Hourly weather conditions** were collected via Open-Meteo for the station in Athens, Greece (location: latitude 37.996483, longitude 23.709677)

- **Key variables used**:

Variable	**Description**
is_day	Binary indicator of daytime conditions (1 = day, 0 = night)
temperature_2m	Air temperature at 2 meters above ground, expressed in degrees Celsius (^{o}C)
relative_humidity_2m_pct	Relative humidity during the trip, expressed as a percentage
rain_mm	Precipitation depth in millimeters

- Weather data **temporally matched** with driving observations

- **Aggregated to trip-level and road segment-level** based on timestamps

Research Question 1

How can driving behavior, road infrastructure, road crashes, traffic, and weather **datasets be fused to enable the integrated assessment** of safe and green mobility at trip and spatial levels?

RQ1

RQ2

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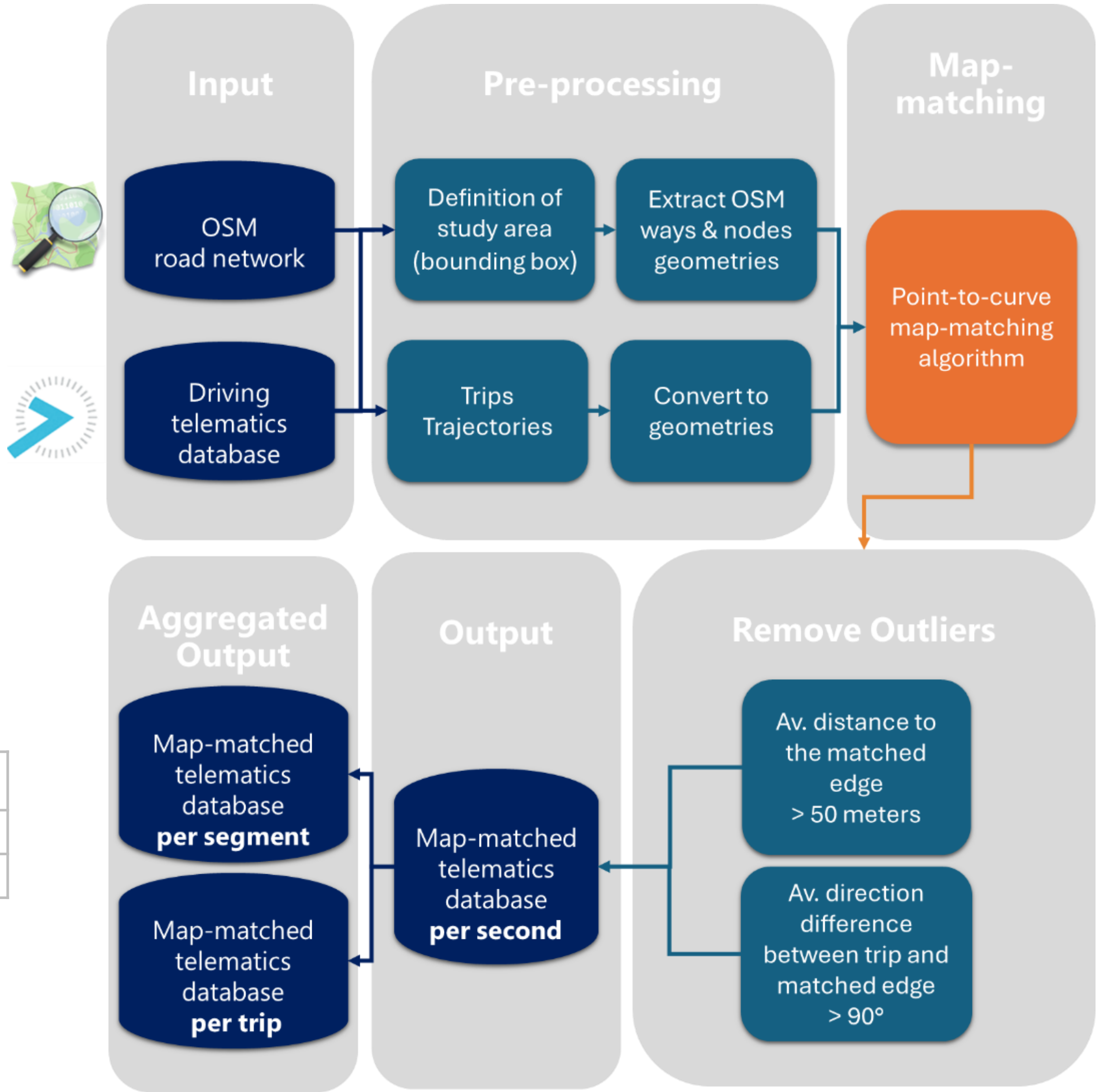
Naturalistic Driving Data Map-matching

Naturalistic driving data map-matching **converts driving trajectories into a network-referenced dataset** by assigning each one-second driving observation to a road segment

- **Input**: OSM road network and naturalistic driving trajectories
- **Pre-processing**: Define study area, extract network, and convert trajectories to spatial geometries
- **Map-matching**: Assign each GPS observation to the nearest road segment using a point-to-curve algorithm
- **Outlier removal**: Filter observations based on distance (<50 m) and directional consistency (angle difference <90°)
- **Output**: Map-matched dataset at per-second level

	mean	std	min	Q25	median	Q75	max
Seconds per road segment	743.4	2,584.1	1.0	16.0	88.0	478.0	139,958.0
Unique Trips per road segment	52.3	99.5	1.0	5.0	18.0	56.0	1,821.0

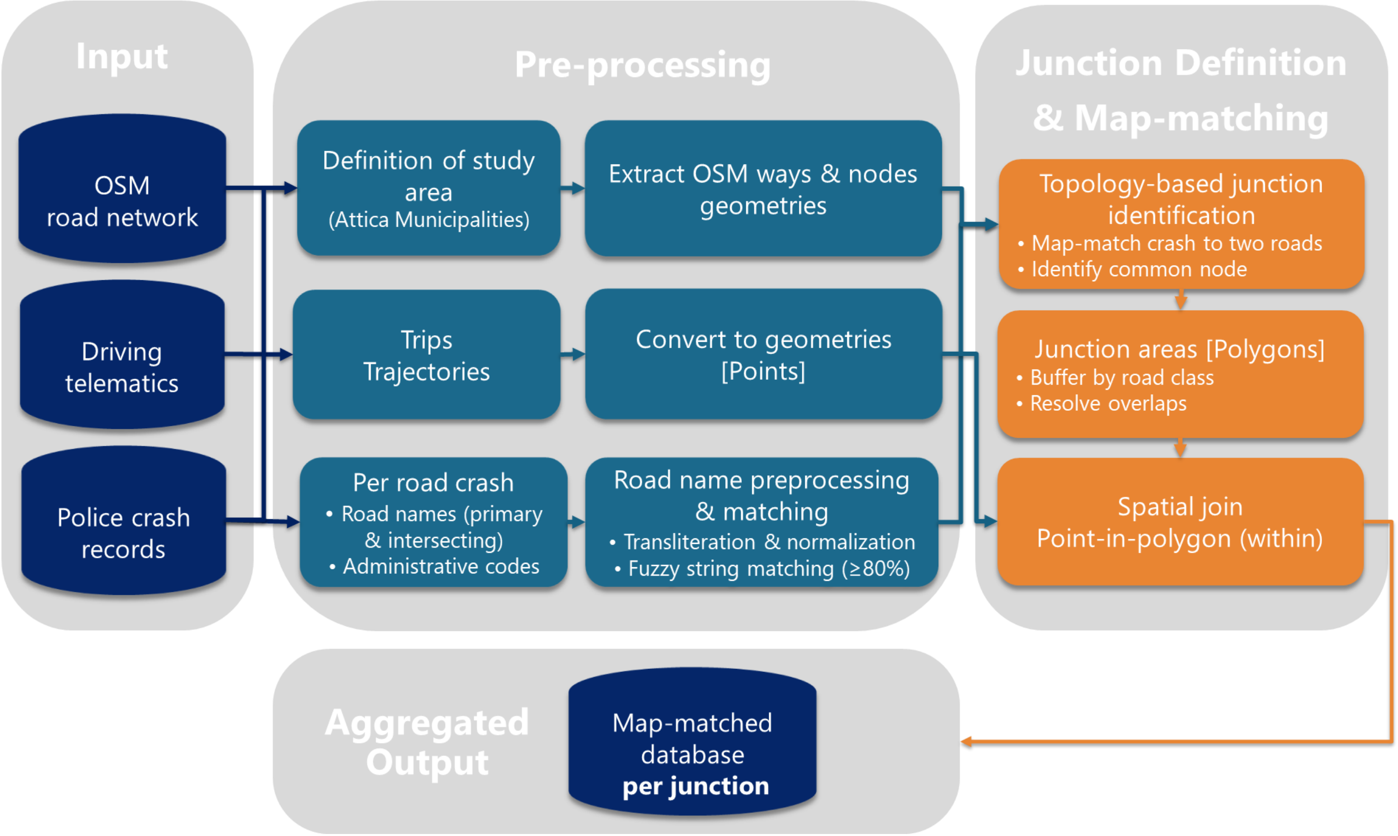
- **Aggregation**: Data aggregated per trip and per road segment for analysis



Crash Map-matching

Spatial attribution of crash records to junctions using a topology-based map-matching framework

- **Input:** OSM road network, driving trajectories, and police crash records
- **Pre-processing:**
  - Extraction of the drivable OSM road network per municipality to ensure consistency with the analysis
  - Conversion of trajectories (driving seconds) to spatial geometries (Points)
  - Standardization and fuzzy matching of road names to align crash records with OSM nomenclature
- **Junction definition & Map-matching:**
  - **Crashes were map-matched** to main and intersecting OSM road segments [u, v], and the common node between them was identified and assigned as the junction location
  - **Junctions were converted from points to areas** using buffers based on road hierarchy (20–50 m)
  - **Overlapping buffers** were merged using spatial criteria (Minimum Overlap Ratio and Intersection Over Union) to avoid double counting
  - Driving behavior and fuel data were **spatially joined to junction areas**

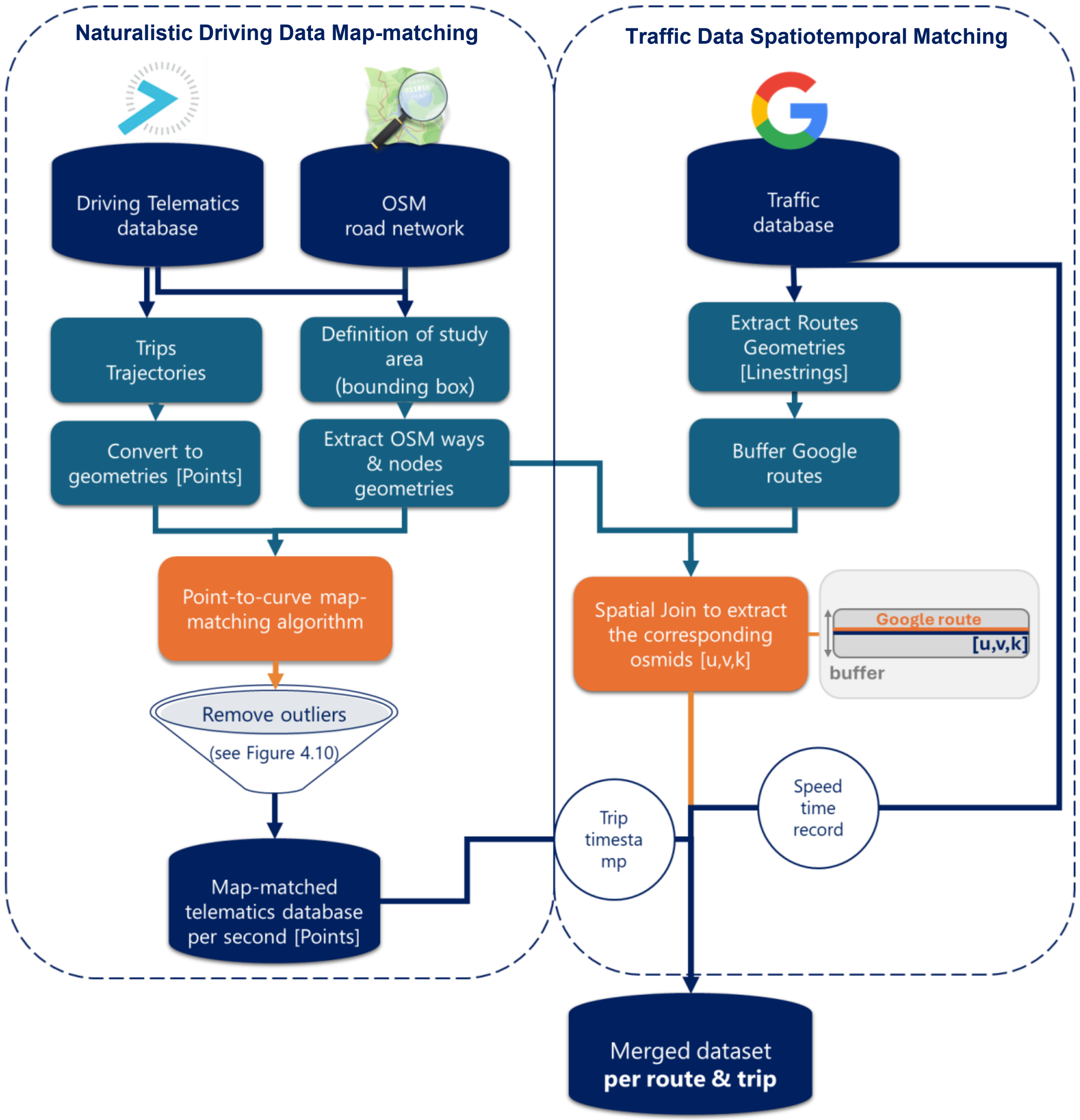


Traffic Data Spatiotemporal Matching

RQ1

Integration of driving telematics and traffic data through a spatiotemporal matching process

- **Naturalistic Driving Data Map-matching:** Map-matched trajectories aligned to the road network (left side of framework)
- **Route processing:** Google route geometries extracted and buffered (10 m) to define spatial proximity
- **Spatial matching:** OSM road segments [u, v, k] linked to each route via spatial join
- **Data linkage:** Telematics points assigned to routes based on matched road segments
- **Temporal matching:** Telematics data aligned with Google speed data using timestamps within a ±10-minute window
- **Output:** 8,725 trips successfully matched to 42 routes from a total of 32,815 map-matched trips



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Trip Level | Spatial Level

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1st Module

Research Question 2

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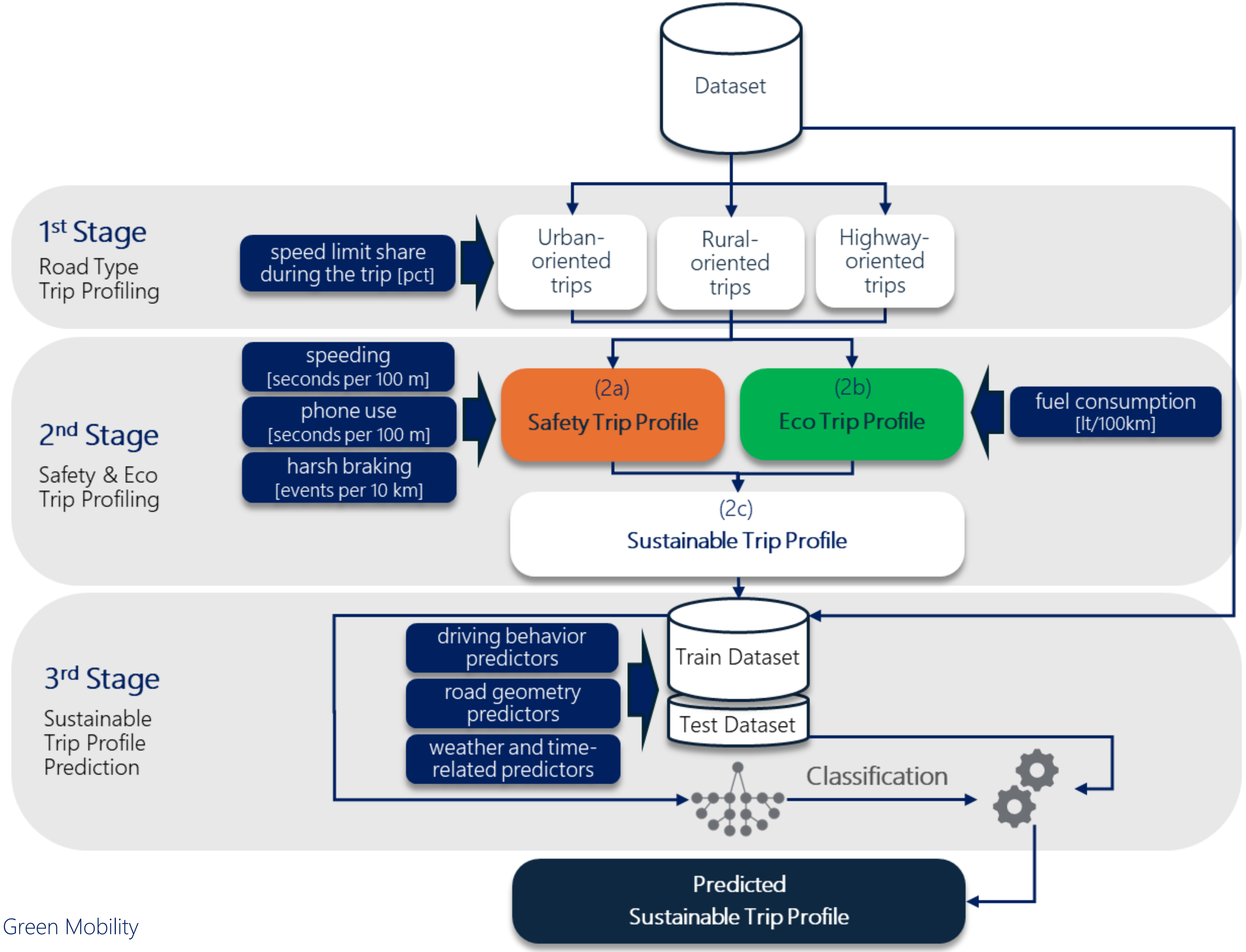
Module 1 – Trip Level Approach

RQ2

Approach

The approach is structured into **3 sequential analytical stages**

- ➢ **1st Stage**
  Trips are categorized based on the share of time spent on each road type
- ➢ **2nd Stage**
  Trips are further categorized:
  - 2ª into road safety profiles
  - 2ᵇ into energy efficiency profiles
  - 2ᶜ and subsequently combined into sustainable trip profiles
- ➢ **3rd Stage**
  The identified sustainability patterns are then predicted



1st Stage – Road Type Trip Profiling

RQ2

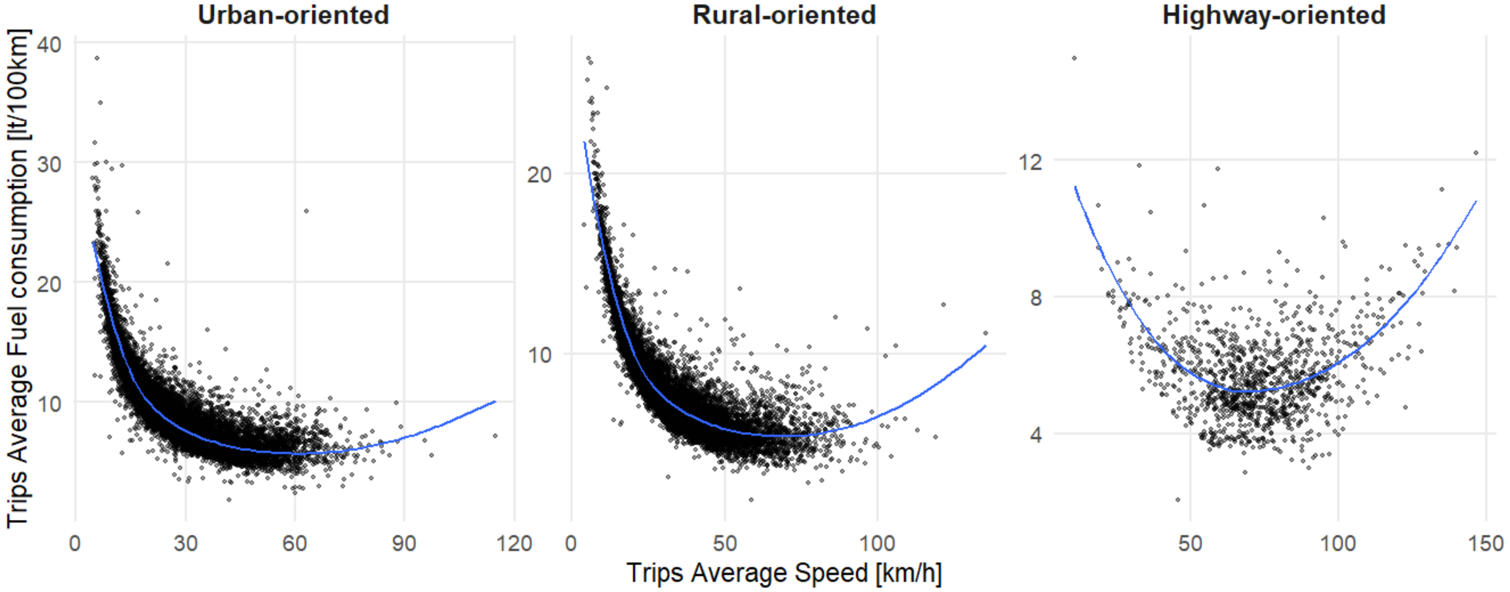
- A rule-based approach assigns each trip to the road type in which it spends **the largest share of driving time**

  Urban road → speed limit< 50 km/h
  Rural road → speed limit = 50-80 km/h
  Highway → speed limit >80 km/h

- **Urban-oriented trips:**
  highest fuel consumption & riskier driving

- **Highway-oriented trips:**
  lowest fuel consumption & more stable driving

- **Fuel consumption follows a U-shaped relationship with driving speed:**
  extremely low & high average trip speeds increase fuel consumption



Road Type Trip Profile	Number of trips	Mean Values						
		Urban share (%)	Rural share (%)	Highway share (%)	Fuel Consumption (L/100km)	Harsh Brakings per 10 km	Mobile Usage per 100 m	Speeding per 100m
Urban-oriented	20,744	76.7	21.9	1.5	9.5	2.0	0.9	0.5
Rural-oriented	10,940	31.5	66.0	2.5	8.2	1.7	0.7	0.4
Highway-oriented	1,104	20.1	19.0	60.1	5.7	0.5	0.3	0.5

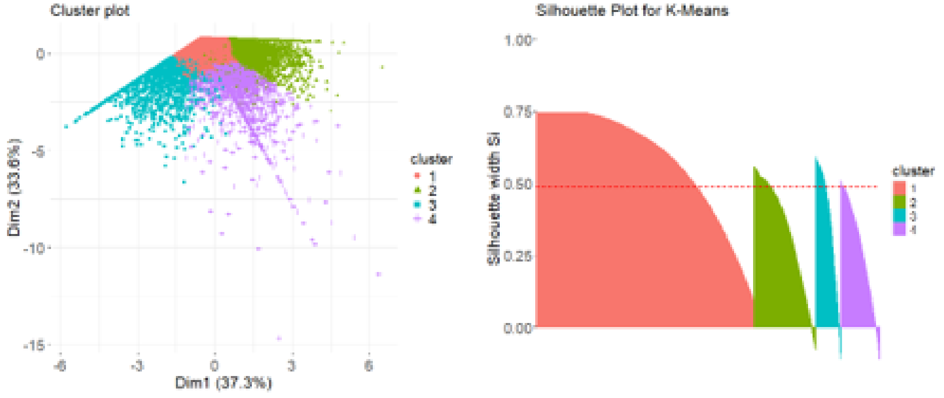
2ª Stage – Safety Trip Profiling

RQ2

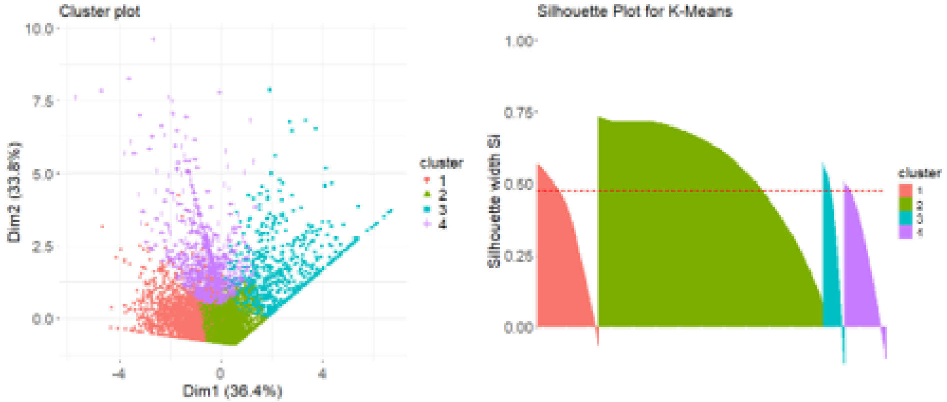
- **K-means clustering** using SSMs: 4 optimal clusters identified - average silhouette widths ranging from 0.474 for rural-oriented trips to 0.492 for highway-oriented trips
- Clusters reflect distinct safety-related behaviors based on **harsh braking, mobile use and speeding rates**
- **Identified profiles**: (1) Low-risk*, (2) Speeding, (3) Distracted, and (4) Aggressive

	Safety Trip Profile	Harsh Brakings per 10 km	Speeding per 100m	Mobile Usage per 100 m	Number of trips	Share (%)	Average Silhouette width
			Urban-oriented trips				
1	**Low-risk**	0.000	1.209	0.000	13,145	63%	0.58
2	**Speeding**	0.145	15.475	0.000	3,739	18%	0.33
3	**Distracted**	0.000	0.337	6.778	1,502	7%	0.37
4	**Aggressive**	0.688	2.299	0.000	2,358	11%	0.27
			Rural-oriented trips				
1	**Speeding**	0.135	12.692	0.000	1,916	18%	0.35
2	**Low-risk**	0.065	1.342	0.000	7,057	65%	0.56
3	**Distracted**	0.097	0.221	5.452	668	6%	0.33
4	**Aggressive**	0.542	1.240	0.000	1,299	12%	0.27
			Highway-oriented trips				
1	**Speeding**	0.034	13.343	0.000	184	17%	0.37
2	**Distracted**	0.040	4.448	2.319	61	6%	0.23
3	**Aggressive**	0.191	5.417	0.000	92	8%	0.24
4	**Low-risk**	0.000	2.254	0.000	767	69%	0.57

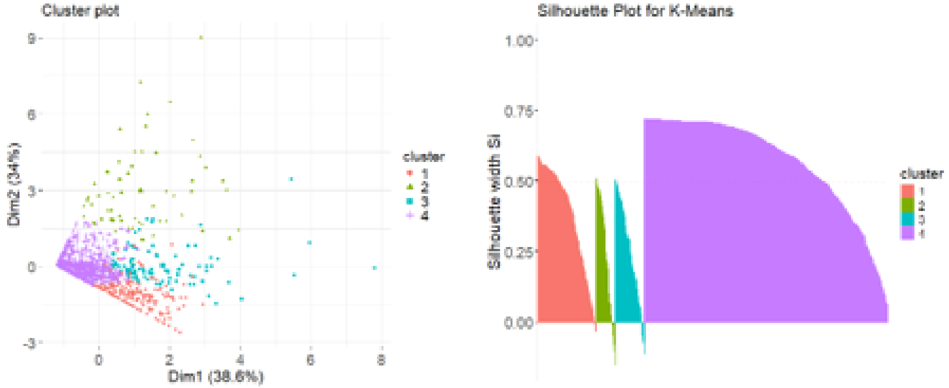
Urban-oriented trips



Rural-oriented trips



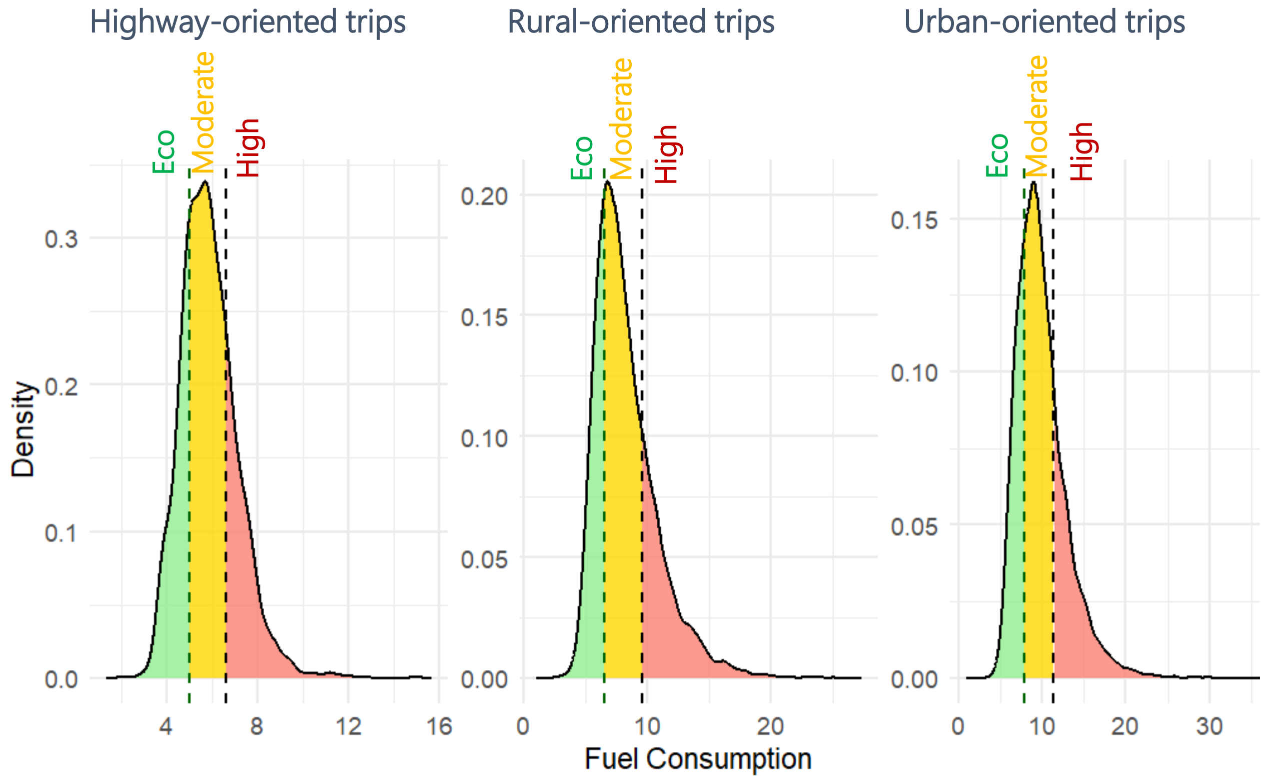
Highway-oriented trips



2^b Stage – Eco Trip Profiling

RQ2

- As a next step, trip profiles were identified based on their fuel-efficiency **across different road types**
- 3 eco trip profiles were identified based on **fuel consumption percentiles**

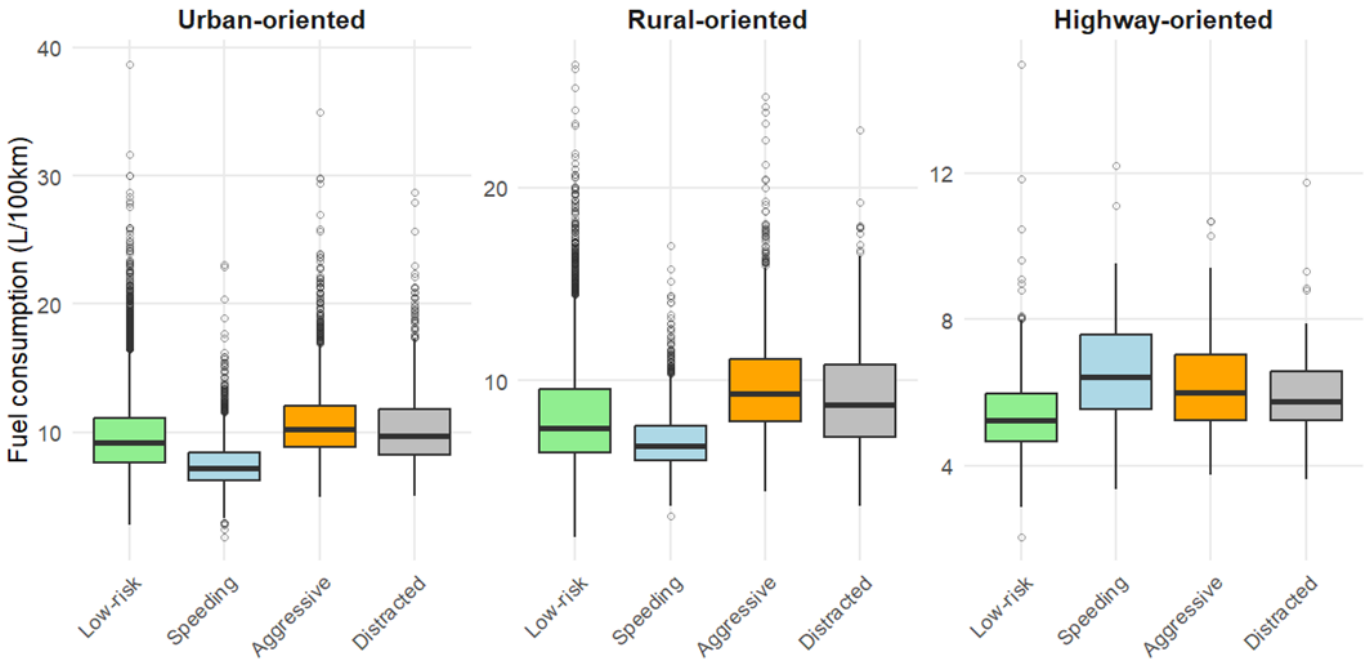


Road Type Trip Profile	Eco Trip Profiles		Number of trips	Median Fuel Consumption per trip (L/100km)
Highway-oriented trips	1	**Eco**	276	4.39
	2	**Moderate**	552	5.53
	3	**Inefficient**	276	7.12
Rural-oriented trips	4	**Eco**	2,735	5.61
	5	**Moderate**	5,470	7.57
	6	**Inefficient**	2,735	11.20
Urban-oriented trips	7	**Eco**	5,186	6.49
	8	**Moderate**	10,372	8.96
	9	**Inefficient**	5,186	12.70

2c Stage – Sustainable Trip Profiling

Descriptive Analysis

- **One way ANOVA** shows significant fuel consumption differences across safety trip profiles $p < 0.001$ across all road contexts
- **Tukey Honestly Significant Difference (THSD) test** confirms "Aggressive" trips consume up to +1.64 L / 100 km more than "Low-risk"
- **"Distracted" trips** also show higher fuel use up to +1.01 L / 100 km compared to "Low-risk"
- **"Speeding" exhibits context dependent trade-offs** with lower fuel consumption in urban and rural contexts but higher on highways +1.25 L/ 100 km
- **"Low-risk trips" consistently show lowest fuel** consumption indicating most sustainable driving behavior



2c Stage – Sustainable Trip Profiling

RQ2

Sustainable Trip Profiles Development

- Safety and eco profiles **combined into 12 detailed sustainable trip profiles** capturing behavior and fuel interactions
- Due to class imbalance safety profiles merged into “Low-risk” and “Risky” **reducing profiles to 6**
- Combined profiles reveal synergies and trade-offs between safety behavior and fuel efficiency
- “Low-risk x Eco” represents the **most sustainable profile** whereas “Risky x Inefficient” is the least sustainable
- **Trade-offs are evident** as “Risky x Eco” combines low fuel with unsafe behavior while “Low-risk x Inefficient” reflects safe but fuel-inefficient driving

	Detailed Sustainable Trip Profiles	Number of trips	Share (%)
1	Low-risk×Eco	4,847	14.8
2	Speeding×Eco	2,827	8.6
3	Aggressive×Eco	226	0.7
4	Distracted×Eco	297	0.9
5	Low-risk×Inefficient	5,450	16.6
6	Speeding×Inefficient	388	1.2
7	Aggressive Inefficient	1,562	4.8
8	Distracted×Inefficient	797	2.4
9	Low-risk×Moderate	10,672	32.5
10	Speeding×Moderate	2,624	8.0
11	Aggressive×Moderate	1,961	6.0
12	Distracted×Moderate	1,137	3.5

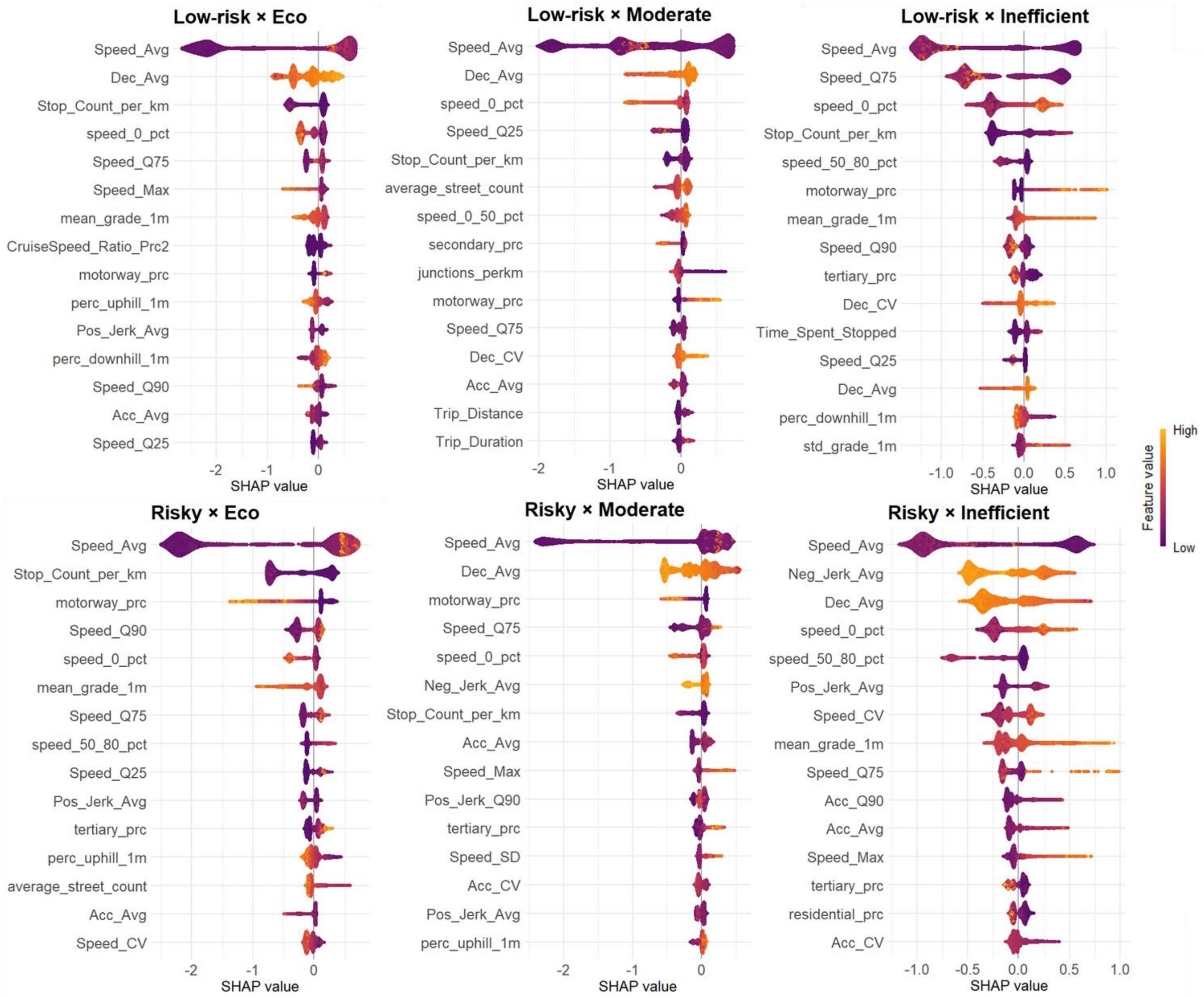
	Combined Sustainable Trip Profiles	Number of trips	Share (%)
1	Low-risk×Eco	4,847	14.8
2	Risky×Eco	3,350	10.2
3	Low-risk×Inefficient	5,450	16.6
4	Risky×Inefficient	2,747	8.4
5	Low-risk×Moderate	10,672	32.5
6	Risky×Moderate	5,722	17.5

3rd Stage – Prediction

RQ2

- **4 multinomial supervised classification models** including XGBoost, Random Forest, Decision Tree, and k-NN, aiming to predict the 6 identified sustainable trip profiles
- **ML predictors** include driving behavior road geometry traffic weather and temporal variables
- **XGBoost demonstrates the strongest overall performance**, achieving the highest overall test accuracy of 60% with macro-F1 of 59% and the lowest false alarm (8%)
- **SHAP analysis** was conducted to provide interpretable model outputs

1. **Low-risk×Eco**: Moderate speeds, few stops and smooth braking
2. **Risky×Inefficient**: Low speeds, frequent stops, high speed variability and steep grades
3. **Risky×Eco**: Higher speeds, limited stopping and lower motorway share
4. **Low-risk×Inefficient**: Low speeds, frequent stops and higher motorway share
5. **Low-risk×Moderate**: Lower speed regimes and frequent stopping
6. **Risky×Moderate**: Higher speeds and stronger braking

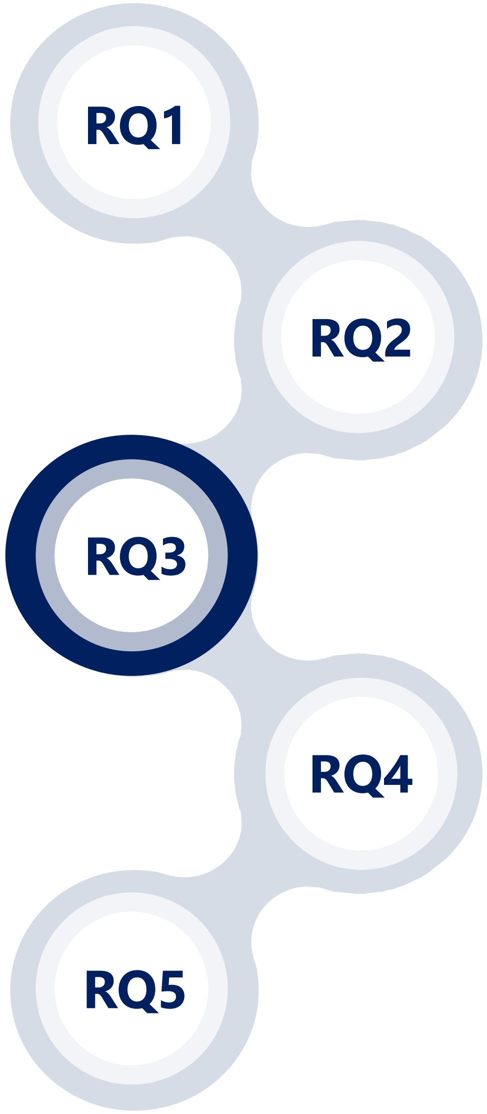


Research Motivation 1
Systematic Literature Review & Research Questions 2
Methodological Framework & Data Collection 3
Pattern Identification of Safe & Green Mobility 4
Trip Level
Spatial Level
Joint Modeling of Safe & Green Driving 5
Sustainable Driving Efficiency Assessment 6
Main Research Findings 7
Innovative Contributions & Challenges 8

1st Module

Research Question 3

How can driving behavior, road infrastructure, road crashes, traffic, and weather **datasets be fused to enable the integrated assessment** of safe and green mobility at trip and spatial levels?



How can sustainable trip patterns be identified by integrating SSMs and fuel consumption? Is it possible to predict and explain them through behavioral and contextual features?

How can crash risk and fuel consumption hotspot spatial patterns be systematically identified and spatially compared across road junctions?

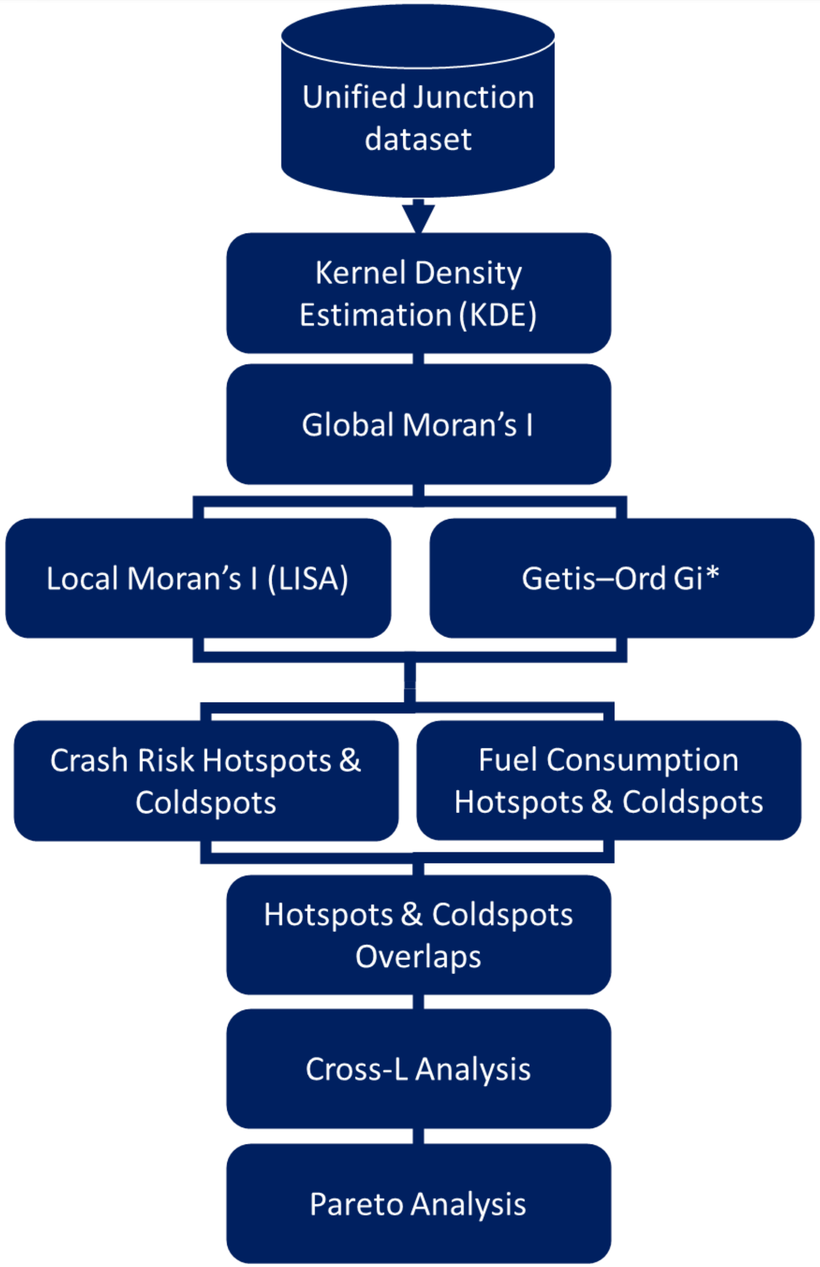
How can safe and green driving outcomes be jointly modeled at the trip and road segment levels? Do they share common mechanisms that explain their divergence, or co-occurrence?

How can sustainable driving efficiency be assessed at the trip level, by integrating safety, fuel consumption, and travel time, and translated into road efficiency?

Module 1 – Spatial Level Approach

RQ3

- ➢ **Kernel Density Estimation** to identify spatial distribution patterns
- ➢ **Global spatial analysis** using Moran's I to assess overall spatial autocorrelation
- ➢ **Local spatial analysis** using LISA and Getis–Ord Gi* to detect hotspots and coldspots
- ➢ **Cross type spatial analysis** to examine crash and fuel consumption spatial relationship
- ➢ **Pareto analysis** to identify the junctions presenting the best trade-offs between safety and fuel efficiency

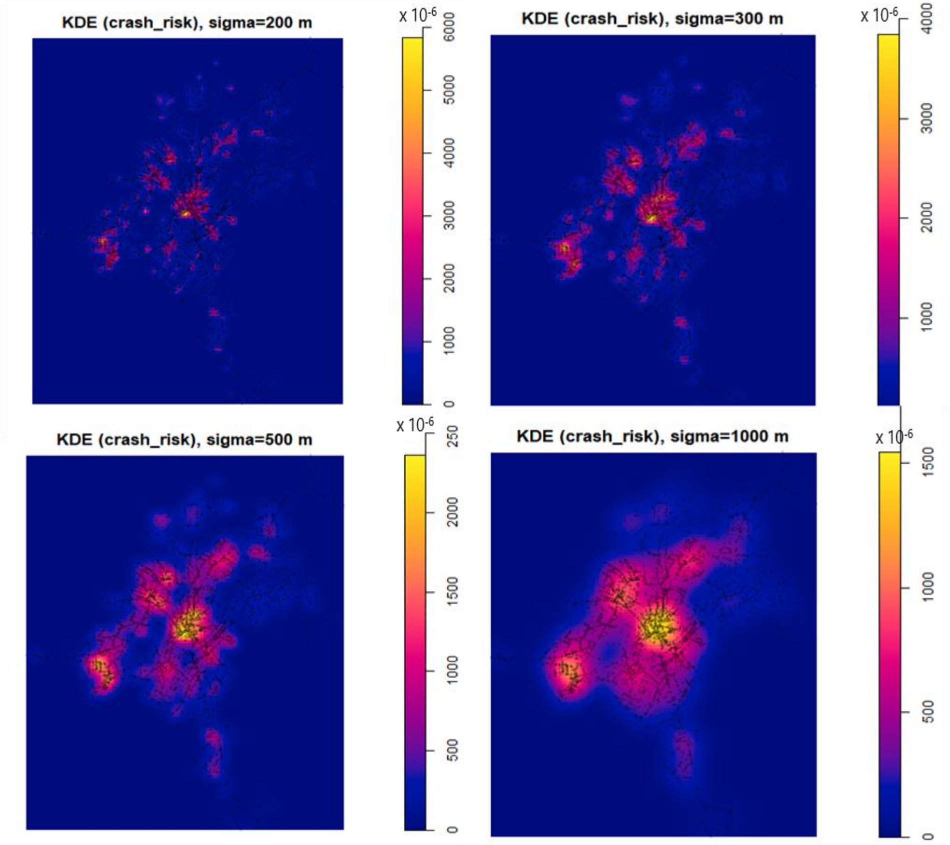


Kernel Density Estimation

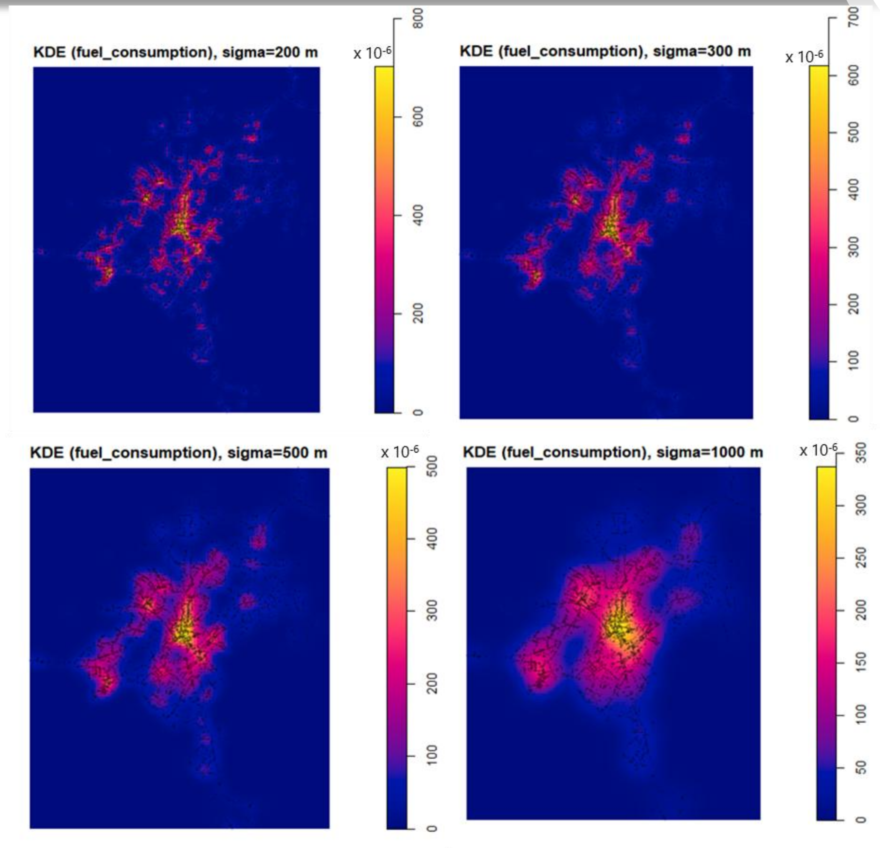
RQ3

Safe Mobility

- The indicator used to identify crash risk spatial patterns at junctions was **crashes count per 1,000 trips**
- **KDE identified consistent crash risk hotspots,** with central Athens and Piraeus remaining high-risk across all bandwidths
- **A 300 m bandwidth** best balances detail and clarity



Green Mobility



- The indicator used to identify fuel consumption hotspots was the total fuel consumed by trips passing through each junction, **expressed in liters per 1,000 trips**
- **KDE identified consistent fuel consumption hotspots,** with the central urban core showing persistently elevated fuel consumption levels across all bandwidths
- **A 300 m bandwidth** best balances detail and clarity

Global & Local Spatial Analysis

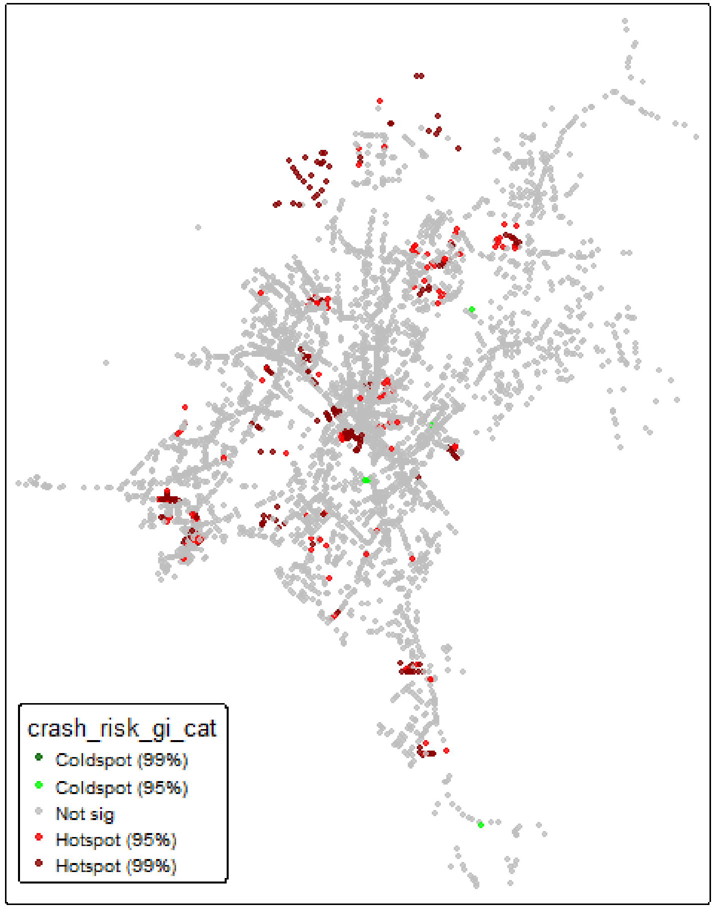
- **Global spatial autocorrelation** was then assessed using Moran's I to formally test whether crash risk and fuel consumption exhibits statistically significant spatial clustering
- A **sensitivity analysis** was conducted using indicative k-nearest neighbor weights across a wide range of neighborhood sizes (k = 1–100)
- **A moderate value of k = 8** was selected as a balance between overly local definitions, and very large neighborhoods
- However, results show that **global spatial clustering is consistently present** with Moran's I remaining positive and statistically significant for all examined k values

Neighborhood sizes (k)	Crash Risk		Fuel Consumption		Median distance to k-th nearest junction (m)
	Moran's I	Moran's I p-value	Moran's I	Moran's I p-value	
1	0.279	**0.000**	0.343	**0.000**	88
5	0.189	**0.000**	0.194	**0.000**	247
8	0.157	**0.000**	0.162	**0.000**	331
10	0.137	**0.000**	0.148	**0.000**	378
15	0.110	**0.000**	0.131	**0.000**	479
20	0.093	**0.000**	0.115	**0.000**	563
25	0.082	**0.000**	0.104	**0.000**	636
50	0.059	**0.000**	0.080	**0.000**	931
70	0.048	**0.000**	0.069	**0.000**	1,106
100	0.039	**0.000**	0.063	**0.000**	1,332

Local Spatial Analysis

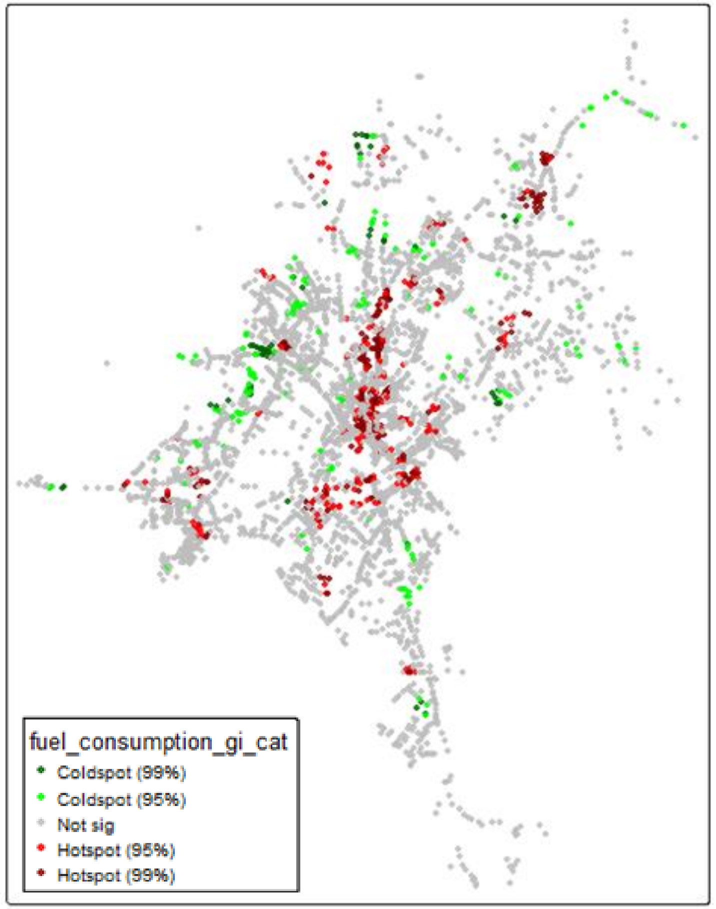
RQ3

- **Getis–Ord Gi*** identified 182 crash risk hotspots at 99% confidence level and 305 at 95% confidence
- **Coldspots were limited,** with most junctions not statistically significant
- Crash risk hotspots form **spatially continuous zones,** concentrated in central Athens and Piraeus



Safe Mobility

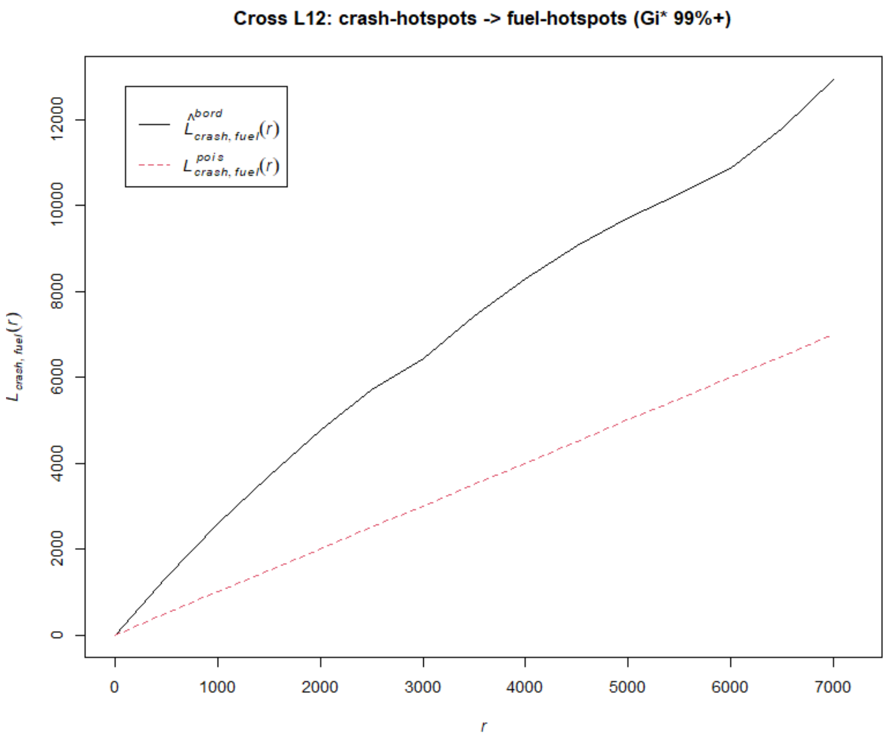
Green Mobility

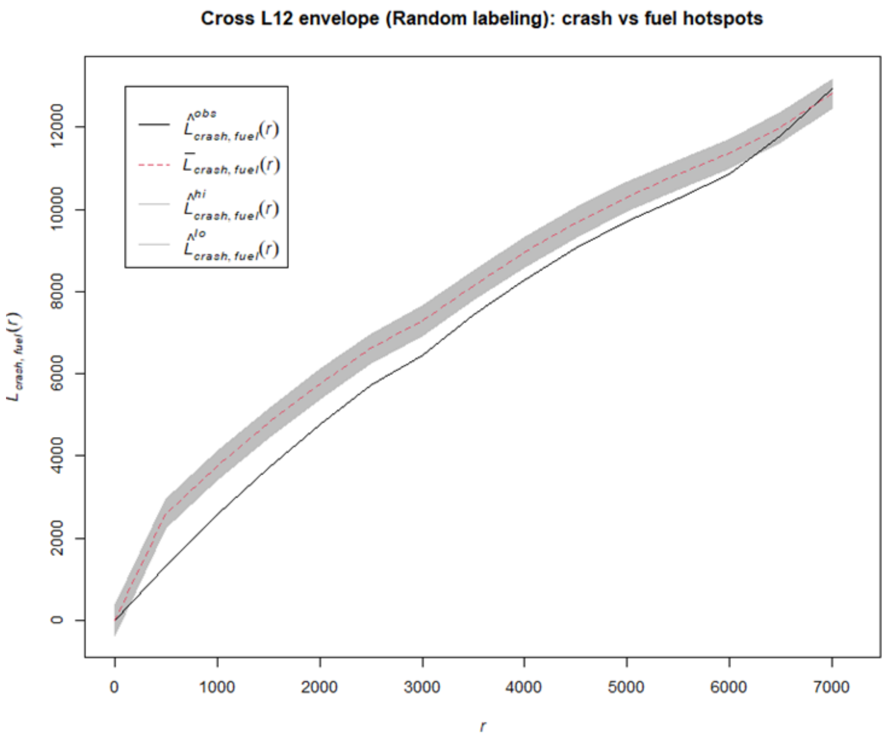


- **Getis–Ord Gi*** identified 232 fuel consumption hotspots at 99% confidence level and 465 at 95% confidence
- **Coldspots** are more pronounced, with 56 at 99% and 222 at 95% confidence
- **Hotspots form spatially continuous zones**, concentrated in the dense urban core and along major corridors

Cross L-12 Spatial Analysis

RQ3

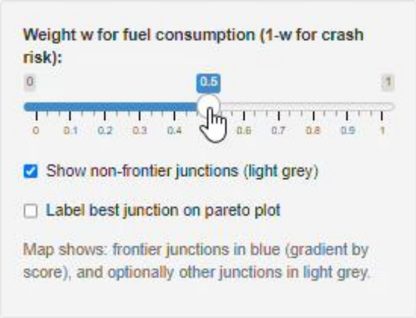


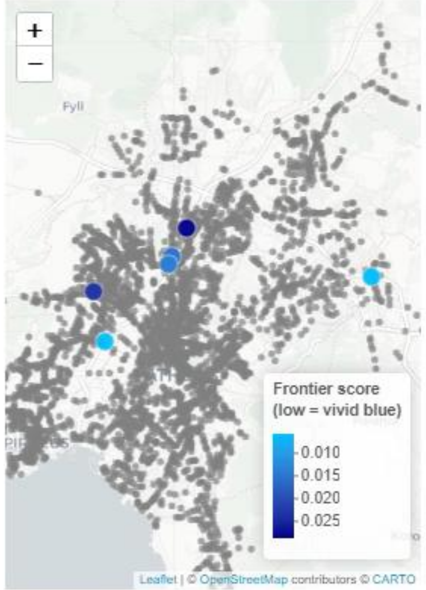


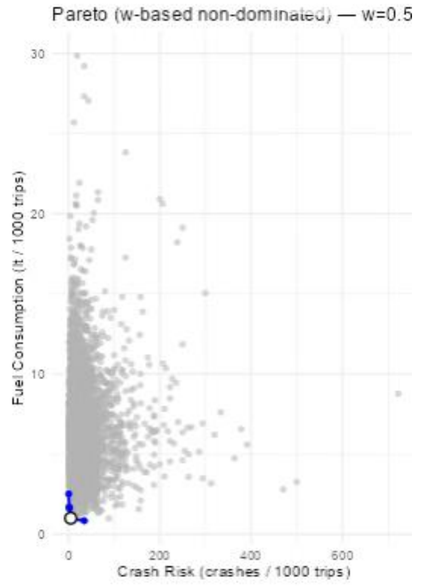
- **Direct overlap between crash and fuel hotspots is limited,** but proximity analysis reveals spatial relationships beyond co-location
- Cross-type L-function shows **fuel hotspots tend to occur near crash hotspots,** indicating a positive spatial association
- Simulation results reveal **spatial segregation up to ~3 km,** meaning hotspots occur in nearby but distinct junctions
- Beyond ~6 km, no significant relationship is observed, suggesting **the association is local rather than citywide**
- Overall, **hotspots cluster in the same urban areas but differ at the junction level,** implying different underlying mechanisms

Eco-Safety Trade-offs

RQ3







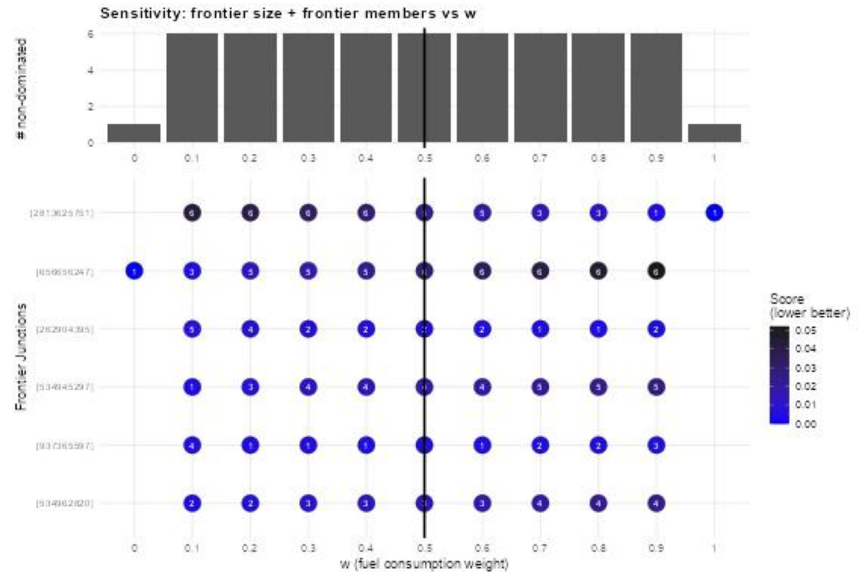
- ➢ To identify the junctions that represent the **best trade-offs between crash risk and fuel economy**

- ➢ **Pareto analysis** evaluates junctions based on crash risk vs fuel consumption (both minimized)

- ➢ **Dominance principle:**
  - Junctions are non-dominated if no other junction performs better in both objectives, forming the Pareto frontier (blue line)
  - The frontier represents the best achievable eco-safety compromises, where improving one objective requires a deterioration in the other

- ➢ **Sensitivity Analysis:**
  - A composite score combines normalized fuel consumption and crash risk using a weight w, allowing identification of preferred trade-off solutions based on policy priorities

$$\textbf{Score} = w \cdot Fuel_{norm} + (1 - w) \cdot Speeding_{norm}$$



Research Motivation 1
Systematic Literature Review & Research Questions 2
Methodological Framework & Data Collection 3
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Joint Modeling of Safe & Green Driving 5
Trip Level Spatial Level
Sustainable Driving Efficiency Assessment 6
Main Research Findings 7
Innovative Contributions & Challenges 8

2nd Module

Research Question 4

RQ1

How can driving behavior, road infrastructure, road crashes, traffic, and weather **datasets be fused to enable the integrated assessment** of safe and green mobility at trip and spatial levels?

RQ2

How can sustainable trip patterns be identified by integrating SSMs and fuel consumption? Is it possible to predict and explain them through behavioral and contextual features?

RQ3

How can crash risk and fuel consumption hotspot spatial patterns be systematically identified and spatially compared across road junctions?

RQ4

How can safe and green driving outcomes be jointly modeled at the trip and road segment levels? Do they share common mechanisms that explain their divergence, or co-occurrence?

RQ5

How can sustainable driving efficiency be assessed at the trip level, by integrating safety, fuel consumption, and travel time, and translated into road efficiency?

SEM Analysis – trip level

RQ4

- **Structural Equation Modeling (SEM)** applied at the trip level (~33,000 trips) to capture direct and indirect relationships between driving dynamics, contextual factors, eco-safety outcomes
- 5 Latent Variables
- Endogenous Variables
  - Fuel consumption (L/100 km)
  - Safety-related indicators:
    - → Speeding (events per 100 m)
    - → Distracted driving (events per 100 m)
    - → Aggressive driving (events per 10 km)
- The examined goodness-of-fit indices and the signs of the estimated coefficients indicate an **excellent model fit** [Comparative Fit Index (CFI) = 0.947]

	SEM Components	Parameters	Estimate	Std.Err	z-value	P(>|z|)
Latent Variables	Driving_Volatility	stop_count_per_km	1.000	-	-	-
		speed_0_pct	0.099	0.001	195.037	0.000
		cruise_speed_pct	-0.418	0.009	-44.620	0.000
	Road_Network	pct_primary	1.000	-	-	-
		pct_residential	-2.207	0.060	-36.840	0.000
		inzone	-2.633	0.074	-35.463	0.000
	Road_Geometry	pct_grade_flat_1m_sc	1.000	-	-	-
		pct_grade_hard_1m_sc	-1.387	0.013	-109.803	0.000
		std_grade_1m_sc	-0.738	0.004	-164.035	0.000
	Exogenous_Conditions	is_day	1.000	-	-	-
		temperature_2m_sc	2.191	0.028	79.289	0.000
		relative_humidity_2m_pct_sc	-0.868	0.012	-75.455	0.000
	Harsh_events_per_10km	Harsh_Acc_per_10km	1.000	-	-	-
		Harsh_Brk_per_10km	0.931	0.024	38.616	0.000
Regressions	Fuel_lit_per100km	Intercept	8.923	0.017	540.384	0.000
		Driving_Volatility	2.326	0.012	199.519	0.000
		Road_Network	-3.252	0.201	-16.140	0.000
		Road_Geometry	-1.278	0.061	-20.994	0.000
		Exogenous_Conditions	-0.289	0.043	-6.774	0.000
	Speeding_per_100m	Intercept	0.500	0.004	139.362	0.000
		Driving_Volatility	-0.201	0.004	-51.232	0.000
		Road_Network	0.615	0.082	7.457	0.000
		Road_Geometry	-0.021	0.027	-0.798	0.425
		Exogenous_Conditions	-0.077	0.019	-4.077	0.000
	MobileUsage_per_100m	Intercept	0.801	0.011	74.710	0.000
		Driving_Volatility	0.130	0.012	10.541	0.000
		Road_Network	-1.818	0.263	-6.914	0.000
		Road_Geometry	-0.258	0.085	-3.023	0.003
		Exogenous_Conditions	0.279	0.060	4.631	0.000
	Harsh_events_per_100km	Driving_Volatility	0.138	0.015	8.926	0.000
		Road_Network	-2.961	0.332	-8.914	0.000
		Road_Geometry	-0.554	0.106	-5.218	0.000
		Exogenous_Conditions	-0.040	0.075	-0.539	0.590
Covariances	speed_0_pct	pct_primary	0.003	0.000	20.710	0.000
		is_day	0.002	0.000	11.718	0.000
	Driving_Volatility	Road_Network	-0.041	0.001	-33.153	0.000
		Road_Geometry	-0.036	0.001	-32.490	0.000
		Exogenous_Conditions	0.019	0.001	13.087	0.000
	Road_Network	Road_Geometry	0.004	0.000	30.825	0.000
		Exogenous_Conditions	0.000	0.000	0.641	0.521
	Road_Geometry	Exogenous_Conditions	0.000	0.000	1.934	0.053
	Harsh_events_per_10km	Fuel_lit_per100km	0.512	0.019	26.395	0.000
		Speeding_per_100m	0.206	0.008	24.454	0.000
		MobileUsage_per_100m	0.017	0.026	0.671	0.502
	Fuel_lit_per100km	Speeding_per_100m	0.141	0.005	30.183	0.000
		MobileUsage_per_100m	0.048	0.015	3.307	0.001
	Speeding_per_100m	MobileUsage_per_100m	-0.053	0.006	-8.223	0.000

Interpretation & Insights

Latent Variables & Regressions

Driving Volatility

- ↑ stop–go, ↓ cruising → unstable driving flow
- ↑ Driving volatility → ↑ consumption, ↑ aggressive driving, ↑ distraction, ↓ speeding

Road Context

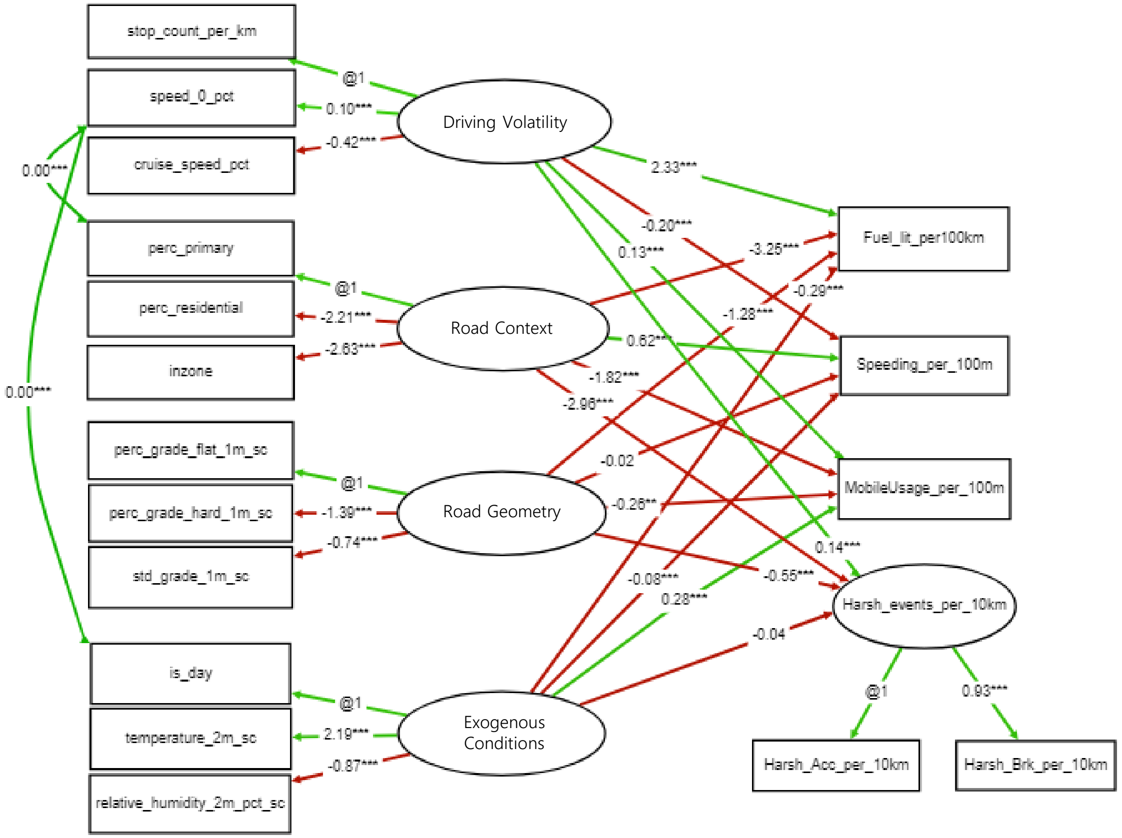
- ↑ primary roads vs residential/in-zone → higher-capacity, smoother-flow environments
- ↑ Primary roads → ↓ consumption, ↓ aggressive driving, ↓ distraction, ↑ speeding

Road Geometry

- ↑ grades & variability → steeper and more variable grade routes
- ↑ Steep/variable grades → ↑ consumption, ↑ aggressive driving, ↑ distraction

Exogenous Conditions

- ↑ daylight, ↑ temperature, ↓ humidity→ favorable environmental conditions
- ↑ Favorable conditions → ↓ consumption, ↓ speeding, ↑ distraction



Covariances

↑ fuel consumption ↔ ↑ aggressive driving, ↑ speeding, ↑ distraction

- Inefficient trips tend to **also be unsafe**
- Fuel-inefficiency and unsafe driving **co-occur** driven by **unobserved trip level factors**

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Pattern Identification of Safe & Green Mobility 4

Joint Modeling of Safe & Green Driving 5

Trip Level | **Spatial Level**

Sustainable Driving Efficiency Assessment 6

Main Research Findings 7

Innovative Contributions & Challenges 8

2nd Module

SEM Analysis – segment level

RQ4

- SEM applied at the road segment level (~35,000 road segments) to **capture direct and indirect relationships** between segment road characteristics, driving behavior, environmental conditions and eco-safety outcomes

- 5 Latent Variables

- Endogenous Variables
  - Fuel consumption (L/10 km)
  - Safety-related indicators:
    - → Speeding (events per 100 m)
    - → Distracted driving (events per 100 m)
    - → Aggressive driving (events per km)

- The examined goodness-of-fit indices and the signs of the estimated coefficients indicate an **excellent model fit** [Comparative Fit Index (CFI) = 0.947]

	SEM Components	Parameters	Estimate	S.E	z-value	P(>|z|)
Latent Variables	Driving_Volatility	stops_prc	1.000	-	-	-
		stops_duration_days	0.148	0.002	75.032	0.000
		speed_cv_mps	0.608	0.002	288.99	0.000
	Road_Network	residential_road	1.000	-	-	-
		primary_road	-0.243	0.007	-34.122	0.000
		oneway_num	0.371	0.011	33.496	0.000
	Road_Geometry	street_count_origin_node	1.000	-	-	-
		length_scaled	-2.557	0.098	-25.973	0.000
		segment_elevation_100m_1m	-0.934	0.047	-20.069	0.000
	Exogenous_Conditions	is_day_1	1.000	-	-	-
		weekday_1	-0.101	0.018	-5.725	0.000
		temperature_cat_1	-1.056	0.029	-35.903	0.000
		temperature_cat_3	0.557	0.015	36.839	0.000
	Harsh_events_per_km	ha_per_km	1.000	-	-	-
		hb_per_km	1.965	0.114	17.216	0.000
Regressions	fuel_cons_median_per10km	Intercept	0.746	0.002	410.477	0.000
		Driving_Volatility	0.189	0.008	23.327	0.000
		Road_Network	0.485	0.017	29.236	0.000
		Road_Geometry	0.142	0.027	5.213	0.000
		Exogenous_Conditions	0.055	0.033	1.681	0.093
	speeding_per_100m	Intercept	0.342	0.005	65.546	0.000
		Driving_Volatility	-0.423	0.029	-14.535	0.000
		Road_Network	-0.196	0.042	-4.624	0.000
		Road_Geometry	-1.859	0.122	-15.173	0.000
		Exogenous_Conditions	-0.291	0.118	-2.463	0.014
	mobile_per_100m	Intercept	1.025	0.007	145.191	0.000
		Driving_Volatility	0.353	0.034	10.462	0.000
		Road_Network	0.379	0.046	8.248	0.000
		Road_Geometry	0.969	0.114	8.526	0.000
		Exogenous_Conditions	0.176	0.139	1.269	0.204
	Harsh_events_per_km	Driving_Volatility	0.238	0.013	18.552	0.000
		Road_Network	0.076	0.011	7.008	0.000
		Road_Geometry	-0.109	0.025	-4.371	0.000
		Exogenous_Conditions	0.037	0.032	1.183	0.237
Covariances	stops_duration_days	primary_road	0.004	0.000	33.283	0.000
		residential_road	-0.004	0.000	-23.075	0.000
		length_scaled	0.023	0.001	31.148	0.000
	is_day_1	weekday_1	0.007	0.000	41.627	0.000
	oneway_num	segment_elevation_100m_1m	-0.086	0.002	-36.301	0.000
	Driving_Volatility	Road_Network	0.008	0.001	13.767	0.000
		Road_Geometry	0.007	0.001	13.373	0.000
		Exogenous_Conditions	-0.001	0.000	-5.551	0.000
	Road_Network	Road_Geometry	0.033	0.001	26.999	0.000
		Exogenous_Conditions	-0.002	0.000	-5.888	0.000
	Road_Geometry	Exogenous_Conditions	-0.002	0.000	-8.882	0.000
	Harsh_events_per_km	fuel_cons_median_per10km	0.003	0.001	5.215	0.000
		mobile_per_100m	-0.001	0.002	-0.581	0.561
		speeding_per_100m	-0.007	0.002	-4.055	0.000
	fuel_cons_median_per10km	mobile_per_100m	0.011	0.002	5.019	0.000
		speeding_per_100m	-0.007	0.002	-3.694	0.000
	mobile_per_100m	speeding_per_100m	-0.014	0.008	-1.728	0.084

Interpretation & Insights

RQ4

Latent Variables & Regressions

Driving Volatility

- ↑ **stopping & speed variability** → unstable segment flow
- **↑ Driving volatility → ↑ consumption, ↑ aggressive driving, ↑ distraction, ↓ speeding**

Road Context

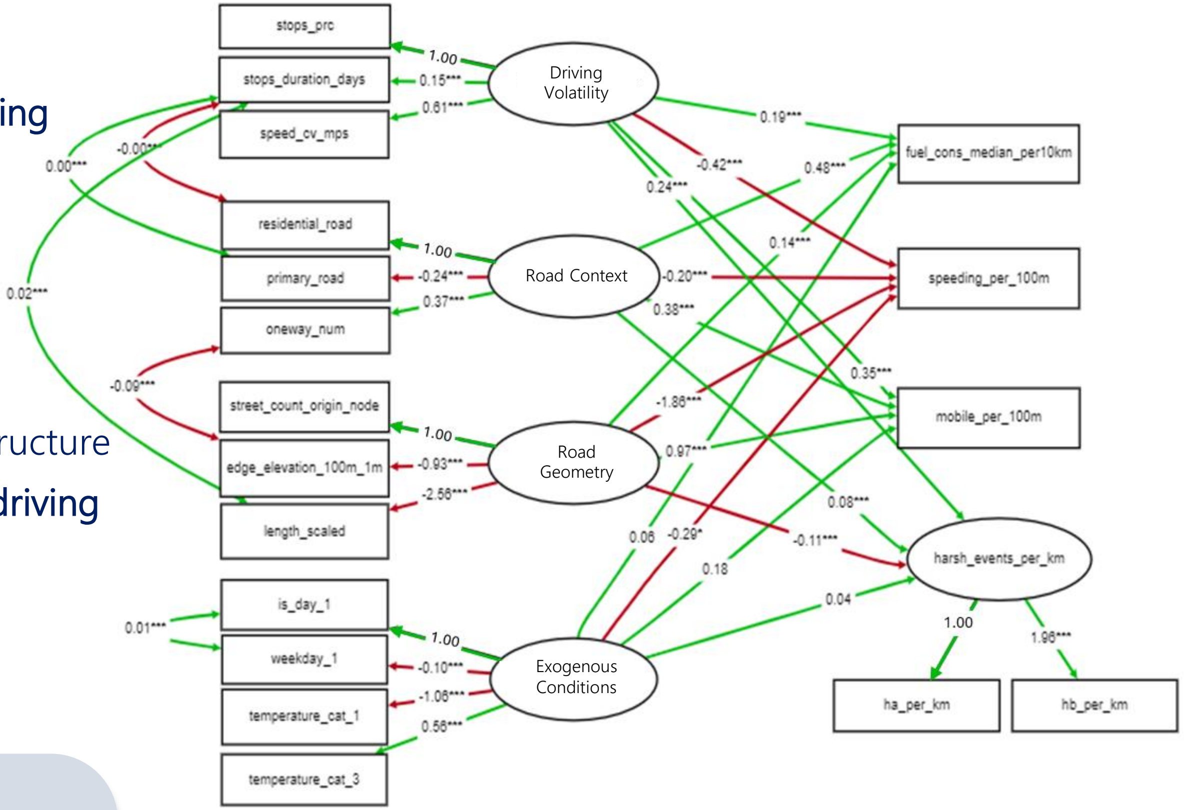
- ↑ **residential / one-way vs primary** → constrained, lower-capacity environments
- **↑ Local roads → ↑ consumption, ↑ aggressive driving, ↑ distraction, ↓ speeding**

Road Geometry

- ↑ **shorter segments, ↑ junction density, ↓ elevation** → more complex segment structure
- **↑ Complex geometry → ↑ consumption, ↑ distraction, ↓ speeding, ↓ aggressive driving**

Exogenous Conditions

- ↑ **nighttime, ↑ weekday travel, ↓ temperature** → less favorable conditions
- **↑ Favorable conditions → ↓ speeding**



Covariances

↑ fuel consumption ↔ ↑ aggressive driving, ↑ distraction, ↓ speeding

- Speeding follows a distinct pattern, **not co-occurring** with inefficient driving
- Co-occurrence reflects **shared segment conditions** rather than direct causal effects

Research Motivation 1

Systematic Literature Review & Research Questions 2

Methodological Framework & Data Collection 3

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Joint Modeling of Safe & Green Driving 5

Sustainable Driving Efficiency Assessment 6

Main Research Findings 7

Innovative Contributions & Challenges 8

3rd Module

Research Question 5

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RQ2

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RQ3

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RQ4

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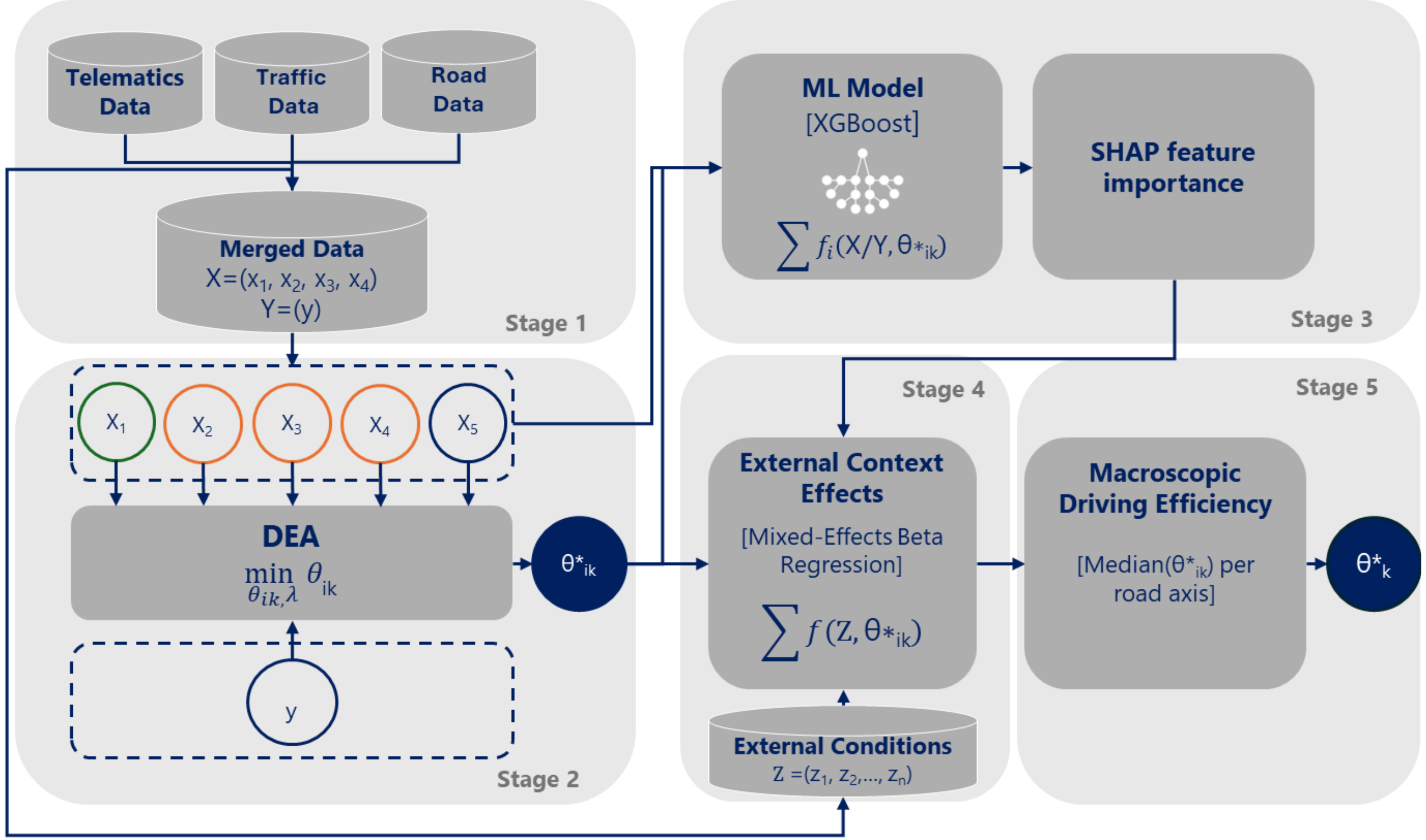
RQ5

How can sustainable driving efficiency be assessed at the trip level, by integrating safety, fuel consumption, and travel time, and translated into road efficiency?

Module 3 - Approach

RQ5

- **Stage 1**: Integrated telematics, fuel, traffic, and road data
- **Stage 2**: Estimated trip efficiency scores via DEA
- **Stage 3**: Explained efficiency drivers using XGBoost and SHAP
- **Stage 4**: Modeled contextual effects with beta regression
- **Stage 5**: Aggregated trip scores to assess road-level sustainability



DEA Results

- Trip-level efficiency was calculated using the **input-oriented Banker, Charnes, and Cooper (BCC) DEA model**
- Trips are treated as **Decision-Making Units** (DMUs)
- **Three specifications with different input sets** (fuel, safety indicators, time) to capture alternative sustainability dimensions
- **Separate DEA models by road type** (X=primary, trunk, motorway) to ensure comparable operating conditions
- **Integrating safety indicators and travel time** (Model 3) improves discriminatory power and captures fuel, safety, and operational efficiency jointly
- Restricted sample (non-zero safety events) (Model 3s) to assess robustness and the **influence of safety behavior on efficiency**
- **Model1 & Model2** show similar results, while **Model3** improves discrimination by incorporating time
- **Model3s** yields higher efficiency due to a more homogeneous, safety-active sample

DEA Model	DEA Inputs & Outputs	
Model1_X	Inputs	fuel_X
		harsh_acc_X, harsh_brk_X, mobile_usage_X
	Output	trip_distance_X
Model2_X	Inputs	fuel_X
		harsh_brk_X, mobile_usage_X
	Output	trip_distance_X
Model3_X	Inputs	fuel_X
		harsh_brk_X, mobile_usage_X
		trip_duration_X
	Output	trip_distance_X

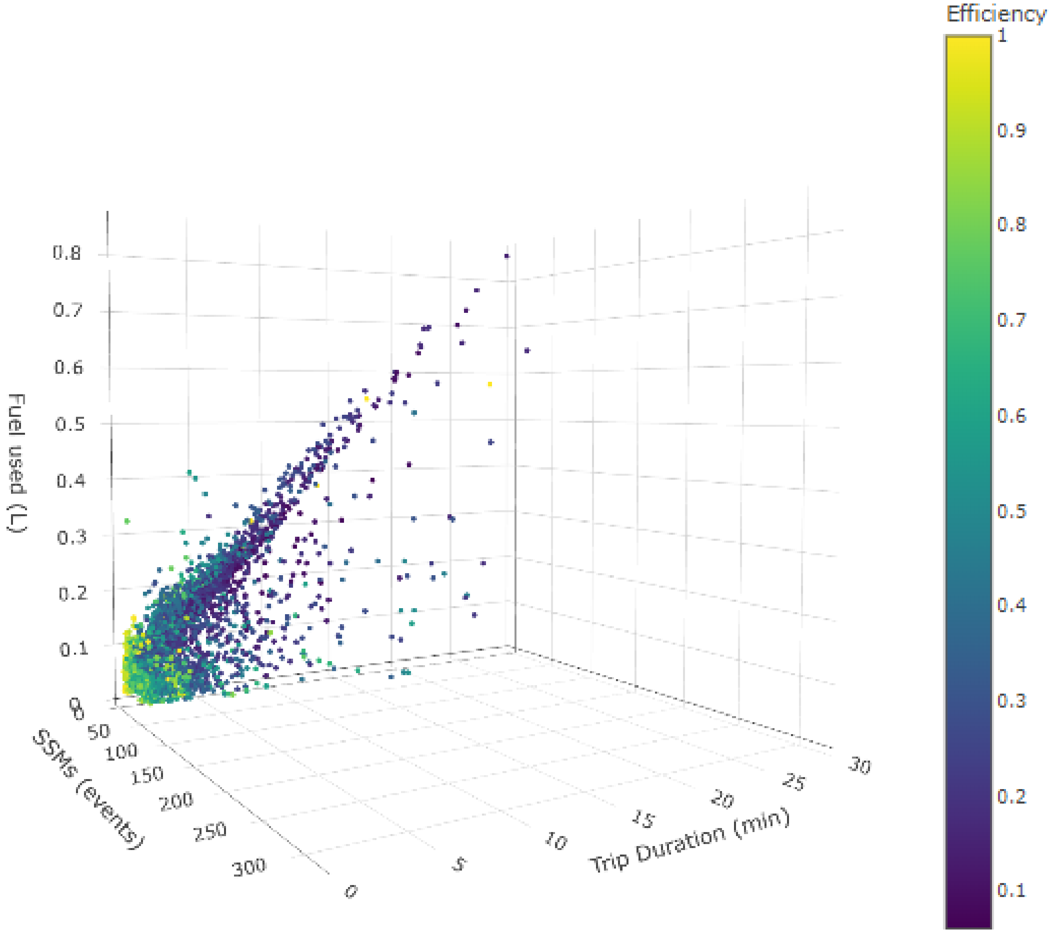
DEA Model	Trips used in DEA	Efficient Trips (%)	Efficiency Score Statistics		
			sd	median	min
Model1_trunk	1,887	0.530%	0.184	0.549	0.100
Model1_motorway	1,982	0.454%	0.189	0.484	0.071
Model1_primary	4,674	0.428%	0.180	0.424	0.073
Model1_all	8,707	0.207%	0.191	0.380	0.060
Model2_trunk	1,887	0.530%	0.184	0.549	0.100
Model2_motorway	1,982	0.454%	0.189	0.484	0.071
Model2_primary	4,674	0.428%	0.180	0.424	0.073
Model2_all	8,707	0.207%	0.191	0.380	0.060
Model3_trunk	1,886	1.113%	0.206	0.629	0.100
Model3_motorway	1,982	1.110%	0.209	0.611	0.076
Model3_primary	4,695	0.639%	0.195	0.423	0.073
Model3_all	8,762	0.377%	0.211	0.385	0.060
Model3s_trunk	439	32%	0.315	0.567	0.081
Model3s_motorway	353	27%	0.263	0.760	0.114
Model3s_primary	1,578	39%	0.303	0.629	0.116
Model3s_all	2,464	34%	0.260	0.713	0.124

DEA Results - Model3

RQ5

Model	Efficiency Groups	Trip distance (m)	Fuel consumption (L/100km)	Mobile usage per 100 km	Harsh brakings per 100km	Trip duration (min/km)	DEA efficiency score
Mode3_trunk	Efficient (0–25% pctl.)	1,120	4.931	280.436	5.087	0.854	0.850
	Moderate (25–75% pctl.)	1,021	6.248	511.276	12.776	1.362	0.608
	Inefficient (75–100% pctl.)	1,181	8.532	1,009.335	22.528	3.575	0.324
Model3_motorway	Efficient (0–25% pctl.)	1,342	4.458	337.126	0.721	0.733	0.817
	Moderate (25–75% pctl.)	1,305	5.201	359.642	4.765	1.001	0.602
	Inefficient (75–100% pctl.)	1,160	8.000	636.653	9.663	3.051	0.279
Model3_primary	Efficient (0–25% pctl.)	1,253	5.984	682.665	14.531	1.352	0.724
	Moderate (25–75% pctl.)	1,112	6.697	774.055	25.730	2.280	0.433
	Inefficient (75–100% pctl.)	1,021	8.447	998.868	25.632	4.924	0.229
Mode3_all	Efficient (0–25% pctl.)	1,221	4.957	366.171	4.069	0.895	0.728
	Moderate (25–75% pctl.)	1,153	7.303	695.026	19.426	1.849	0.401
	Inefficient (75–100% pctl.)	1,072	7.743	1,003.737	24.678	4.342	0.193

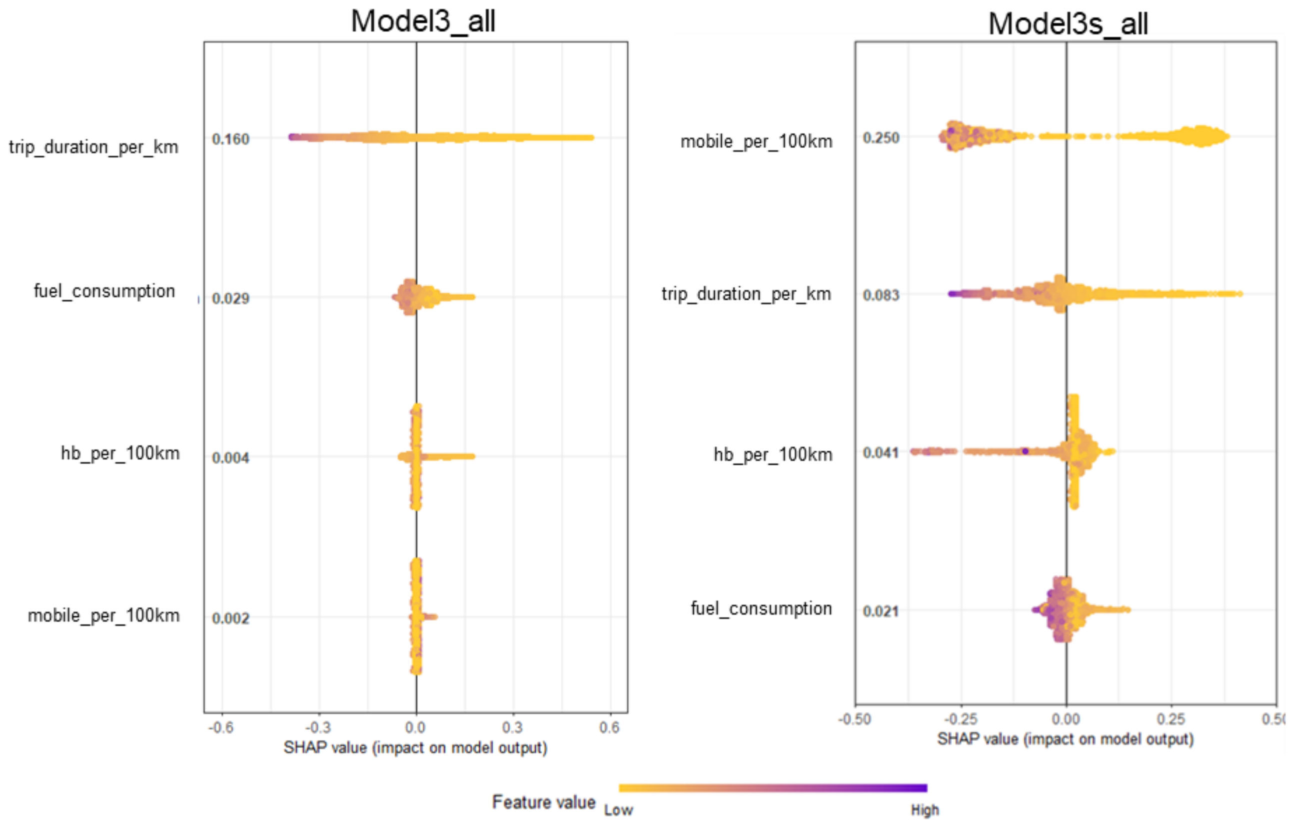
- **Trips classified** as inefficient (<25th), moderate (25th-75th), and efficient (>75th percentile)
- **Higher driving efficiency** is associated with lower fuel use, fewer safety events, and shorter travel time per distance



Results of Explainable ML Stage

RQ5

- **Modeling approach**: XGBoost models approximate DEA efficiency using distance-normalized inputs
- **Model performance**: Model 3 and Model 3s show higher explanatory power ($R^2 \approx 0.90$-0.91), indicating a more structured efficiency measure
- **Key drivers (Model 3)**: Trip duration dominates, followed by fuel, while safety variables have a secondary (penalty-type) role
- **Sensitivity insight (Model 3s)**: Safety variables become dominant when safety events are present
- **Key conclusion**: Model 3 provides the most balanced and interpretable representation of eco-safety-time efficiency



External Context Effects on Efficiency

RQ5

- **8 beta regression** (fixed & mixed effects) exploited to assess how contextual factors influence driving sustainability at trip level
- **Mixed-effects models outperform fixed-effects**, highlighting the role of route-level heterogeneity

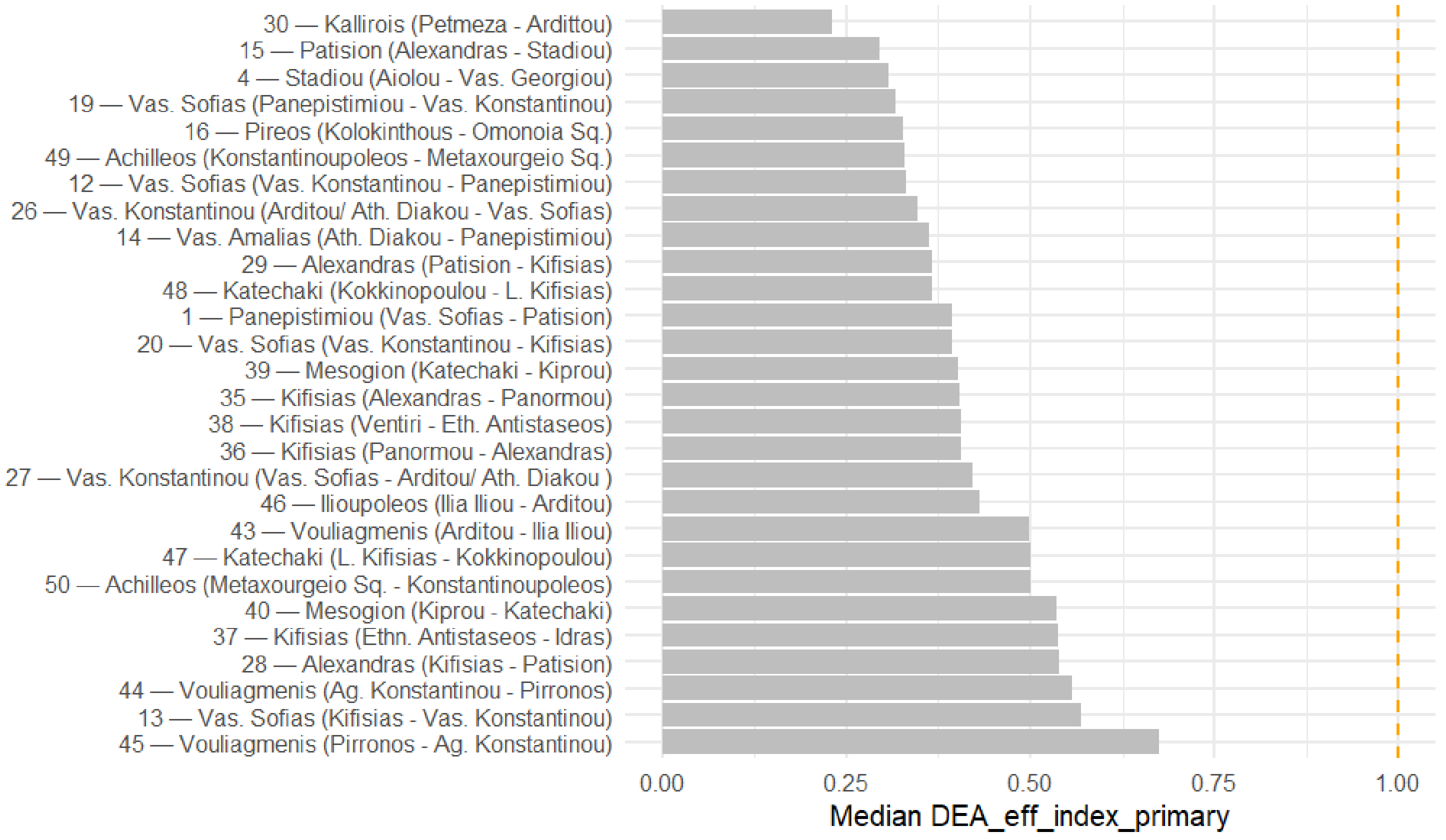
- **Traffic congestion has a strong negative effect on trip driving sustainability** across all road environments
- **Daytime and weekend conditions are associated with lower driving sustainability,** reflecting higher traffic demand or less consistent driving patterns compared to routine weekday trips
- **Higher speed limits and more lanes improve driving sustainability** through smoother traffic flow conditions
- **Steeper road grades reduce driving sustainability** due to increased engine load and speed variability

Variables	Model3_all (Fixed-effects)	Model3_all (Mixed-effects)	Model3_primary (Mixed-effects)	Model3_trunk (Mixed-effects)	Model3_motorway (Mixed-effects)
(Intercept)	-2.030 (**<0.0001**)	-1.642 (**0.000**)	0.091 (0.856)	-2.469 (**0.000**)	0.195 (0.551)
congestion_index	-1.882 (**<0.0001**)	-2.068 (**<0.0001**)	-1.915 (**<0.0001**)	-1.928 (**<0.0001**)	-2.921 (**<0.0001**)
is_day	-0.165 (**0.000**)	-0.146 (**0.000**)	-0.076 (0.166)	-0.074 (0.284)	-0.189 (**0.040**)
Weekend (ref: weekday)	-0.042 (**0.020**)	-0.061 (**0.000**)	-0.079 (**0.005**)	0.083 (**0.033**)	-0.085 (**0.050**)
road_lanes	0.057 (**0.000**)	0.158 (**0.038**)	-0.097 (0.463)	0.367 (**0.001**)	0.428 (**0.000**)
speed_limit	0.037 (**<0.0001**)	0.026 (**0.000**)	0.0142 (**0.011**)	0.033 (**0.000**)	-
road_grade	-0.064 (**<0.0001**)	-0.060 (0.097)	-0.073 (**0.047**)	0.218 (**0.000**)	-0.296 (**0.007**)
Route variance:	–	0.096	0.082	0.019	0.049
AIC:	-8,921	**-10,475**	-3,430	-2,151	-2,072
BIC:	-8,865	**-10,411**	-3,372	-2,101	-2,027
Conditional R^2:	–	0.801	0.664	0.886	0.899
Marginal R^2:	–	0.643	0.461	0.857	0.831

Macroscopic Route Driving Efficiency

RQ5

- **Trip efficiency scores aggregated** using median values to identify systematically efficient/inefficient routes
- Aggregation performed separately **by road class** to ensure fair and comparable rankings
- **Primary roads show higher variability**, while trunk and motorway routes exhibit more homogeneous efficiency
- **Lower-ranked routes likely reflect higher congestion and complexity**, while higher-ranked routes indicate smoother operating conditions
- **Provides a practical tool** to prioritize routes for targeted interventions to improve sustainability (fuel, safety, time)



Research Motivation 1

Systematic Literature Review & Research Questions 2

Methodological Framework & Data Collection 3

Pattern Identification of Safe & Green Mobility 4

Joint Modeling of Safe & Green Driving 5

Sustainable Driving Efficiency Assessment 6

Main Research Findings 7

Innovative Contributions & Challenges 8

Main Research Findings – Module 1

RQ2
RQ3

The identified patterns of safe & green mobility do not constitute independent dimensions, but are characterized by significant and dynamic interactions

At the trip level:

- **Six sustainable trip patterns** are identified through the integration of road safety and fuel consumption indicators
- **Structured synergies** (e.g., Low-risk × Efficient) **and trade-offs** (e.g., Risky × Efficient) **are revealed between safety and fuel efficiency**
- The profiles are predicted with satisfactory accuracy, with driving behavior indicators and road environment complexity emerging as **the dominant determinants**

At the spatial level:

- A total of 182 crash risk hotspots and 232 fuel consumption hotspots are identified at the junction level, **showing limited spatial overlap**
- The two types of hotspots exhibit **significant positive spatial association** at broader urban scales, while demonstrating clear spatial segregation at shorter distances
- A set of junctions is identified that represent **optimal trade-offs between safe and green mobility**

Main Research Findings – Module 2

RQ4

Safe & green driving outcomes are jointly modeled using Structural Equation Models, revealing common underlying mechanisms that predominantly influence both dimensions in the same direction across levels of analysis

At the trip level:

- **High fuel consumption co-occurs with aggressive and distracted driving**, reflecting shared underlying mechanisms
- **Speeding follows partly distinct mechanisms**; however, it still coexists with higher fuel consumption
- Overall, **low-consumption trips tend to be safer**

At the spatial level:

- **Road segments with high fuel consumption** are associated with increased levels of aggressive driving and mobile phone use
- Local geometric and operational road characteristics **constrain the simultaneous occurrence of low fuel consumption and high road safety**, with frequent speeding acting as a key trade-off factor

Main Research Findings – Module 3

RQ5

Sustainable driving efficiency can be quantified through an integrated indicator, enabling its evaluation from the trip level to the road network level

- Data Envelopment Analysis allows the **integrated incorporation** of safety, environmental, and economic dimensions into a single efficiency index, providing a comprehensive representation of sustainable driving
- Travel time emerges as **the most influential internal determinant of the sustainable driving efficiency index,** followed by fuel consumption, while safety indicators primarily act as constraining factors
- **When high-risk events occur**, they become dominant internal determinants of sustainable driving efficiency
- Traffic congestion is identified as **the most significant external determinant**, exerting a systematic negative impact on sustainability
- The aggregation of sustainable driving efficiency indicators from the trip level to the road segment level enables the **evaluation of sustainable mobility at a macroscopic road network level**

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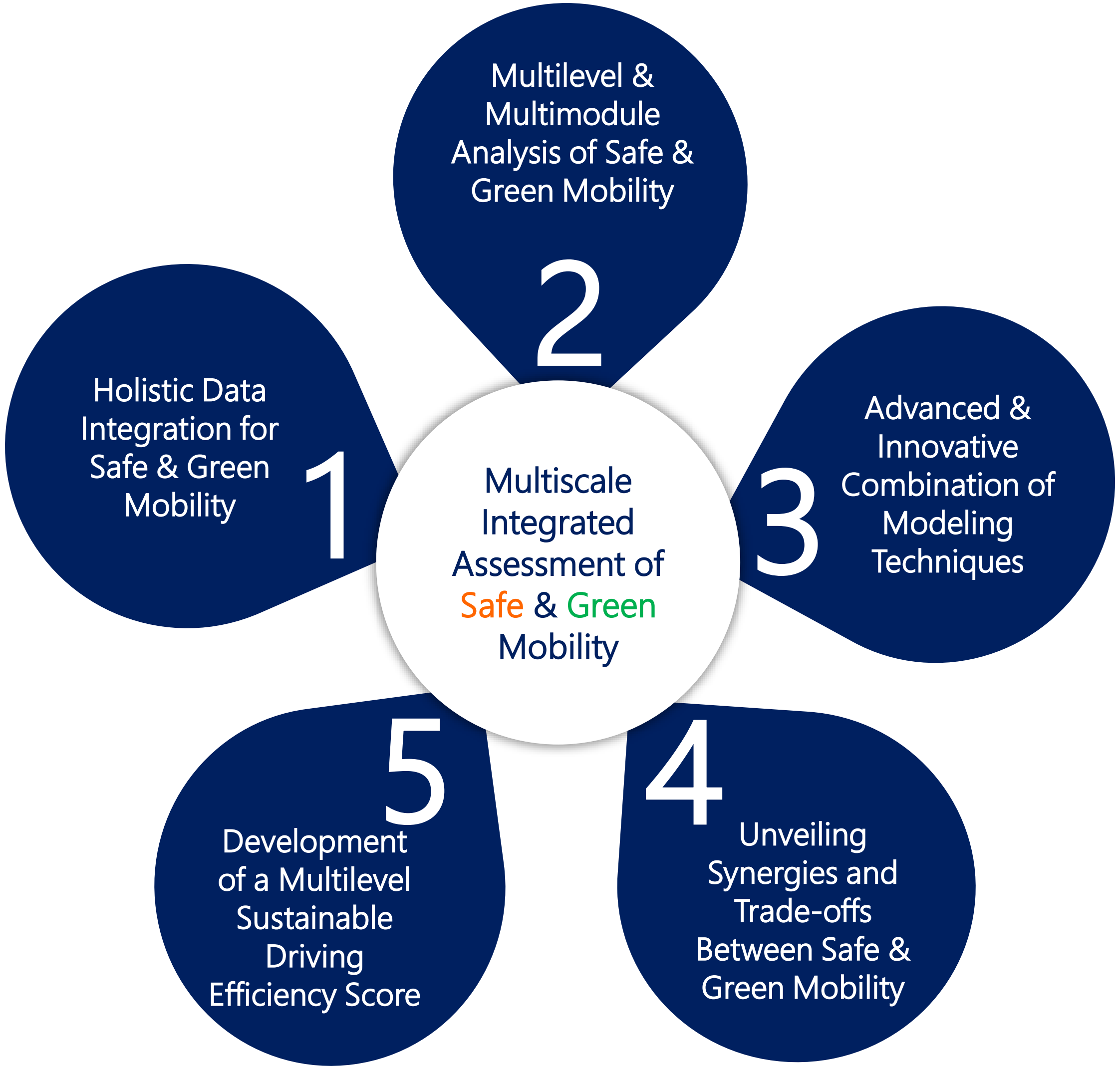
Innovative Contributions



Further Challenges & Directions

Improving Fuel Consumption Estimation
- Leveraging empirical vehicle data and further validating computational approaches

Enhancing the Environmental Dimension
- Integrating emissions data for a more comprehensive and reliable assessment of sustainable mobility

Data Enrichment
- Expanding the coverage of traffic and meteorological data
- Enabling driver identification and the integration of vehicle characteristics

Extending the Spatial and Temporal Scope of Analysis
- Investigating different road environments and seasonal variations

Practical Implementation and Decision Support
- Developing tools to support policy-making, infrastructure planning, and driver guidance for promoting sustainable mobility

A Multilevel Integrated Assessment of Safe and Green Mobility

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