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Exploring the Relationship Between Unsafe Traffic Events and Crash Occurrences Using Smartphone App Data

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Significance of Study

- **Road crashes** are a significant public health issue, with over **1.35 million annual fatalities worldwide**
- Current road safety measures show **slow progress**, necessitating **new** approaches for **crash prediction and prevention**.
- **Unsafe traffic events**, such as harsh accelerations and braking, occur **more frequently** and are **easily obtainable** using smartphone app data.
- Leveraging real-time data from smartphone sensors offers a **proactive approach to traffic safety analysis and intervention**.

State-of-the-art

Driving Behaviour Analysis

Human factors contribute to ~95% of crashes. Analysing behaviours like harsh braking and acceleration is crucial (Singh, 2015).

Sensor Data for Traffic Safety

Smartphone-based data (accelerometers, GPS) has revolutionised behaviours monitoring and safety modelling (Mantouka et al., 2018).

Use of Harsh Event Data

Point-data analysis of harsh events predicts high-risk zones ('hotspots') proactively, improving safety measures (Tselentis et al., 2017).

Research Objectives

- **To assess the correlation** between **unsafe traffic events** (e.g., harsh acceleration, braking) and **crash occurrences**.
- To analyse **spatiotemporal patterns** of these events using smartphone app data to investigate **driver behaviours and safety perception**.
- To develop and evaluate regression models to **enhance crash prediction accuracy** at two of the most used avenues and their intersections in Athens:

  (i) Mesogeion Avenue

  (ii) Vouliagmeni Avenue

Methodology: Data Sources

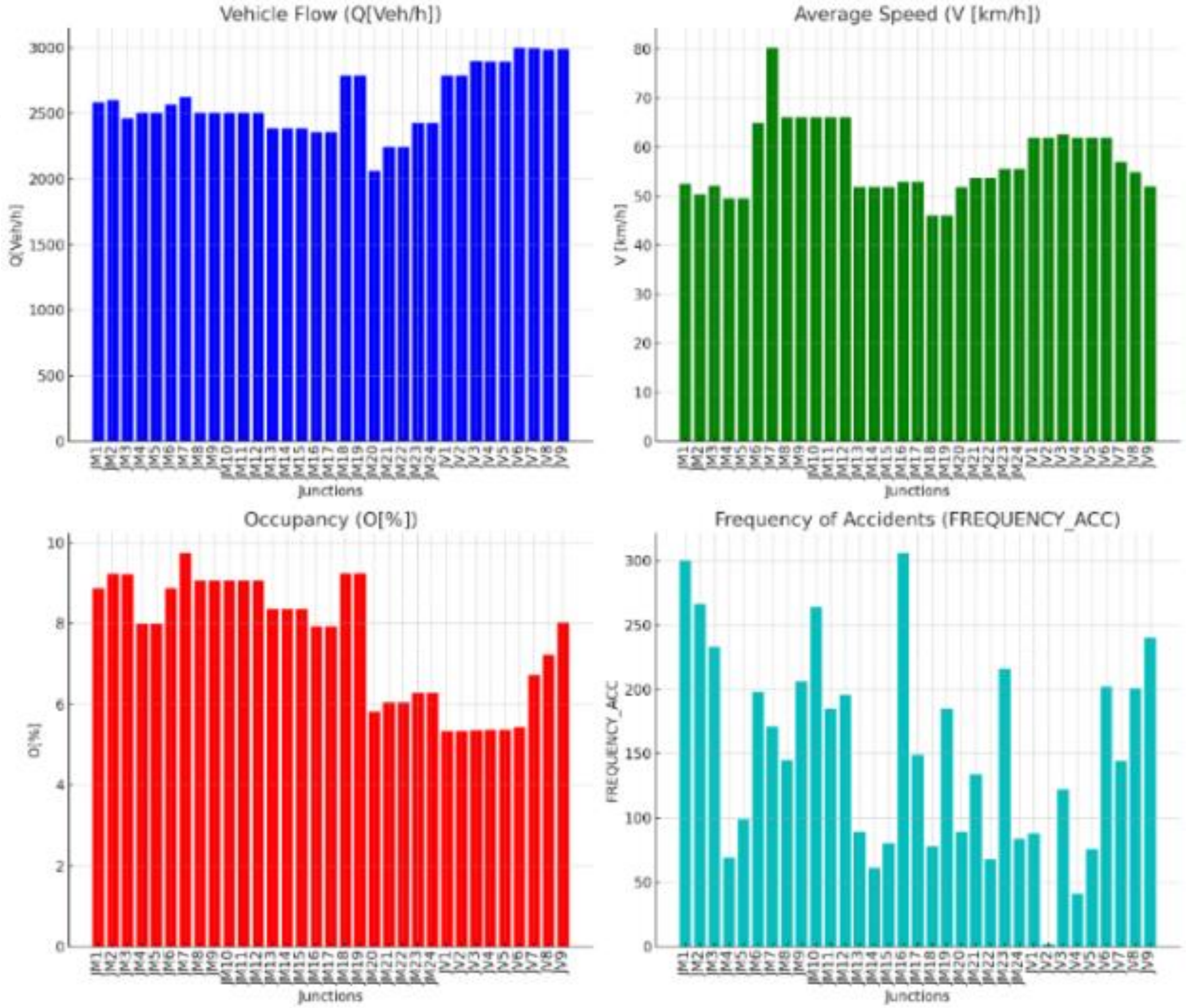
- **Driving Behavior Data:** Collected from **~300 drivers in Athens** using the OSeven smartphone app, recording instances of harsh acceleration and braking.

- **Traffic Metrics:** Obtained from the Attica Traffic Management Center, including **traffic volume, average speeds, and occupancy rates.**

- **Road Characteristics:** Extracted from Google Maps, detailing **lane configurations** and **intersection characteristics.**

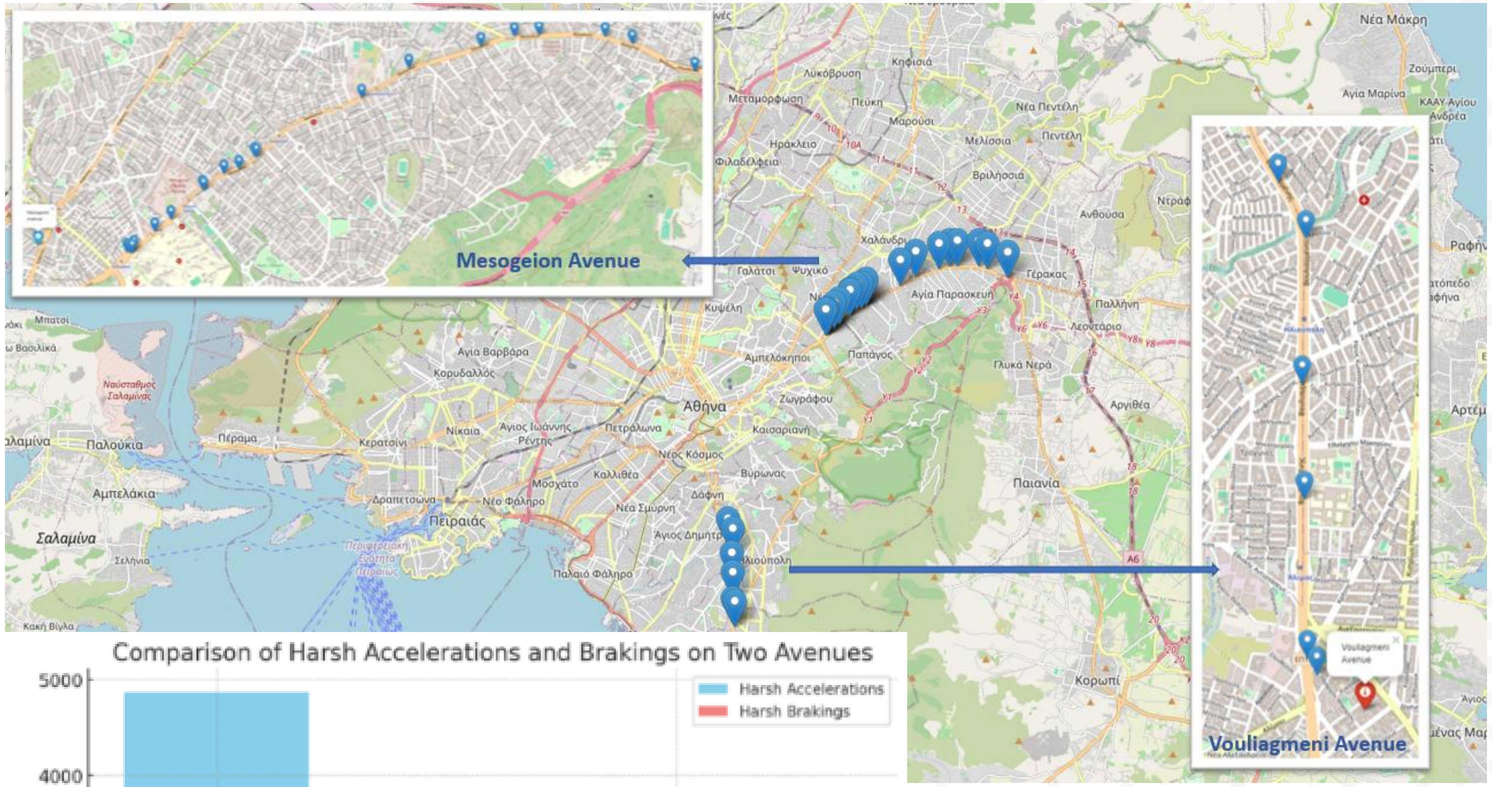
Descriptive Statistics & Patterns

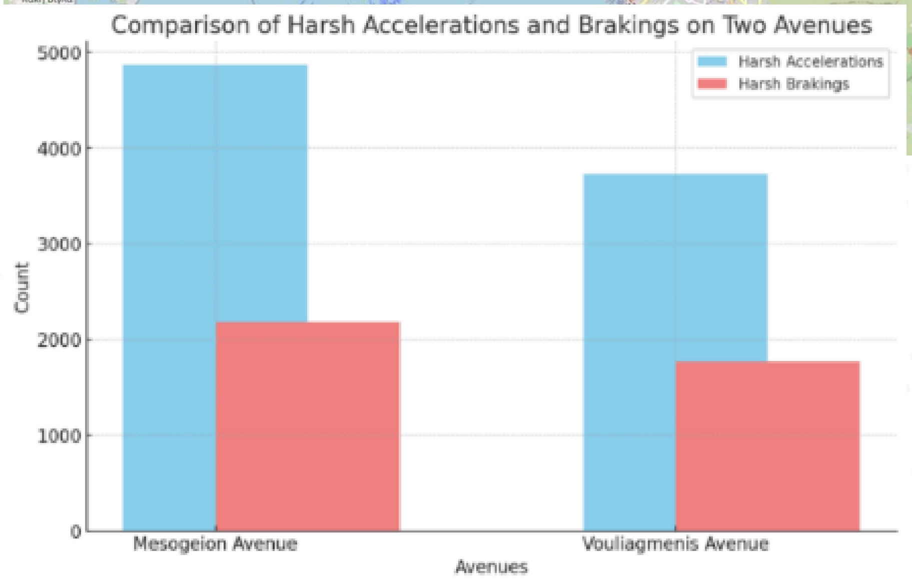
- **Traffic event data** categorised by junctions (avenues of Mesogeion-JM and Vouliagmeni-JV).
- Analysis of variables such as vehicle flow (max J6 – Vouliagmeni), average speed (and max J7 – Mesogeion), occupancy rate (J7-Mesogeion), and frequency of accidents at intersections.
- **Identification** of **high-risk junctions** for targeted intervention



Data Integration & Analysis

- **Spatial Mapping**: **GIS tools** were used to correlate unsafe events with specific road segments and intersections.
- **Data Standardization: Ensured consistency** in data units and formats.
- **Event Detection: Harsh events** are identified via **machine learning algorithms** using smartphone sensor data (accelerometer, GPS).





Modeling Approach

1. **Generalized Linear Models (GLM):** Assessed predictors like speed difference, junction characteristics, and traffic metrics.
2. **Generalized Linear Mixed Models (GLMM):** Included random effects for road junction types to capture variability in crash frequency.
3. **Model Diagnostics:** AIC values, deviance, and VIF scores for model selection and validation.

Generalized linear models results

Exploring the relationship between unsafe traffic events and crash occurrence using harsh acceleration events

glm(formula = FREQUENCY_ACC ~ MIN_Speed_Diff + MAX_Speed_Diff + MAX_Event_Speed + STD_Event_Speed + Right_Exits + Outgoing_Lanes + Sideway, family = poisson, data = Vdata)

Base GLM model results						Random intercepts GLMER model:					
Coefficients:						Fixed effects:					
	Estimate	Std.Error	z value	Pr(>|z|)			Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	3.901915	0.135481	28.8	< 2e-16	***	(Intercept)	3.609952	0.224784	16.06	< 2e-16	***
MIN_Speed_Diff	-0.10434	0.011044	-9.448	< 2e-16	***	MIN_Speed_Diff	-0.082331	0.011598	-7.099	1.26E-12	***
MAX_Speed_Diff	0.0821	0.005783	14.196	< 2e-16	***	MAX_Speed_Diff	0.076991	0.00591	13.027	< 2e-16	***
MAX_Event_Speed	0.018499	0.001451	12.752	< 2e-16	***	MAX_Event_Speed	0.015155	0.001523	9.954	< 2e-16	***
STD_Event_Speed	-0.128158	0.008623	-14.863	< 2e-16	***	STD_Event_Speed	-0.108751	0.009211	-11.807	< 2e-16	***
Right_Exits	0.299347	0.026149	11.448	< 2e-16		Right_Exits	0.198172	0.030031	6.599	4.14E-11	***
Outgoing_Lanes	-0.126292	0.016905	-7.471	0.00000000000008	***	Outgoing_Lanes	0.003163	0.024918	0.127	0.898988	
Sideway	0.046146	0.03461	1.333	0.1820		Sideway	0.119132	0.035797	3.328	0.000875	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

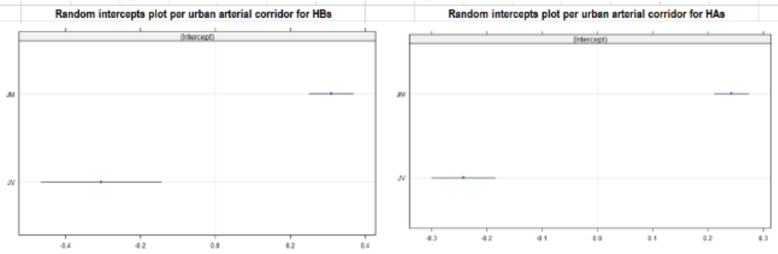
Exploring the relationship between unsafe traffic events and crash occurrence using harsh braking events

glm(formula = FREQUENCY_BRK ~ MIN_Speed_Diff + MAX_Speed_Diff + MAX_Event_Speed + STD_Event_Speed + Right_Exits + Outgoing_Lanes + Sideway, family = poisson, data = Vdata)

Base GLM model results						Random intercepts GLMER model:					
Coefficients:						Fixed effects:					
	Estimate	Std.Error	z value	Pr(>|z|)			Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	37.638361	5.876399	6.405	0.0000000001504	***	(Intercept)	32.554388	6.144945	5.298	1.17E-07	***
MIN_Speed_Diff	-0.095534	0.015099	-6.327	0.0000000002498	***	MIN_Speed_Diff	-0.05591	0.020027	-2.792	0.005242	**
MAX_Speed_Diff	2.861064	0.445999	6.415	0.0000000001409	***	MAX_Speed_Diff	2.432157	0.470467	5.17	2.35E-07	***
MAX_Event_Speed	0.026445	0.001967	13.446	< 2e-16	***	MAX_Event_Speed	0.024633	0.002078	11.855	< 2e-16	***
STD_Event_Speed	-0.103621	0.010318	-10.043	<2e-16	***	STD_Event_Speed	-0.089453	0.011272	-7.936	2.10E-15	***
Right_Exits	0.263377	0.061958	4.251	0.0000212902784	***	Right_Exits	0.225168	0.063591	3.541	0.000399	***
Outgoing_Lanes	-0.101075	0.04165	-2.427	0.015200	*	Outgoing_Lanes	-0.042743	0.046657	-0.916	0.359619	
Sideway	0.493532	0.074886	6.59	0.0000000000439	***	Sideway	0.568168	0.078439	7.243	4.37E-13	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Random intercepts plot per urban arterial corridor.



Likelihood Ratio Test (LRT) results.

Exploring the relationship between unsafe traffic events and crash occurrence using harsh acceleration events

LRT results:

Likelihood ratio test

Model 1: FREQUENCY_ACC ~ MIN_Speed_Diff + MAX_Speed_Diff + MAX_Event_Speed + STD_Event_Speed + Right_Exits + Outgoing_Lanes + Sideway

Model 2: FREQUENCY_ACC ~ MIN_Speed_Diff + MAX_Speed_Diff + MAX_Event_Speed + STD_Event_Speed + Right_Exits + Outgoing_Lanes + Sideway + (1 | Junct_Type)

	#Df	LogLik	Df	Chisq	Pr(>Chisq)	
1	8	-340.1				
2	9	-318.01	1	44.185	0.00000000003	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

LRT = significant, so GLMER is better

Exploring the relationship between unsafe traffic events and crash occurrence using harsh braking events

Likelihood ratio test

Model 1: FREQUENCY_BRK ~ MIN_Speed_Diff + MAX_Speed_Diff + MAX_Event_Speed + STD_Event_Speed + Right_Exits + Outgoing_Lanes + Sideway

Model 2: FREQUENCY_BRK ~ MIN_Speed_Diff + MAX_Speed_Diff + MAX_Event_Speed + STD_Event_Speed + Right_Exits + Outgoing_Lanes + Sideway + (1 | Junct_Type)

	#Df	LogLik	Df	Chisq	Pr(>Chisq)	
1	8	-138.31				
2	9	-135.82	1	4.9793	0.02565	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

LRT = significant, so GLMER is better

VIF scores results.

Exploring the relationship between unsafe traffic events and crash occurrence using harsh acceleration events

VIF scores for the Base GLM model:

MIN_Speed_Diff	MAX_Speed_Diff	MAX_Event_Speed	STD_Event_Speed	Right_Exits	Outgoing_Lanes	Sideway
2.036474	1.853465	1.772092	1.77632	1.768705	3.948076	1.465606

VIF scores for the Random intercepts GLMER model:

MIN_Speed_Diff	MAX_Speed_Diff	MAX_Event_Speed	STD_Event_Speed	Right_Exits	Outgoing_Lanes	Sideway
1.903179	1.860567	1.868247	1.843664	2.180624	3.54389	1.219679

Exploring the relationship between unsafe traffic events and crash occurrence using harsh braking events

VIF scores for the Base GLM model:

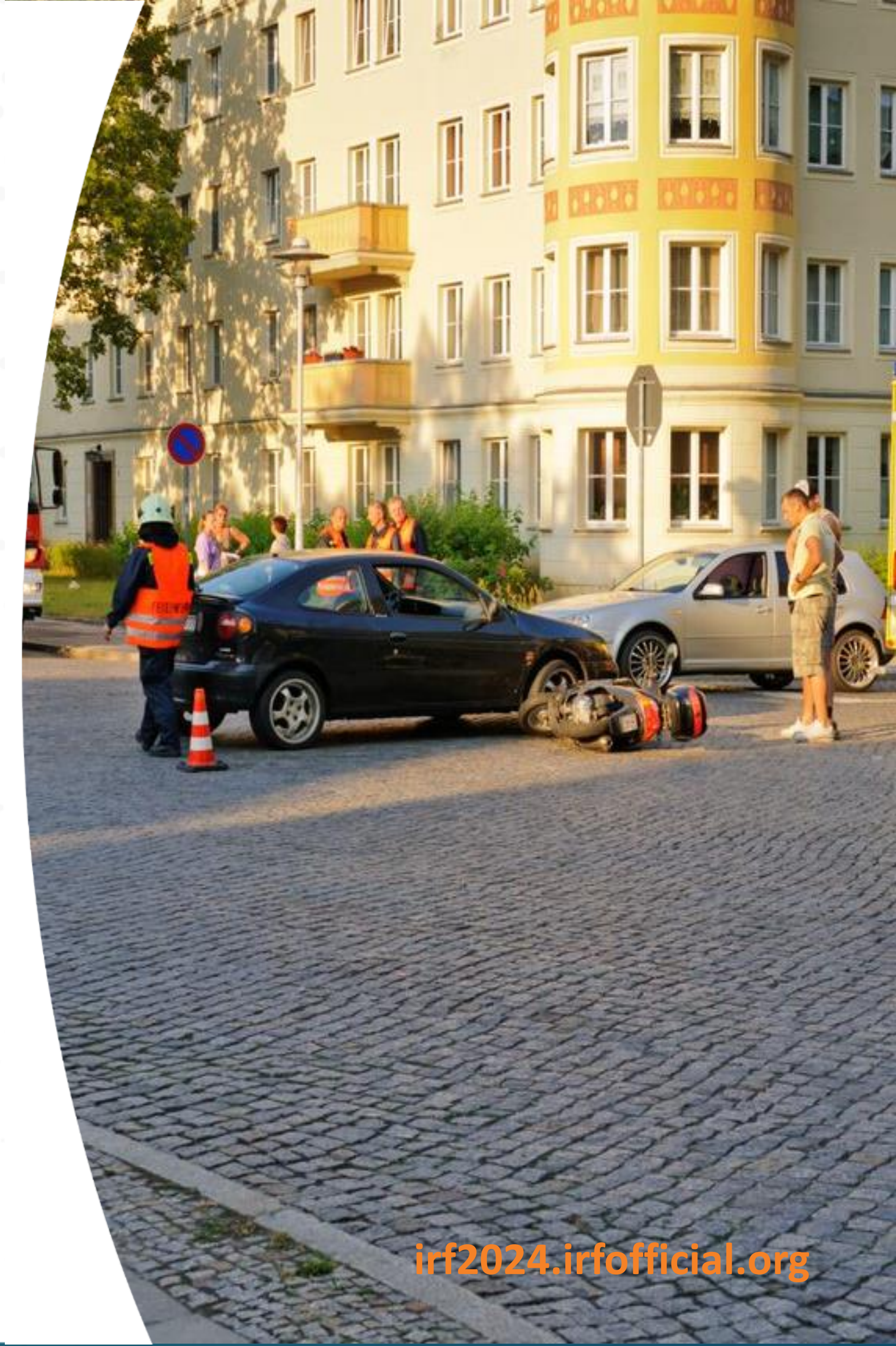
MIN_Speed_Diff	MAX_Speed_Diff	MAX_Event_Speed	STD_Event_Speed	Right_Exits	Outgoing_Lanes	Sideway
2.162926	1.106514	1.813739	1.725633	2.031507	2.88136	1.404447

VIF scores for the Random intercepts GLMER model:

MIN_Speed_Diff	MAX_Speed_Diff	MAX_Event_Speed	STD_Event_Speed	Right_Exits	Outgoing_Lanes	Sideway
1.173837	1.076654	1.991475	2.006422	2.036128	1.96741	1.451817

Results: Predictive Models & Insights

- **Key Predictors:** Speed differences, right exits, and side lanes significantly affect crash frequencies.
- **Model Performance:** GLMM outperformed GLM by considering random effects across junction types, providing a better understanding of crash occurrence patterns.
- **VIF values** (<5) indicate that the predictors are reasonably independent and do not distort the model's results
- **Implications:** Speed variability and junction design features are critical for safety improvements. Mesogeion is more prone to crashes compared to those of Vouliagmeni Avenue.



Limitations & Future Work

Limitations of Current Study:

- Small sample size of junctions may affect generalizability.
- Excluded factors like weather, demographics, and vehicle types can enhance applicability across different contexts.

Future Research Directions:

- Expand data collection to include broader sources, such as weather conditions and vehicle types.
- Conduct detailed behavior analysis to uncover additional risk factors.
- Incorporate machine learning models for improved risk prediction.

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