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Predictive and Proactive Traffic Safety Evaluation and Management in the Era of Smart Cities

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C2SMART
CONNECTED CITIES WITH
SMART TRANSPORTATION



Safety Facts

- Each year, there are about **1.2 million road traffic deaths** and **20-50 million injured worldwide**.
- Road traffic injuries are the leading cause of death for children and young adults aged 5–29 years.



In the U.S.

39,254

LIVES LOST ON U.S.
ROADS IN 2024

11,904

DRUNK-DRIVING
FATALITIES

11,288

SPEEDING-RELATED
TRAFFIC DEATHS

Road Crash Data Caveat

Traditional traffic safety approaches are reactive:

- Requires *large* historical crash samples
- Interventions occur *after* incidents happen

Emerging Paradigm: Predictive & Proactive Safety Management

- Modern smart cities leverage data and advanced analytics to **anticipate risks before crashes occur**

This talk covers:

- Emerging Technologies for Safety Data Collection
- Surrogate Safety Measures: provide early indicators of unsafe conditions
- Innovative predictive & proactive safety methods
- AI-Driven Safety Monitoring: AI + sensors for real-time insights

VISION ZERO

Total Crashes in NYC (2025)

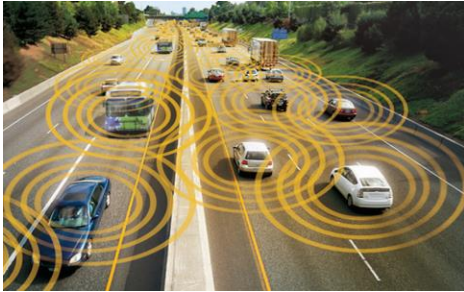
Source: NYCDOT



Emerging Technologies for Safety Data

In the era of smart cities, the collection of **safety-related data** becomes easier due to various emerging technologies.

Emerging Data Collection Methods



Connected Vehicles (CVs)



Drones



Video Data

New Data Generated:
Basic Safety Messages, Trajectories, Risk Events etc.

Proactive Safety Evaluation & Monitoring

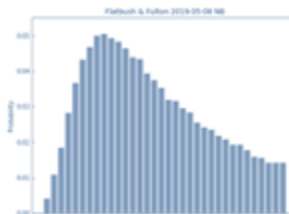
Drone/CV data -> **Trajectories**



Traffic risk can be quantified



**Surrogate
safety
measures**



Suitable for proactive safety monitoring:

- Detect potential safety-related anomalies that may cause high traffic risk.
- Provide intervention.

What Are Surrogate Safety Measures?

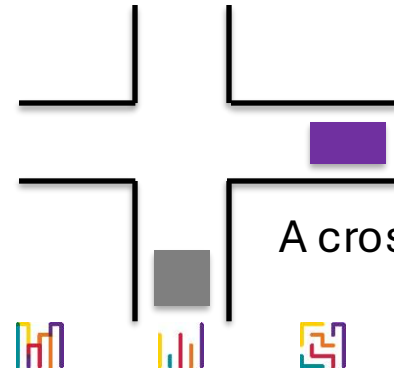
- **Surrogate Safety Measures (SSMs):**
 - Capture near-misses and conflicts
 - Can be extracted from **vehicle trajectories**
 - Enable **proactive safety** assessment
- **Crashes tell us where safety failed—SSMs tell us where safety is about to fail**
 - Risks captured by SSMs are **highly correlated with crashes**
 - Recent study show SSMs can achieve ~85% successful crash identifications

Why Use SSMs?

- Crashes are rare & delayed signals
- SSMs provide frequent, real-time risk indicators
- Support early intervention



A rear-end conflict



A crossing conflict

Xie, K., Yang, D., Ozbay, K. and Yang, H., 2019. Use of real-world connected vehicle data in identifying high-risk locations based on a new surrogate safety measure. *Accident Analysis & Prevention*.

Wang, Y., Xu, C., Liu, P., Li, Z. and Chen, K., 2024. Assessing the predictability of surrogate safety measures as crash precursors based on vehicle trajectory data prior to crashes. *Accident Analysis & Prevention*.



Commonly Used SSMs



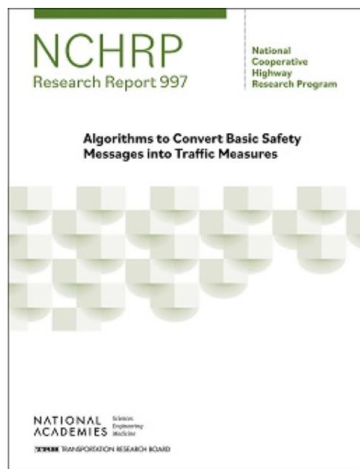
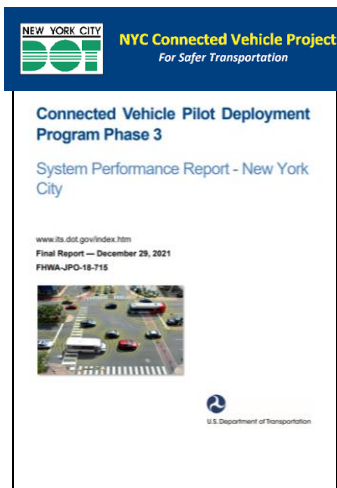
Safety Measure	Definition
Time-to-Collision (TTC)	The time remaining before two vehicles would collide if they continue at their current speeds and paths
Modified TTC (MTTC)*	An enhanced version of TTC that accounts for acceleration/ deceleration (More realistic, behavior-aware)
Hard Braking (HB)	When a vehicle's deceleration is greater than a pre-determined threshold
Deceleration Rate to Avoid Collision (DRAC)	The minimum deceleration rate required by the following vehicle to come to stop (or match the leading vehicle's speed) to avoid a crash
Time-To-Collision with Disturbance (TTCD)	The time to collision modified by imposing a hypothetical deceleration to the leading vehicle

***Reference:** Ozbay, K., Yang, H., Bartın, B., & Mudigonda, S. (2008). **Derivation and validation of new simulation-based surrogate safety measure.** Transportation research record, 2083(1), 105-113.



Convert Connected Vehicle Information into Traffic Safety Measures

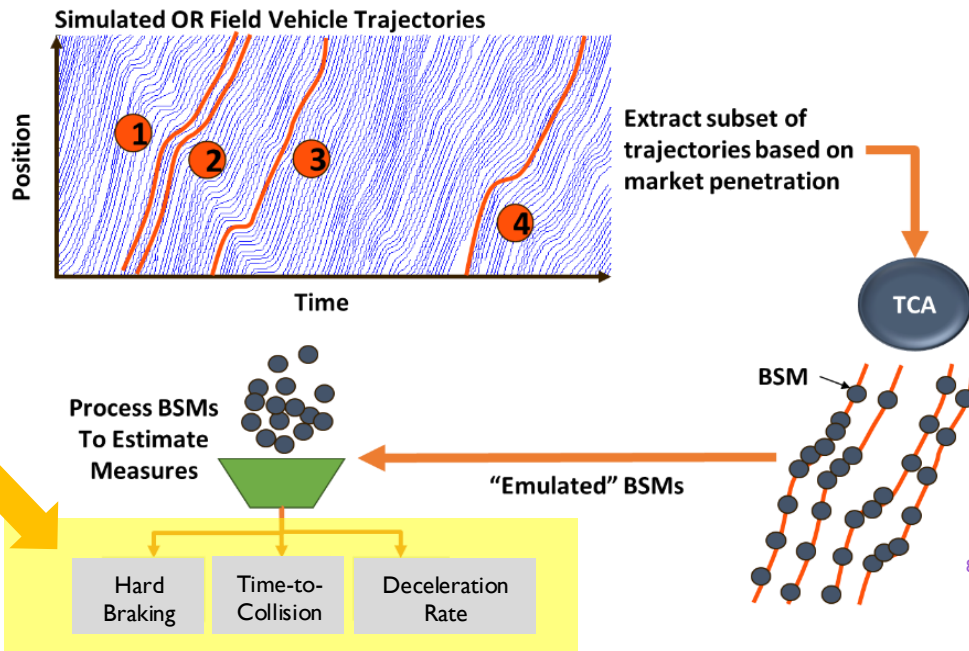
Basic Safety Messages (BSM) generated by CVs has the potential to transform transportation systems management, traveler safety and mobility, and system productivity.



NYC DOT & NYU C2SMART,
Cambridge Systematics,
Transcore/JHK, **Connected Vehicle Pilot Deployment Program Phase 3 – System Performance Report** - New York City

Noblis & NYU C2SMART,
NCHRP Research Report 997 - Algorithms to Convert Basic Safety Messages into Traffic Measures

From vehicle trajectories to BSMs to Safety measures



Convert Connected Vehicle Information into Traffic Safety Measures



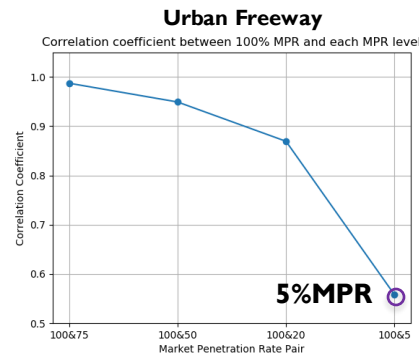
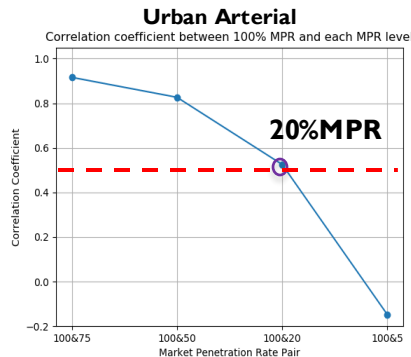
Three high-priority safety measures for performance monitoring, traffic management, and traveler information

SSM thresholds are location-dependent, can vary significantly with roadway geometry, traffic conditions, and local driving behavior

Identify minimum MPR required for reliable application of the method

Threshold	Urban Intersection	Urban Freeway
HB	3m/s ²	2m/s ²
DRAC	3m/s ²	2.5m/s ²
TTCD	1.5m/s ²	1.5m/s ²

*Also depends on time bin and trajectory window size.



Functional Data Analysis

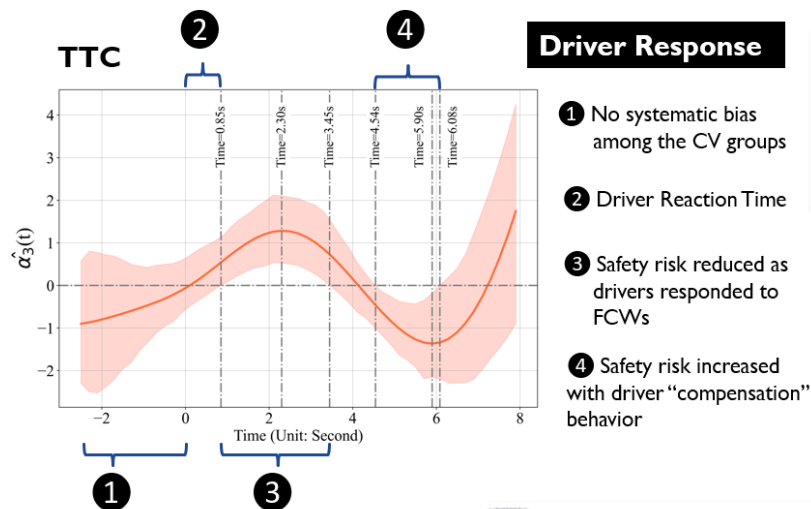
A continuous-time approach to modeling trajectory data for safety evaluation



- **Traditionally:** Aggregating traffic risk at different temporal and spatial levels
- **Functional data analysis approach:** Modeling safety measures as **time functions** reveals driver responses that are rarely captured by statistical methods

Methodology: Models time series of a variant of the time exposed time-to-collision safety indicator directly to detect safety-related anomalies using video data

Driver Response Functions Generated from NYC CV Pilot

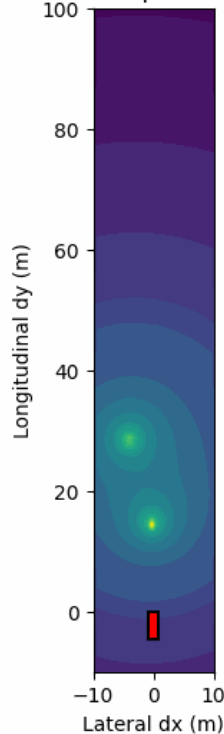


Safety Risk Field – Behavior-Informed Safety Measure

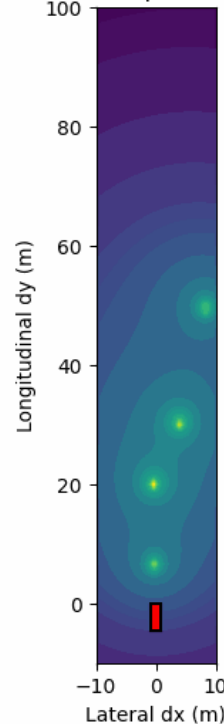
A spatial-temporal “map” of how collision risk varies across space and time based on vehicle interactions.

- Captures drivers' intended clearance based on speed, vehicle type, and driving task
- Calibrated from naturalistic gap-maintenance relative to vehicles, boundaries, and lane markers

Safety Potential Energy Field
Timestamp=1417000



Safety Potential Energy Field
Timestamp=1183700



Collision eventually happened (even though ego vehicle braked)!

Ego vehicle brakes and manages to **avoid the collision.**

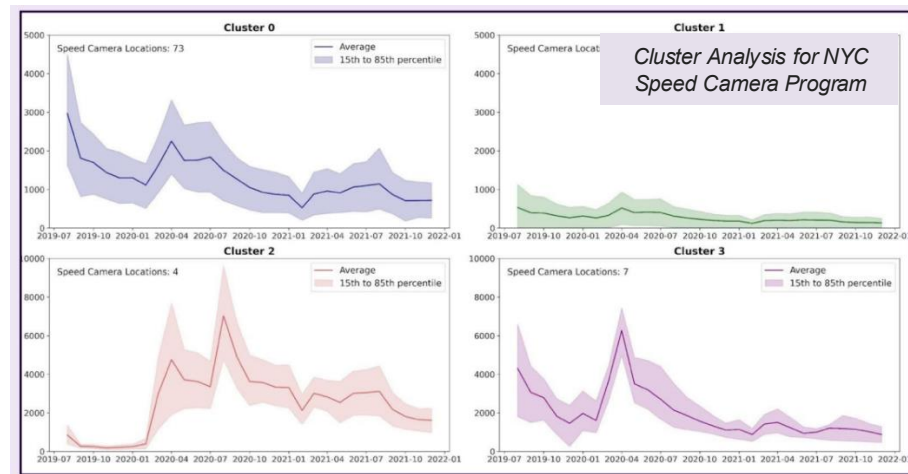
Survival Analysis with Random Effects (SARE)



SARE: A statistical method that models time between crashes

- Significantly reduces crash data waiting time, enabling faster safety evaluation and intervention
- Accounts for varying implementation timing (e.g., speed cameras)
- Relax the requirement of control group

Application Example: Using SARE to model inter-crash times and site heterogeneity, we found speed cameras were associated with a ~14% reduction in crashes pre-COVID (CMF ≈ 0.87).

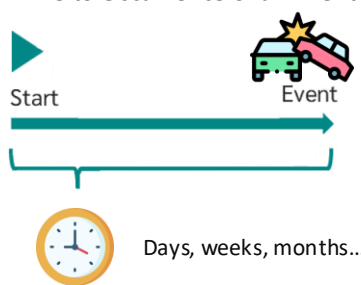


Survival Analysis with Random Effects (SARE)

What is survival analysis?

A method used to model the time until an event occurs (e.g., time until a crash, or incident clearance)

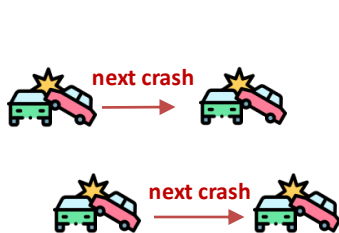
Time to Occurrence of an Event



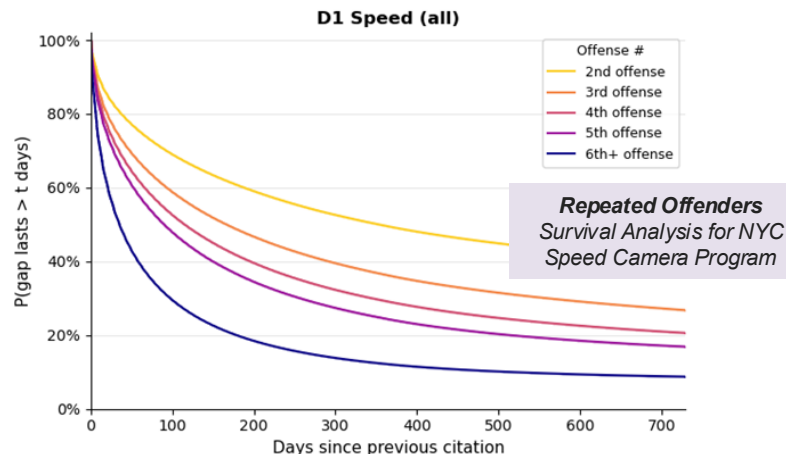
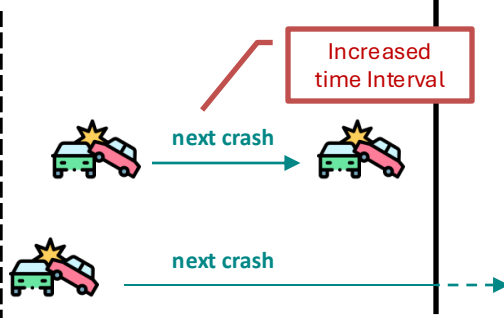
If the time to next crash increases after a safety countermeasure, it suggests improved safety performance, when controlling for exposure and external factors (e.g., traffic volumes).

For a new safety intervention:

Before



After



Liu, Z., Zuo, F., Gao, J., and Ozbay, K., 2026. Learning or Luck? Behavioral Adaptation to Camera Enforcement in New York City (working paper).

Proactive AI & Gen-AI-Enabled Traffic Safety Analysis

Language Vision Models can be used to for proactive safety, turning passive video feeds into an active, automated safety monitoring system.

What it does: Identify risky events in traffic footage by combining language reasoning with visual intelligence to understand complex behaviors and provide real-time insights & dynamic response

Language understanding
(text and speech)



Vision understanding
(images or videos)



AWARD WINING RESEARCH

SeeUnsafe: A multimodal LLM-empowered framework combines the reasoning of an LLM with computer vision.

2025 Vision Zero Research Award and **international recognition** for AI-driven usage of traffic cameras for safety insights to reduce traffic fatalities

Reference: Zhang, R., Wang, B., Zhang, J., Bian, Z., Feng, C. and Ozbay, K., 2025. When language and vision meet road safety: leveraging multimodal large language models for video-based traffic accident analysis. *Accident Analysis & Prevention*, 219, p.108077.



Case Example

- We evaluated SeeUnsafe on Toyota Woven Traffic Safety (WTS) Dataset.
- In this example, we successfully reasoned the collision with consistent scene context and object descriptions using SeeUnsafe. The justifications correctly describe the object dynamics.



Ground truth: Collision.



Event class: Normal

Scene context: Sunny day with dry road surface in a curbside area near an intersection, under daytime lighting with moderate mixed traffic.

Object description: Multiple pedestrians.

Justification: The pedestrians maintain a consistent walking pace and direction without any sudden changes or interactions that suggest a near-miss or collision.



Event class: Collision

Scene context: Sunny day with dry road surface in a curbside area near an intersection, under daytime lighting with moderate mixed traffic.

Object description: A white sedan and a male pedestrian.

Justification: The pedestrian's path intersects with the vehicle's trajectory, and the vehicle does not deviate or stop, resulting in a collision with the pedestrian.



Event class: Collision

Scene context: Sunny day with dry road surface in a curbside area near an intersection, under daytime lighting with moderate mixed traffic.

Object description: A pedestrian and a white sedan

Justification: The pedestrian is in direct contact with the sedan, indicating a collision. The vehicle's position suggests it failed to stop in time, resulting in the impact.

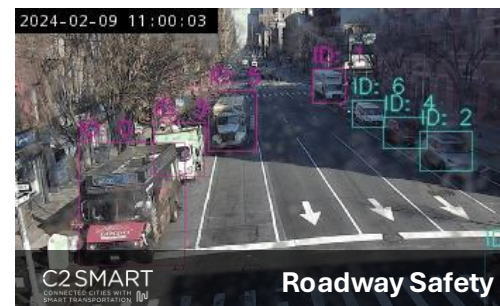
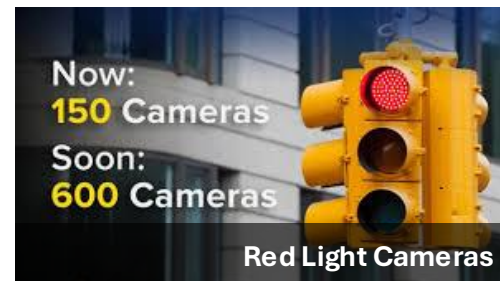
Visual grounding: car id: {5}, person id: {3}

Toward Zero: The Shift We Need

- Shift from reactive to predictive safety using real-time data and AI
- Detect risk early with surrogate safety measures (near-misses, conflicts)
- Evaluate faster using inter-crash analysis (e.g., SARE)

👉 We need faster adoption of these solutions—deployed responsibly and effectively—to achieve Vision Zero

👉 Advancing this vision requires continued partnership across agencies, researchers, and industry



Work with us!

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