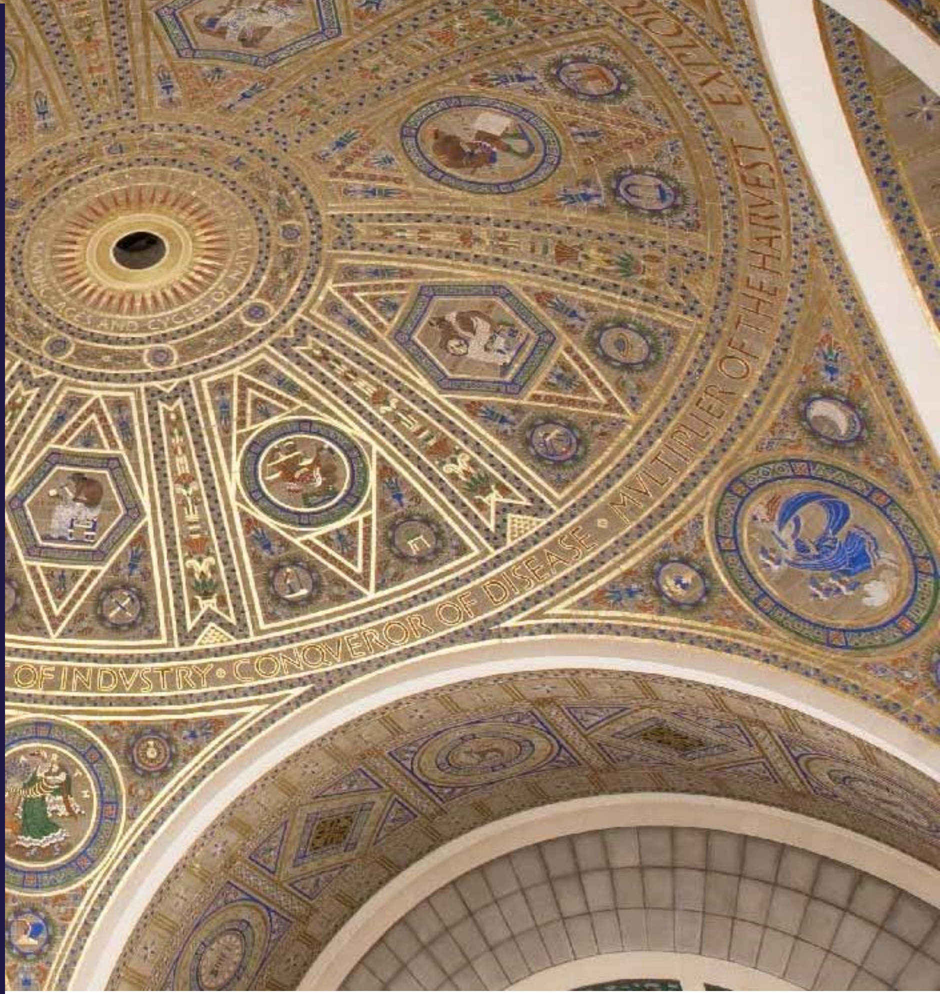
NATIONAL ACADEMIES *Sciences Engineering Medicine*

TRB TRANSPORTATION RESEARCH BOARD

TRB Webinar: Progress and Opportunities for In-Vehicle Impairment Detection

September 23, 2024

3:00 – 4:30 PM



PDH Certification Information

1.5 Professional Development Hours (PDH) – see follow-up email

You must attend the entire webinar.

Questions? Contact Andie Pitchford at TRBwebinar@nas.edu

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AICP Credit Information

1.5 American Institute of Certified Planners Certification Maintenance Credits

You must attend the entire webinar

Log into the American Planning Association website to claim your credits

Contact AICP, not TRB, with questions

Purpose Statement

Purpose Statement HERE

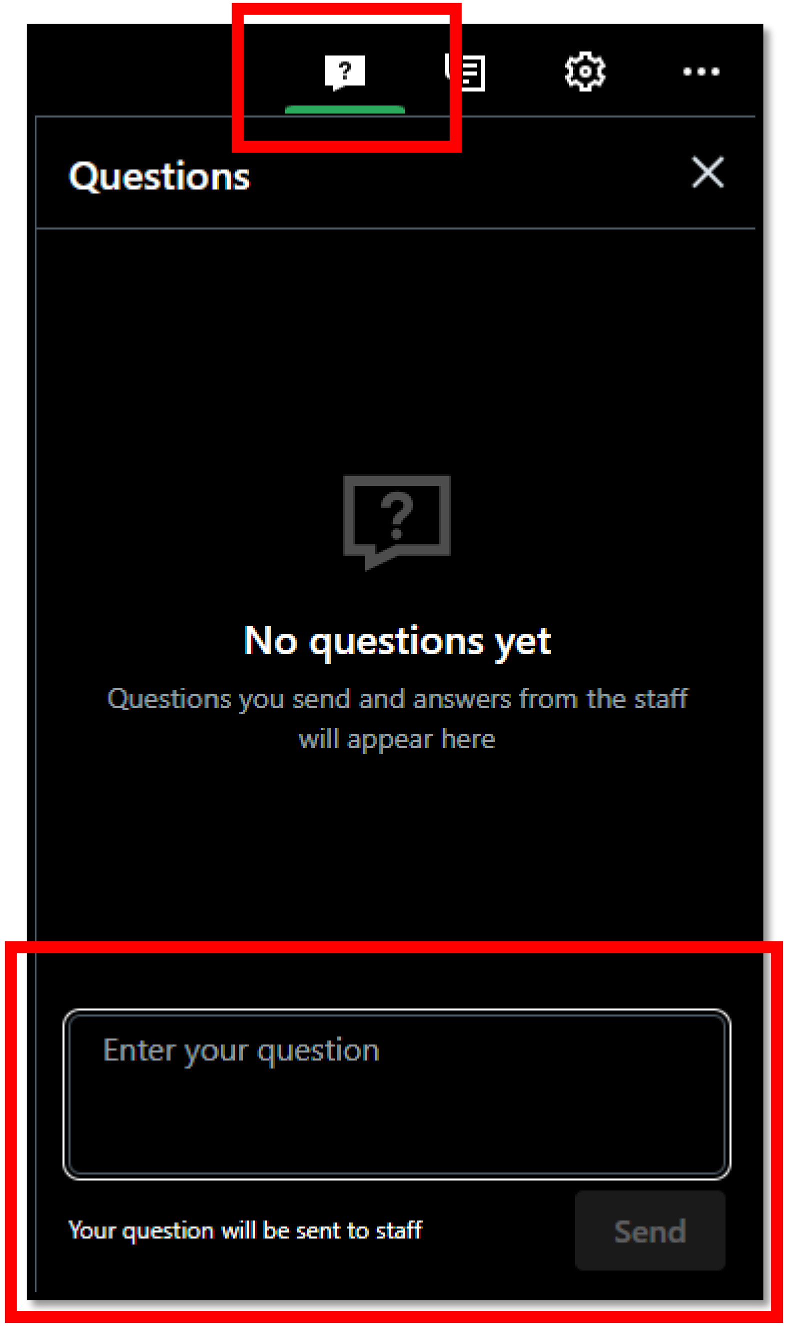
Learning Objectives

At the end of this webinar, you will be able to:

- Make objective economic and planning decisions based on the impact of a pandemic on impaired driving behaviors
- Evaluate the potential impact of decisions designed to mitigate pandemic-related impaired driving behaviors
- Assess areas where additional research on the topic is needed

Questions and Answers

- Please type your questions into your webinar control panel
- We will read your questions out loud, and answer as many as time allows



Today's presenters

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IOWA | Driving Safety Research Institute

Driving Safety Research Institute

Evaluation of Impairment Detection Technology

Progress and Opportunities for In-Vehicle Impairment Detection

23 September 2024

Overview

- Approach
- Some Examples
- Some Thoughts

Approach

Define Detection States

What state is are we trying to detect?

- Drowsiness
- Distraction
- Drunk
- Drugged

- General Impairment
- Something Else

From what are we trying to differentiate ?

- Optimal driving
- Normal range of driving
- An individuals normal driving

What is Ground Truth?

→ Critical question

→ What are you trying to detect?

- That the driver is in a particular state
- That the driver is ***impaired*** in a particular state

→ Is the state easily identified or are proxies necessary?

→ What is the relationship between potential measures of state and your definition of ground truth?

What is Ground Truth?

Type	Measure	Description
Drowsiness	Cumulative time awake	The number of hours since the participant awoke
	Time of day	Clock time at the start of the drive
	KSS	Subjective self-rating of sleepiness, measured before and after all drives, as well as every 30 minutes while waiting
Distraction	Task status	Did the task start? Is the task currently active?
	Task performance	How well the participant performs the task [accuracy, speed]
	Screen touches	Marked for each touch of the screen
Alcohol	BrAC	BrAC measured pre- and post-drive, and estimate of BrAC for each minute of the drive based on the individual alcohol decline curve
	BAC	BAC measured every minute based on Transdermal BAC collected every 20 seconds

What Variables Predict State?
What Variables Differentiate between States?

Driver Measures

- Eye gaze orientation (deg)
- Face location, orientation (cm, deg)
- Percent road center gaze
- Facial features (brow movement, mouth movement, etc.)
- Blink frequency (blinks per minute)
- Blink duration (sec)
- Heartbeat inter-beat interval (sec)
- Respiration TEDD score

Vehicle Measures

- Throttle Position, brake pedal force
- Acceleration, deceleration
- Steering reversal rate
- Steering wheel holds
- Steering AmpD2Theta
- Weighted steering phase
- Ratio of steering bandwidth in a high frequency band.

What Variables Predict State?
What Variables Differentiate between States?

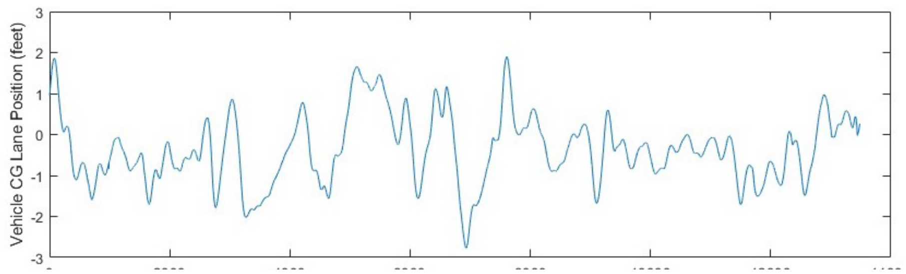
Environmental Measures

- Headway time
- Time to collision
- Time to lane crossing
- Lane position
- Lane departure frequency
- Lane departure severity
- Speed in relation to posted limit

How to Get the Data: We Need Sensors

→ Vehicle data

- Speed
- Lane Keeping
- Steering/Throttle/Brake Inputs
- Lane Departures



→ Other Sensors

- Driver Monitoring System
- Other Novel Sensors
  - Heart rate
  - Respiration
  - Galvanic Skin Response

HRV	Cognition
Low	Decreased
High	Improved

What Might Confound State Detection

- → Does our data just contain what we are trying to detect
  - Might there be other types of impairment present?
    - Controlled studies have an important advantage in this regard
- → Some concerns
  - How much sleep? Are they actually just drowsy and not drunk?
  - When did they eat? Are they just lethargic?
  - Are they hot or cold? Is that effecting facial measures?

Generalizing

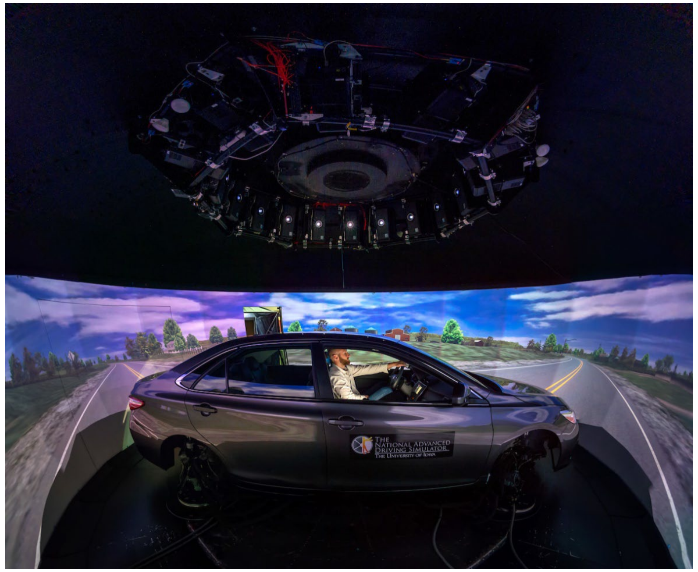
- → Does the population represent those that will drive?
  - Older driver, younger drivers, teens learning to drive
- → What about facial features?
- → What about skin tone?
- → What happens if they are wearing a parka and gloves?
  - What about a scarf that obscures part of the face
- → What about glasses or contacts?
- → Do different driving styles matter?

We Need Data: Human Subject Studies

- These can be complex and time consuming
- Need to make sure you are collecting data that informs modeling
- Your “standard” protocol may not get you what you need
- Subject selection is important
  - What is the population?

How to Get the Data: Platforms

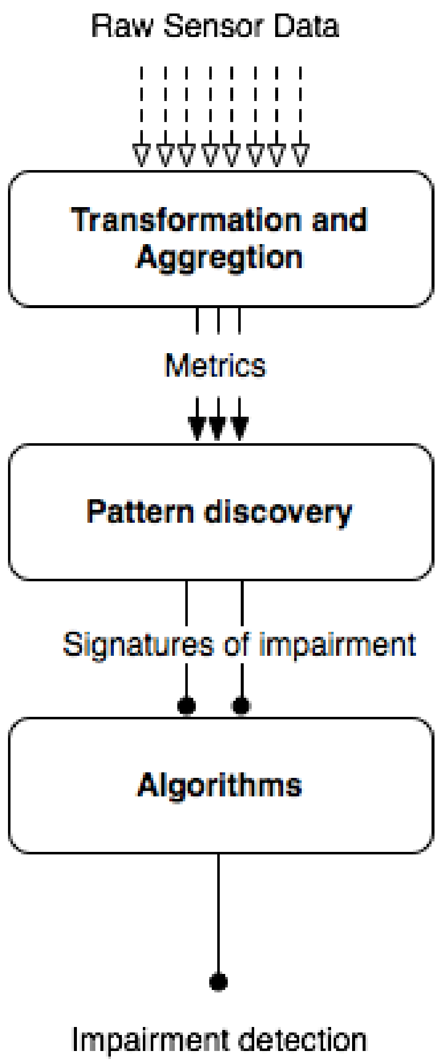






Algorithm Development and Assessment

- Use several ways to slice data and train models
  - Baseline alert behavior vs. drowsy behavior
  - Alert and drowsy behavior vs. intoxicated behavior (1 or 2 levels)
  - Models that use vehicle data or driver behavior or physiological signals
  - Models that combine all types of data
  - Models trained on data aggregated across participants (average behavior)
  - Models trained within-subject (individualized behavior)
- Incorporate severity as an additional input
  - Extreme lane departures
  - Extreme steering
  - Extreme eye closures
  - Extreme speed variability

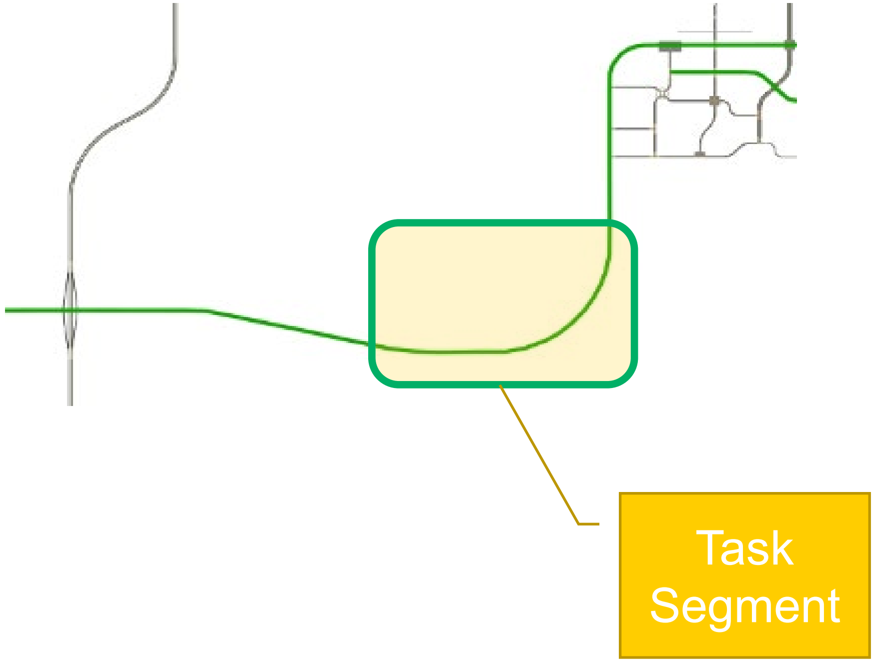


Model Training

- → Supervised models use dependent measures and a model type (e.g. random forest, support vector machine) to learn the relationship between the measure values and the ‘ground truth’
- → Model training typically uses 70-80% of the dataset, reserving 20-30% dedicated for testing
- → Illustrative train/test scenario
  - Each task is experienced 40 times in track A and 40 times in Track B
  - There are 13 tasks per drive
  - A theoretical model trained using every task might use a training set of 64x13=832 events, and a test set of 16x13=208 events. This is an 80/20 split

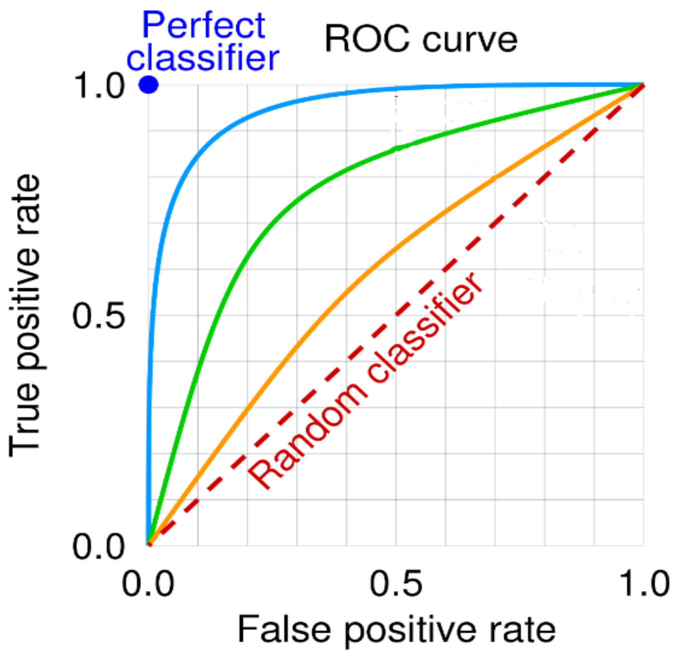
Matched Cases and Controls

- → Each task is placed on a fixed road segment
- → When training models, we will only use data from non-distraction drives on the same road segments
- → Benefits
  - We keep other variables constant, like road curvature, number of lanes, scenery, etc.



Detection Timeliness

- → Vary the window size of data used to train
  - Always starting from the beginning of the task
- → Train models for each window size
  - Results in a family of models
- → Plot results of entire family on a receiver operating characteristic (ROC) curve
  - Can pick the ‘best’ model as the one falling closest to the perfect classier
  - Can evaluate the whole class using the area under the curve (AUC)



Receiver operating characteristic curves for families of models. Better performance falls near the upper left corner

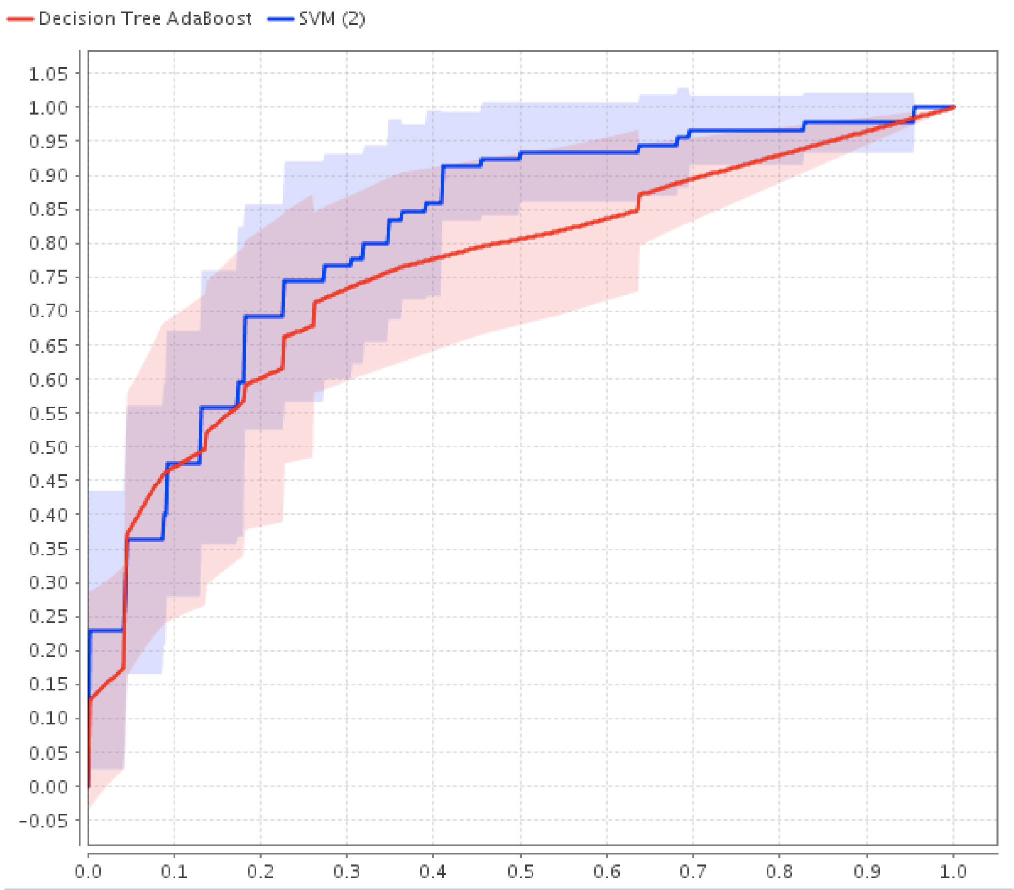
What About Deep Learning Models

- → An alternate to feature driven models
- → Requires lots of data
- → Training data exceeds what can generally be obtained from a controlled study
- → Models are black boxes
  - Generally, perform well, but
  - Difficult to interpret and
  - Harder to predict generalizability

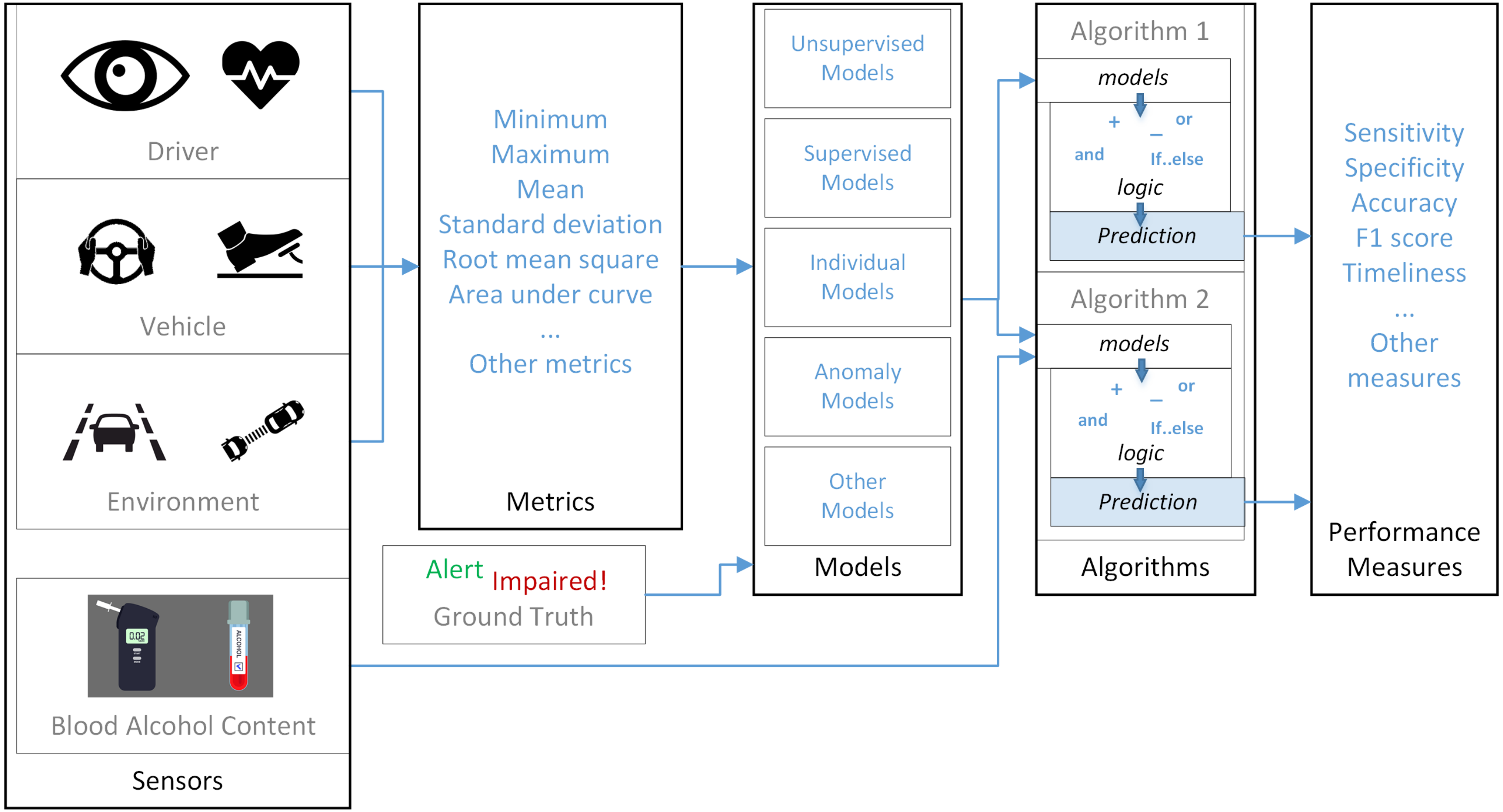
Some Examples

Alcohol Impairment

- Can detect alcohol impairment from just vehicle-based measures
- How much of this would be confounded with drowsiness?



Alcohol Impairment



Algorithm Development and Assessment: Considerations from an Alcohol Example

→ Alcohol detection differs from drowsiness or distraction

- It is a one-time detection, not episodic or regular
- Countermeasures are expected to be more severe

→ Therefore…

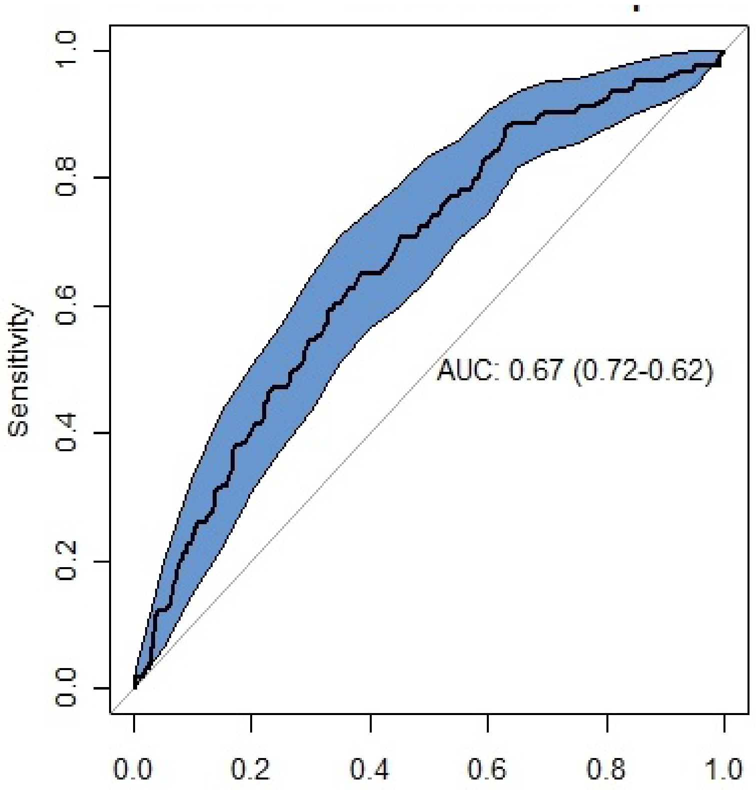
- We should prioritize avoiding false alarms (false positives)
- We should be confident we're not confusing intoxication with drowsiness, even if they co-exist

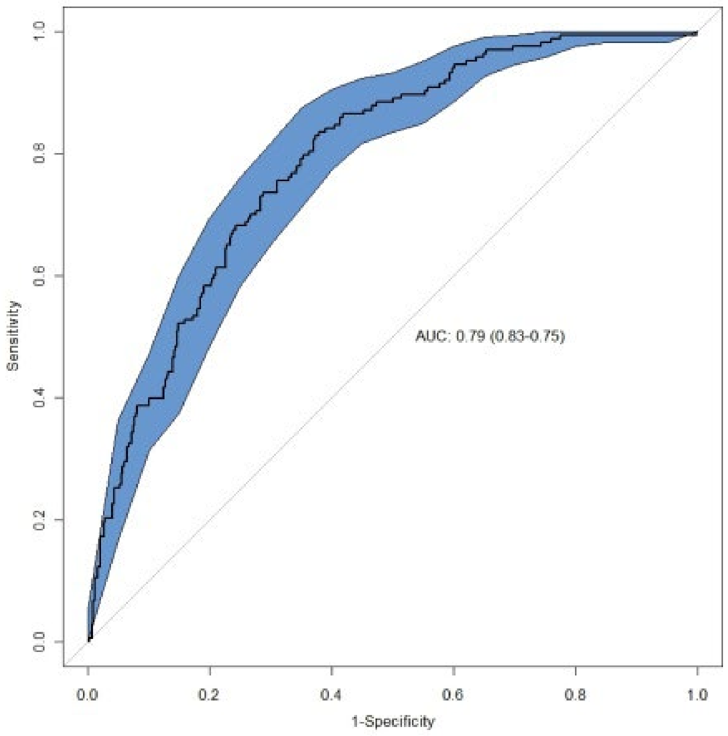
→ How?

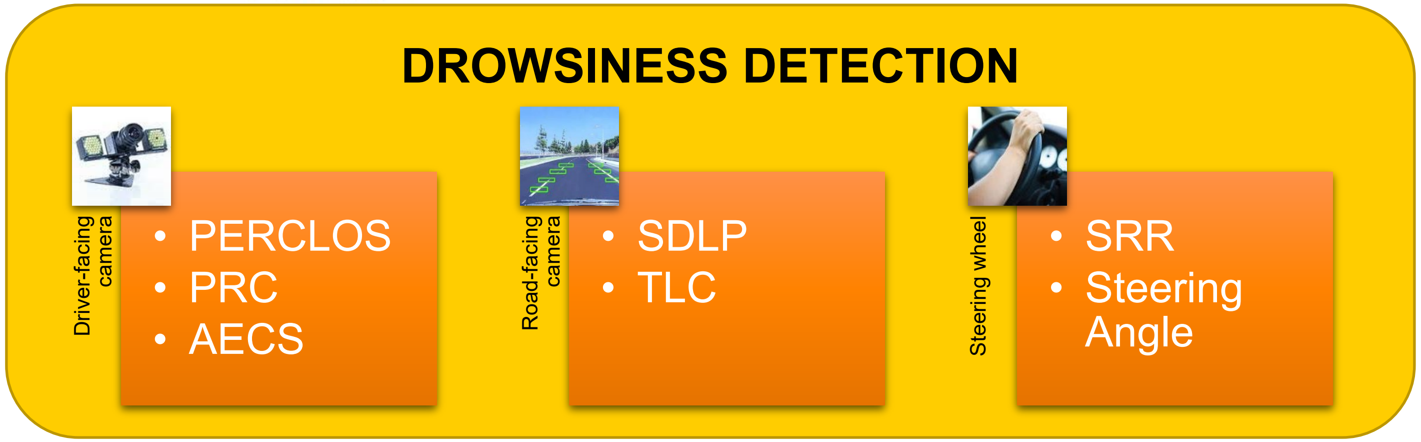
- Look for an accumulation of evidence
- Look for repeated indications of impairment
- Look for severe behavioral infractions (e.g. inter-lane weaving)

Drowsiness

- Steering and time to line crossing can be used to detect
- Camera-based detection improves performance

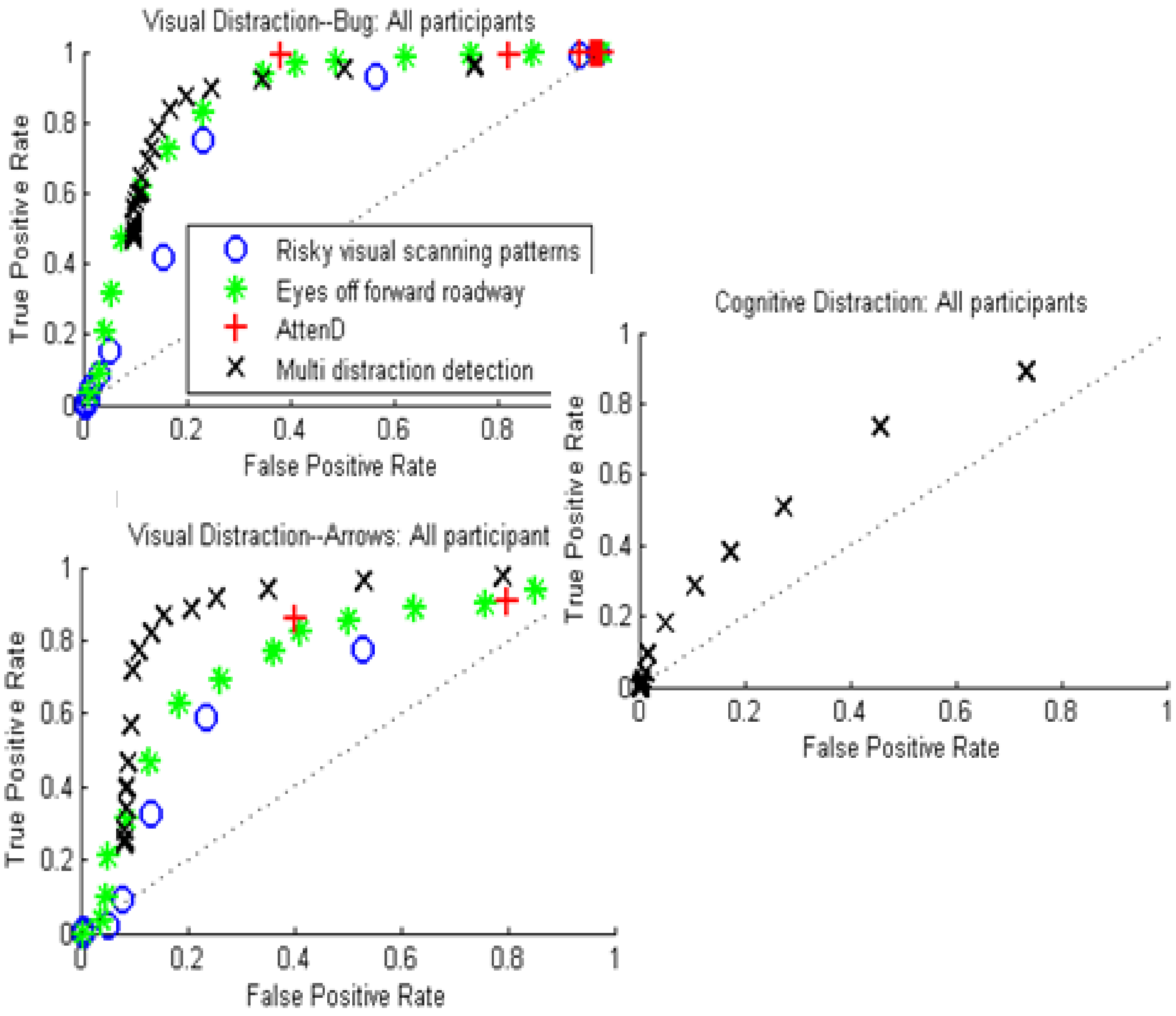






Distraction

- Vision-based algorithms work well for visual-manual distractions
- Cognitive distraction more complex to detect



Some Thoughts

Time and Driving Environment

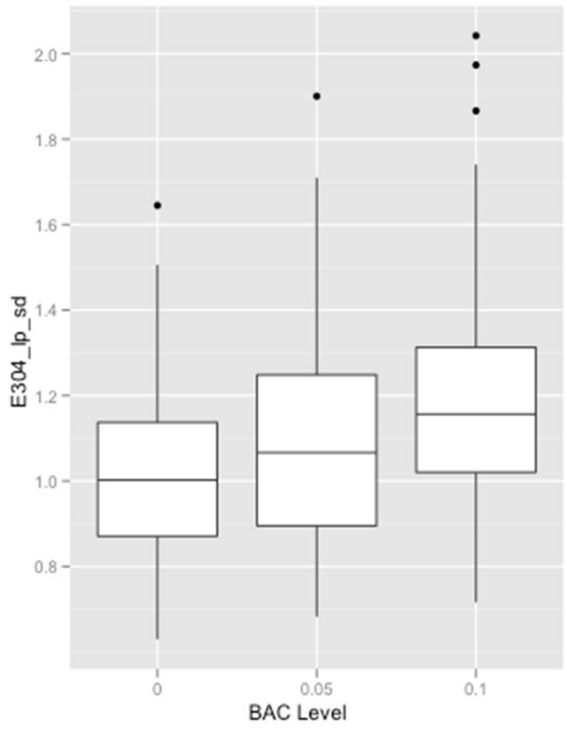
- More data improves detection
  - Accumulating evidences
  - Shorter time-windows have more variability and provide less utility
    - Baseline driving performance appears more stable over 2 minutes

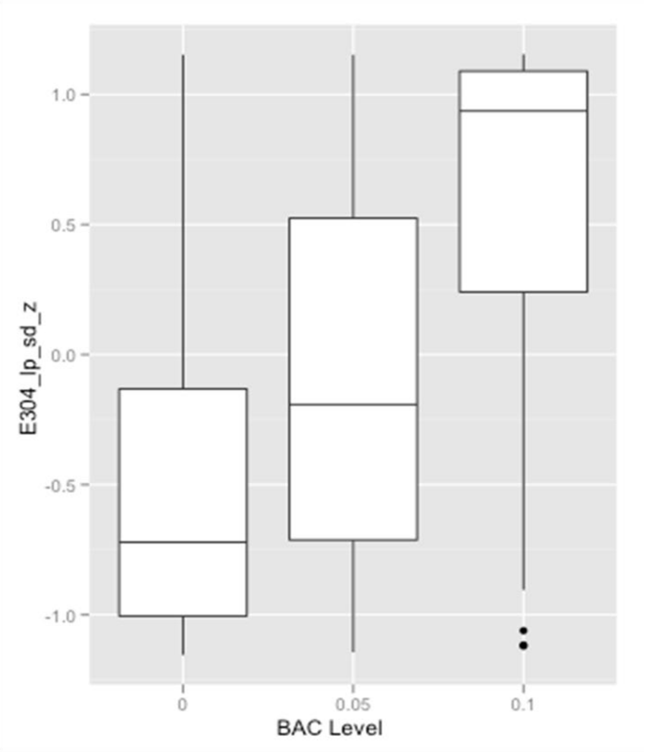
- Easier to differentiate with higher driving demand

	Accuracy	AUC
Urban		
Decision tree	78.6 (5.6)	.79 (.10)
SVM	78.7 (7.4)	.82 (.10)
Freeway		
Decision tree	72.2 (5.2)	.71 (.06)
SVM	71.6 (1.9)	.68 (.15)
Rural		
Decision tree	77.6 (3.6)	.81 (.05)
SVM	77.4 (5.4)	.82 (.07)
SFST	**81.8 (5.9)**	**.76 (.09)**

Individualized vs Generic Models

- Everyone is different
  - You and I don't drive the same!
- More sensitivity to individualized models
  - But how does it learn?
  - What happens until it learns?





Timescales

→ The timescale of an impairment can be used to help differentiate from other types of impairment
  - Distraction (fast)
  - Drowsiness (slower but episodic, trends worse over time)
  - Intoxication (slow, worst at trip start and gradually improves, but interacts with drowsiness)

Safety

- → How to make the connection to safety?
- → We consider number and severity of lane departures
- → Generally, we have not modeled impairment using factors such as:
  - Latent hazards, reaction time, decision theory (e.g. yellow light dilemma)
  - …though they could be considered

Anomaly detection

- → Another way to deal with impairment is to train based on normal driving and detect anything out of the ordinary
- → Has the benefit of capturing many different types of impairment
- → Has the disadvantage of not identifying the impairment and not being able to customize the intervention to the impairment

IOWA | Driving Safety Research Institute

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Find us on:

Road Safety Evolution:
Leveraging Advanced Interior Sensing Technologies to Address Driver Impairment and Fitness to Drive

Tyler Warga

Product Manager, Interior Sensing Solutions

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In 2021, there were over 24,000 fatalities on public roads in the U.S. due to driver impairment

Source: *NHTSA ANPRM Released January 2024*

Legislation and consumer tests drive the market

Consumer testing

- **EUNCAP**: Driver drowsiness, distraction, unresponsive, child presence
- **CNCAP**: Driver drowsiness, distraction
- **CNCAP**: Child presence detection
- **IIHS**: Driver monitoring (L2)
- **EUNCAP**: Child presence (direct only)
- **JNCAP**[3]: Driver drowsiness, distraction
- **EUNCAP**[3]: Occupant monitoring, enhanced driver monitoring incl. DUI/fit-to-drive, seat belt routing
- **CNCAP**[3]: Additional test scenario for cognitive distraction and drowsiness
- **EUNCAP**[3]: Enhanced passive safety, intoxication, enhanced driver state evaluation

2020 – 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029

Regulation

- **UNECE R157:** Driver availability recognition (L3)
- **GSR:** Driver drowsiness[1]
- **GB/T:** Driver drowsiness, dangerous behavior
- **GSR:** Driver drowsiness[2] Driver distraction[1]
- **UNECE R171:** DCAS (L2)
- **UNECE R171:** DCAS (step 2[3], e.g. hands free)
- **IIJA**[4] Impaired driving detection and child presence
- **AIS-184**[3]: Driver drowsiness
- **GSR:** Driver Distraction[2]
- **UNECE**: CLIV[3] Children left in vehicle
- **UNECE**: drowsiness[3] and distraction[3]
- **GSR:** Drafting for GSR III starts (i.e., Step 2 for ADDW)

[1] New types | [2] New cars | [3] Effective date & requirements tbd | [4] Effective date defined in Infrastructure Investment and Jobs Act unknown but expected to include distraction, drowsiness and alcohol detection

Innovations in vehicle sensors enable real-time driver monitoring

Cabin sensing radar

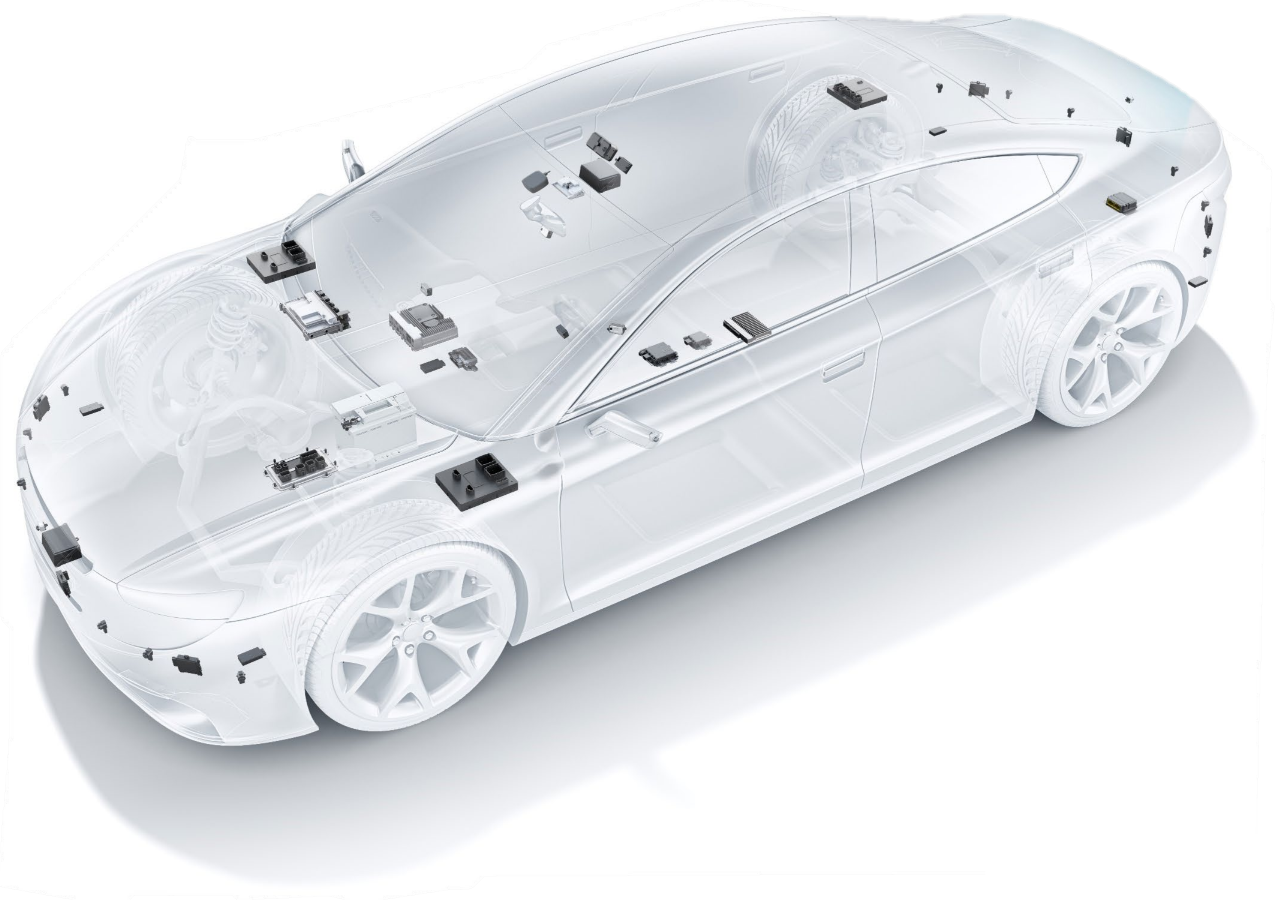
Occupant monitoring camera

Driver monitoring camera

Interior monitoring ECU

Automotive application algorithms

Steering angle software (DDD)



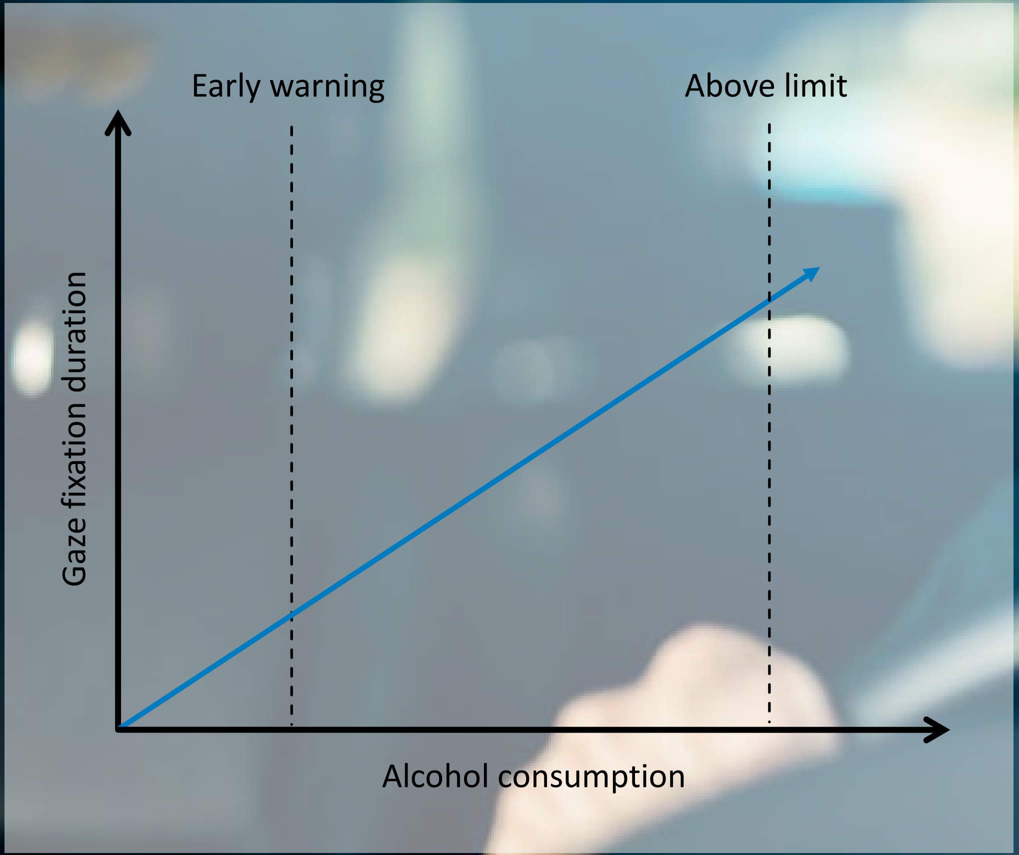

Example base signals to determine driver impairment
Eye gaze
Eye state
Head pose
Body pose
Breathing rate

As installation rates increase, more field data is available and can be used to improve the system algorithms

Bosch IoT collaborative study **Drunk driving**

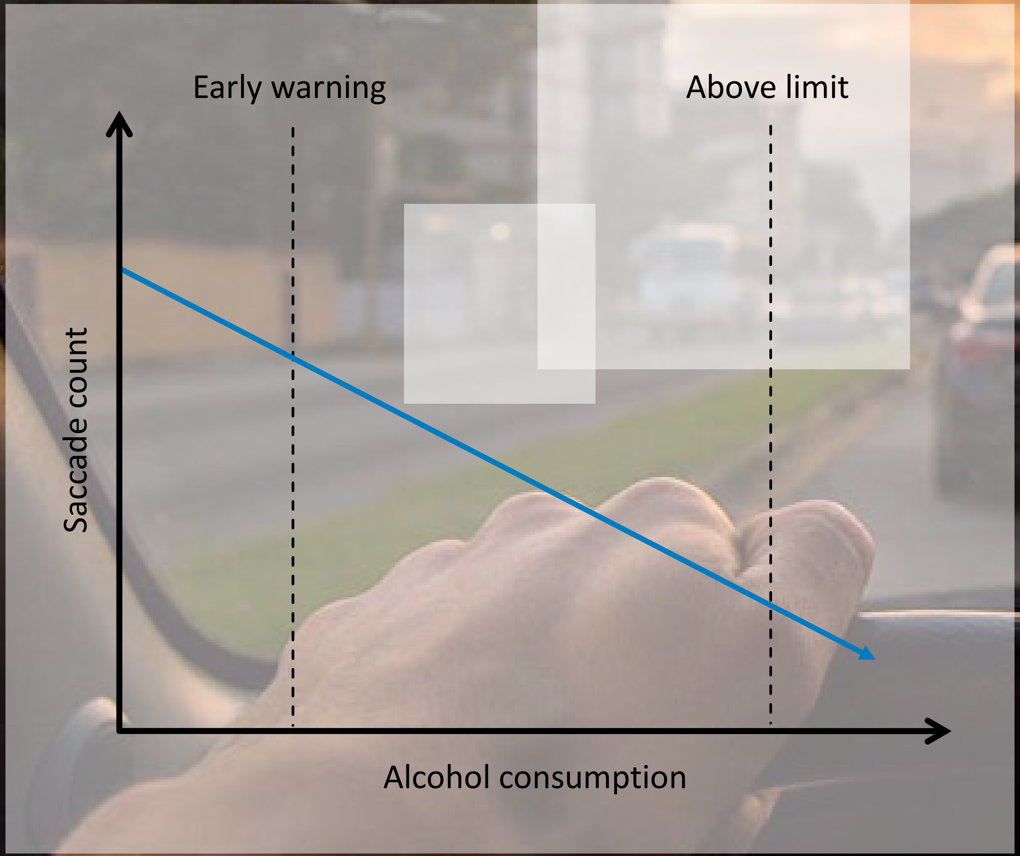
- Determine effectiveness of driver monitoring system in detecting if driver is under the influence
- Driver monitoring system monitored participants while operating simulator

Source: *Bosch IoT Lab*



Longer fixations may be a strong indication for drunk driving

Source: *istockphoto, Bosch IoT lab*



Reduced saccade count is an indicator for drunk driving

Source: *istockphoto, Bosch IoT lab*

Reduced saccade velocity may be an indicator for drunk driving

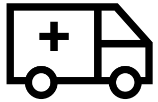
Source: *Bosch IoT collaborative study, istockphoto*

Approaches to detect drunk driving

Driving performance

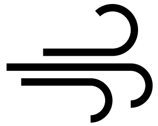
Factors to determine driving performance*

Blood Alcohol Content (BAC)



Administered blood test

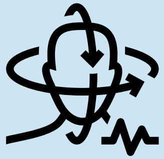
Breath alcohol concentration (BrAC)



Breath system detection

Physical ability

Vehicle information



Driver information

*Other factors may be considered to determine driving performance

First person arrested for drunk driving after slamming his cab into a building in 1897

Source: *History.com*

Installation rates and **consumer acceptance** for Interior sensing solutions are increasing

Developers can use **good quality field data** to help improve system robustness with AI and Machine Learning

Continue implementing Driver Monitoring technologies, in a **phased approach**, to further develop Interior sensing solutions and **enhance driver and passenger safety**

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TRB Webinar: Progress and Opportunities for In-Vehicle Impairment Detection

Consumer Acceptance/Policy Framework

Presented by Dr Amie Hayley* (ahayley@swin.edu.au)

Monday, September the 16th 2024

*Rebecca L Cooper Al and Val Rosenstrauss Fellow
Drugs and Driving Research Unit (DDRU)
Swinburne University of Technology, Australia

Board member: ICADTS (Treasurer)
Founding Chair: ICADTS Working Group for Driver Monitoring Systems (DMS)

Presentation overview

From evaluation to usability – supporting the uptake of systems to prevent impaired driving

1. Current methods and their limitations
2. System design and safety implications
3. Level of intervention and alert functions
4. End user knowledge and acceptance

1. Current methods and their limitations

- Passive prevention approaches → need for modernisation
- Best-practice methods to prevent intoxicated drivers from getting behind the wheel?
- Intelligent safety technologies
  - In-vehicle sensors
  - Driver/operator state monitoring systems (DMS)
    - Eye movements/operator state

2. System design and safety implications

Driver Monitoring Systems (DMS)

1. Devices that collect observable information about the operator
   - Primary safety feature for 5-star European New Car Assessment Program
     - Will be adapted in all new U.S. vehicles from 2026
     - Will soon feature in all new vehicles sold across Australasia (ANCAP)

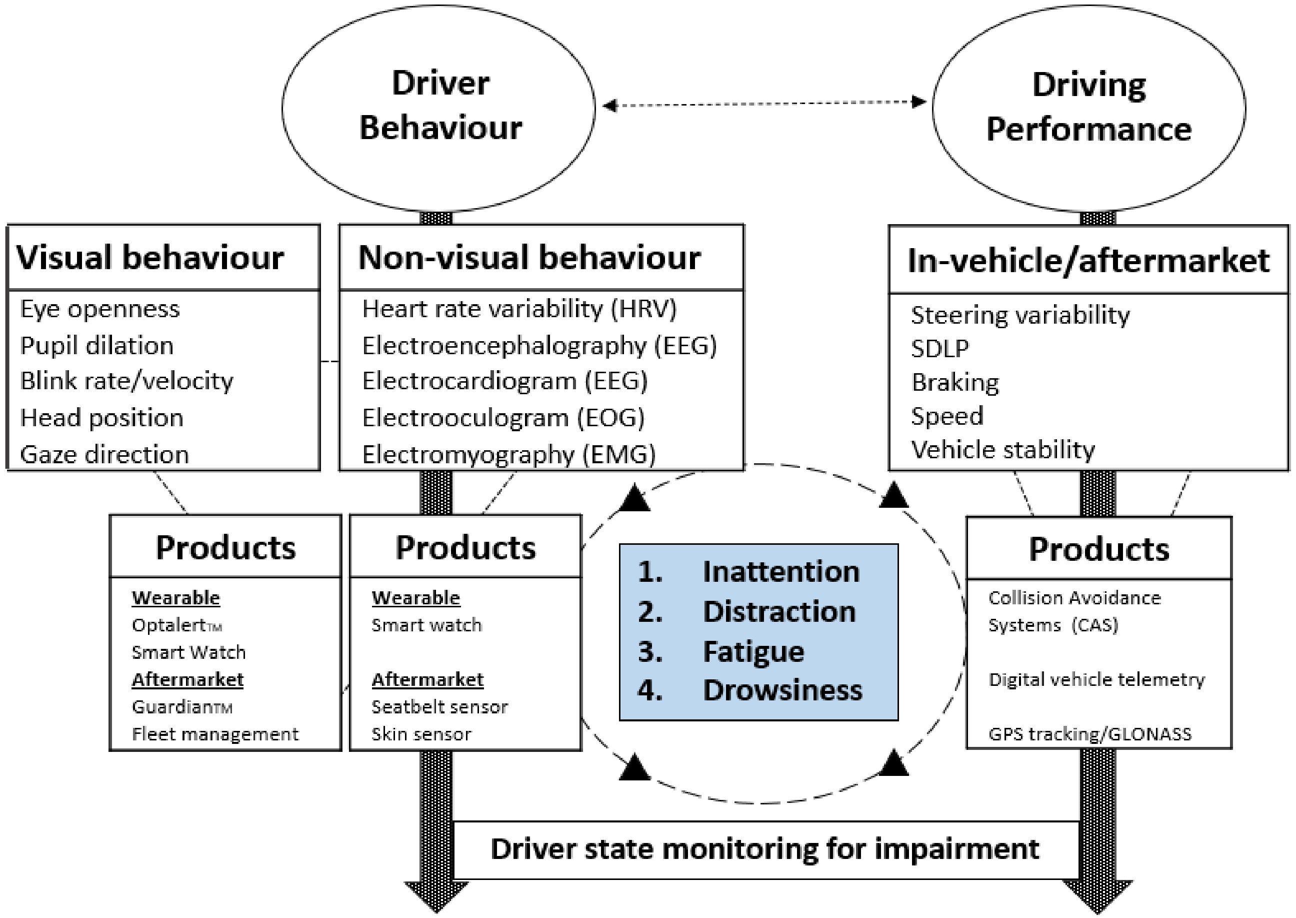
2. Market demand is highly competitive

   Global market share will surpass US$1.4 billion this year (2024)

3. Expected to reduce traffic collisions by as much as 20%

2. System design and safety implications

- Systems are already capable of determining altered state through visual/nonvisual cues
  - Fatigue
  - Inattention
- HMI with increased vehicle automation
- Model for complex psychoactive substance usage
- Fitness to drive assessment using vision-based capabilities
  - ✓ In place in many vehicles
  - ✓ Provide framework for adaptation



Hayley, A. C., Shiferaw, B., Aitken, B., Vinckenbosch, F., Brown, T. L., & Downey, L. A. (2021). Driver monitoring systems (DMS): The future of impaired driving management?. *Traffic Injury Prevention*, *22*(4), 313-317.

2. System designs and safety implications

Factors influencing the appropriateness of interventions

1. **Degree** and **type** of impairment

2. Urgency of new technological development ≠ current progress

3. Autonomous capabilities and the impact on the need for monitoring

4. Application and level of intervention.

   - who is responsible, what are the implications for law, safety or insurance?

3. Level of intervention and alert functions

Key points for optimizing the future of technologies designed to manage driver impairment

System type

1. Passive vs. Active system
2. Detection vs (+?) impairment

Level of Intervention

1. Increasing the sensitivity of other safety support systems
2. In-vehicle warnings
3. Restricting vehicle functions
4. Guiding the vehicle to a stop/prevention from re-starting

3. Level of intervention and alert functions

Key points for optimizing the future of technologies designed to manage driver impairment

System type

1. Passive vs. Active system
2. Detection vs (+?) impairment, conflating the two?

Level of Intervention

1. Increasing the sensitivity of other safety support systems
2. In-vehicle warnings
3. Restricting vehicle functions
4. Guiding the vehicle to a stop/prevention from re-starting

End user knowledge and acceptance

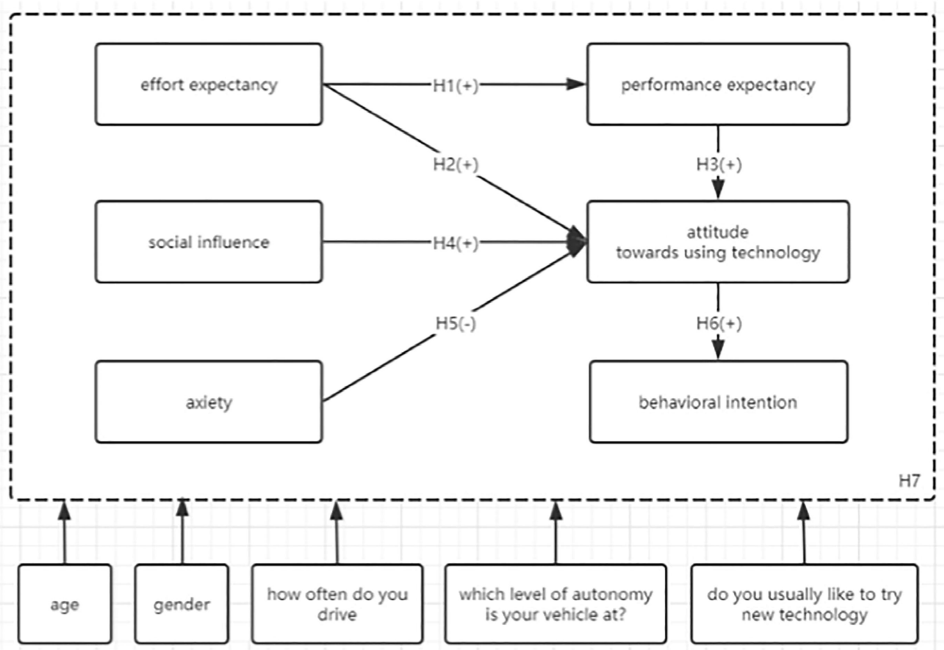
4. End user knowledge and acceptance

Attitudes and perceptions that affect DMS acceptance

1. Intervention
    - Effort required
2. Obtrusiveness
3. Social influence
4. Performance expectancy
5. Attitudes towards new technology

6. Demographics – alcohol use, age, region

1.



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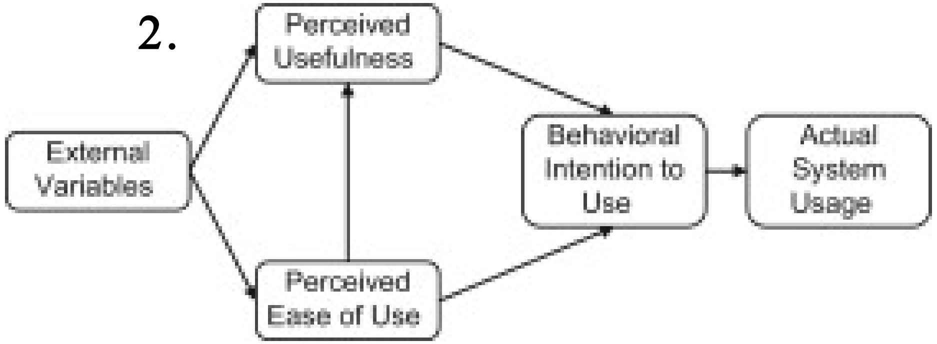


1. Smyth, e al., 2021. Public acceptance of driver state monitoring for automated vehicles: Applying the UTAUT framework

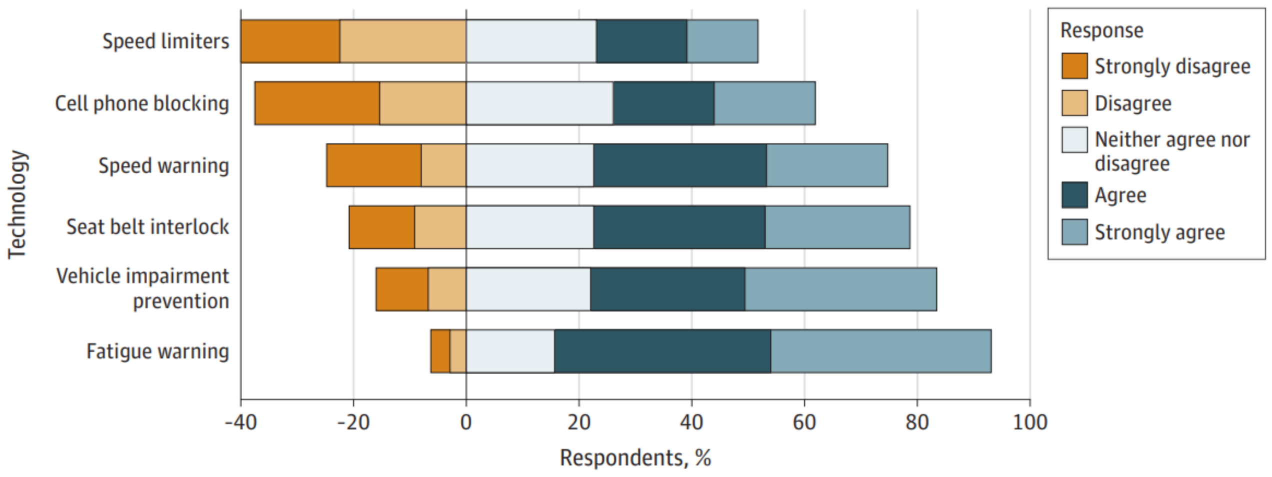
2. Roberts et al., 2012. Warn me now or inform me later: Drivers' acceptance of real-time and post-drive distraction mitigation systems

4. End user knowledge and acceptance - impaired drivers

- Survey of **2,274** adults aged 18 years or older [60.9%] women and [39.1%] men). Overall**, 31.6% response rate.**

- Support for the congressional mandate on vehicle impairment prevention technology was high overall, with **63.4%** of respondents supporting the law.

- Vehicle fatigue warning **(77.3%)** and impairment prevention **(64.9%)** technologies were most supported.



'All new cars should have an automatic sensor to prevent the car from being driven by someone who is over the legal alcohol limit.'

Ehsani et al., 2023. Public Support for Vehicle Technology to Prevent Operation by Impaired Drivers. JAMA Netw. Open.

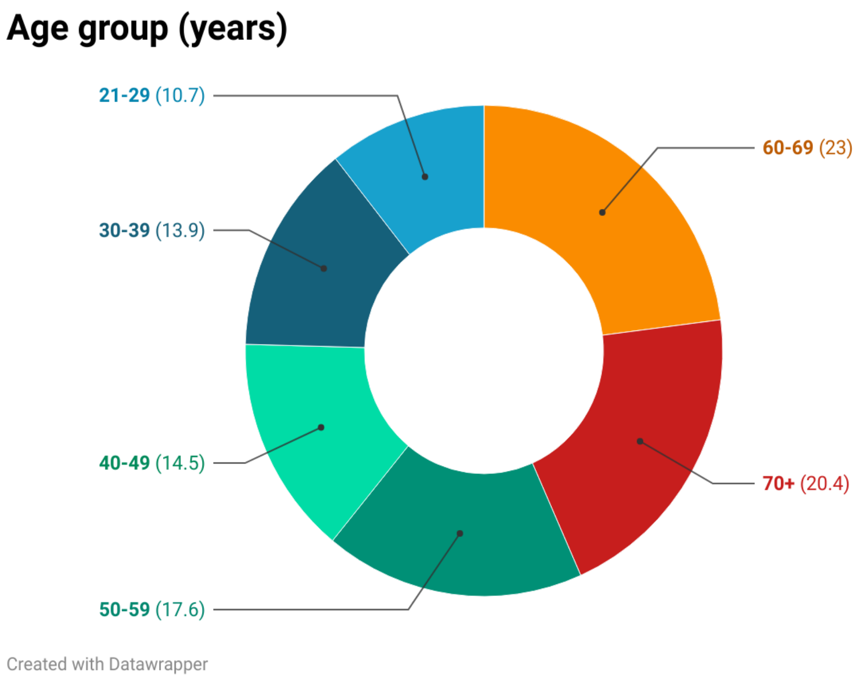
4. End user knowledge and acceptance - impaired drivers

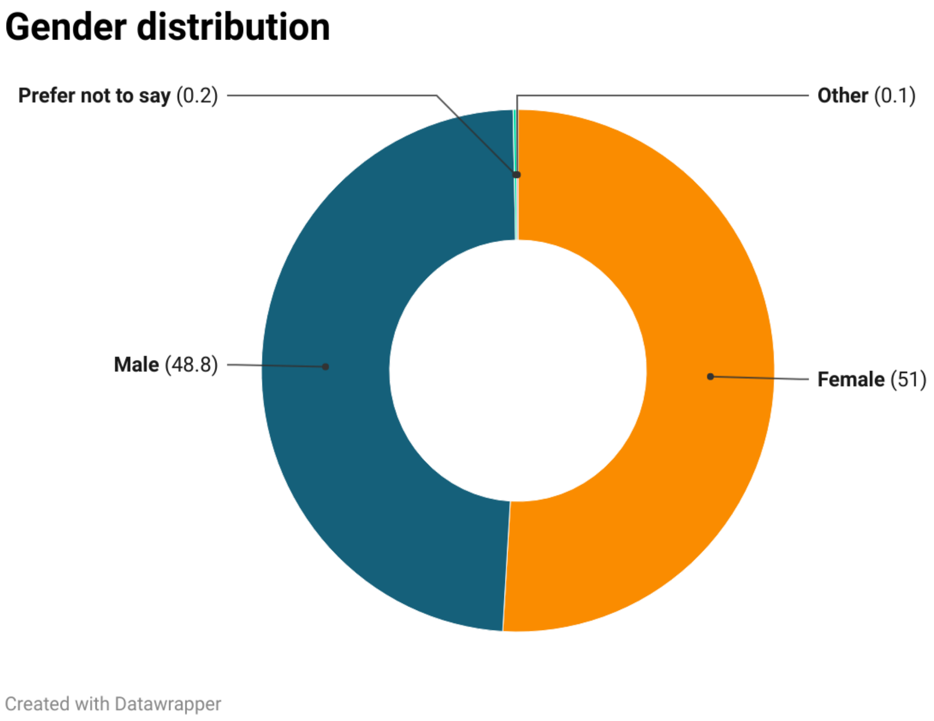
ICADTS working group for Driver Monitoring Systems

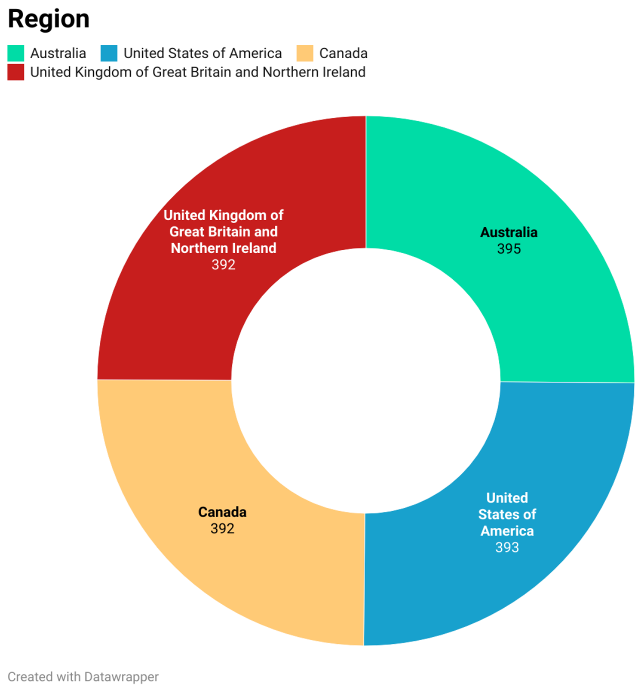
- International user survey of current and active drivers (at least 1/week)
  Australia, North America (USA/Canada), UK (England, Scotland, Wales, and Northern Ireland)
- Online anonymous design
- Demographic characteristics, health factors (alcohol use)
- Driving offences, dangerous driving behaviours
- Knowledge and acceptance of DMS per principal system design
  - Alcohol (BAC) levels
  - Alcohol intoxication
  - Both?

4. End user knowledge and acceptance - impaired drivers

N = 1,567







4. End user knowledge and acceptance

Strategies to support driver acceptance

- Clarity around device intentions and actions
- Allow driver-led override
  - Minor events
- Escalation strategy
  - Higher-risk or dynamic safety scenario
  - May help in case of incapacitated/unresponsive operator
- Collaborative HMI
  - Risk assessment and communication between driver/system
- Driver state assessment

Key takeaways

Future considerations to improve the type/level of interventions and their acceptance

1. System design will influence driver's experience and expectations ➔ safety outcomes.

2. In-vehicle warnings should be balanced, multimodal and scaled to severity of event.

3. Level of intervention should consider driver, environment and situational and/or vehicle factors.

4. Consideration of target driver populations to enhance uptake/acceptability.

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Thank you

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Monday, September the 16th 2024

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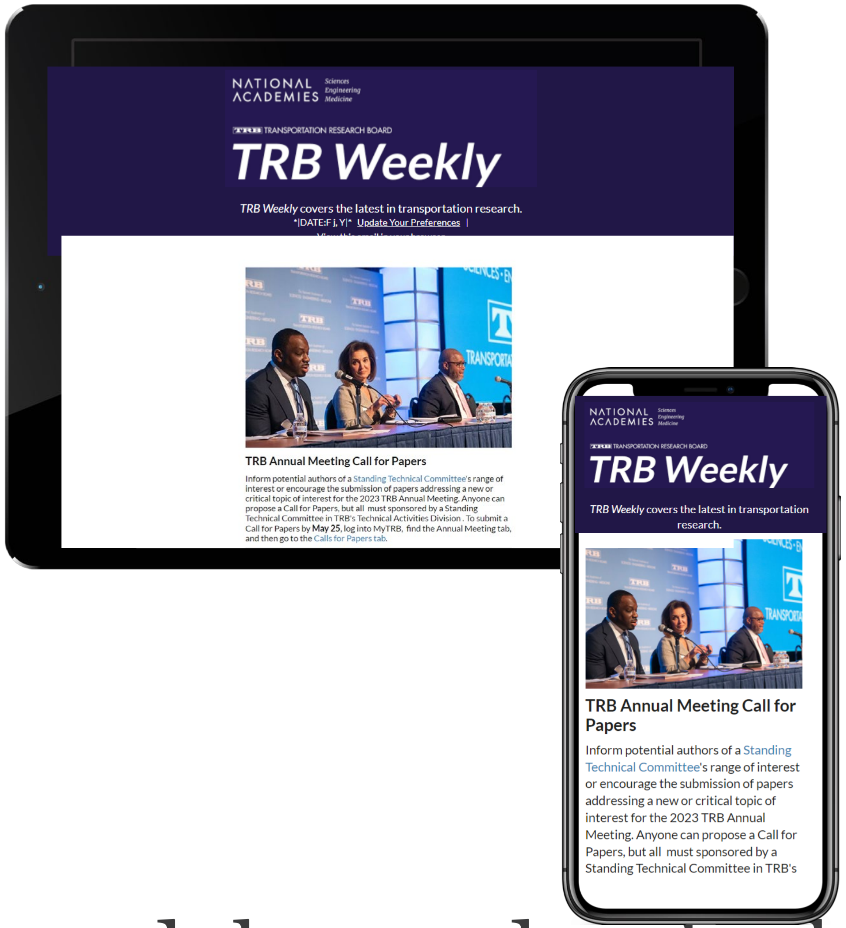

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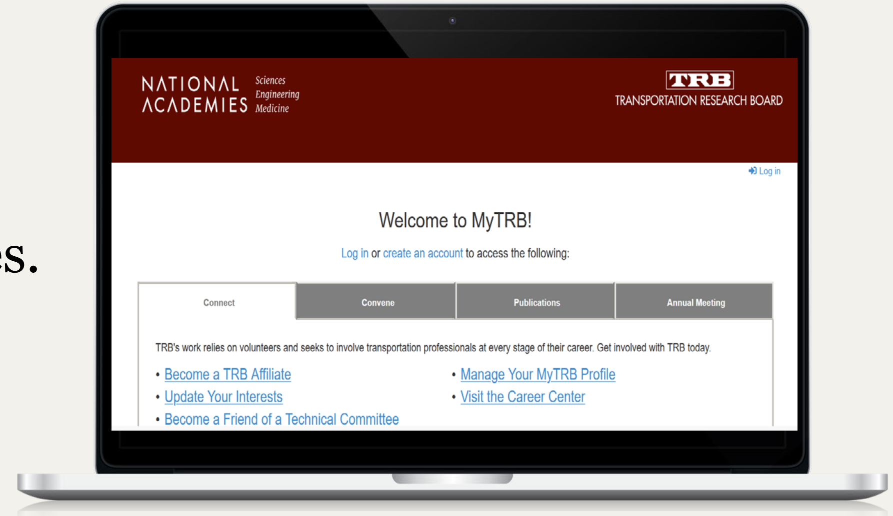

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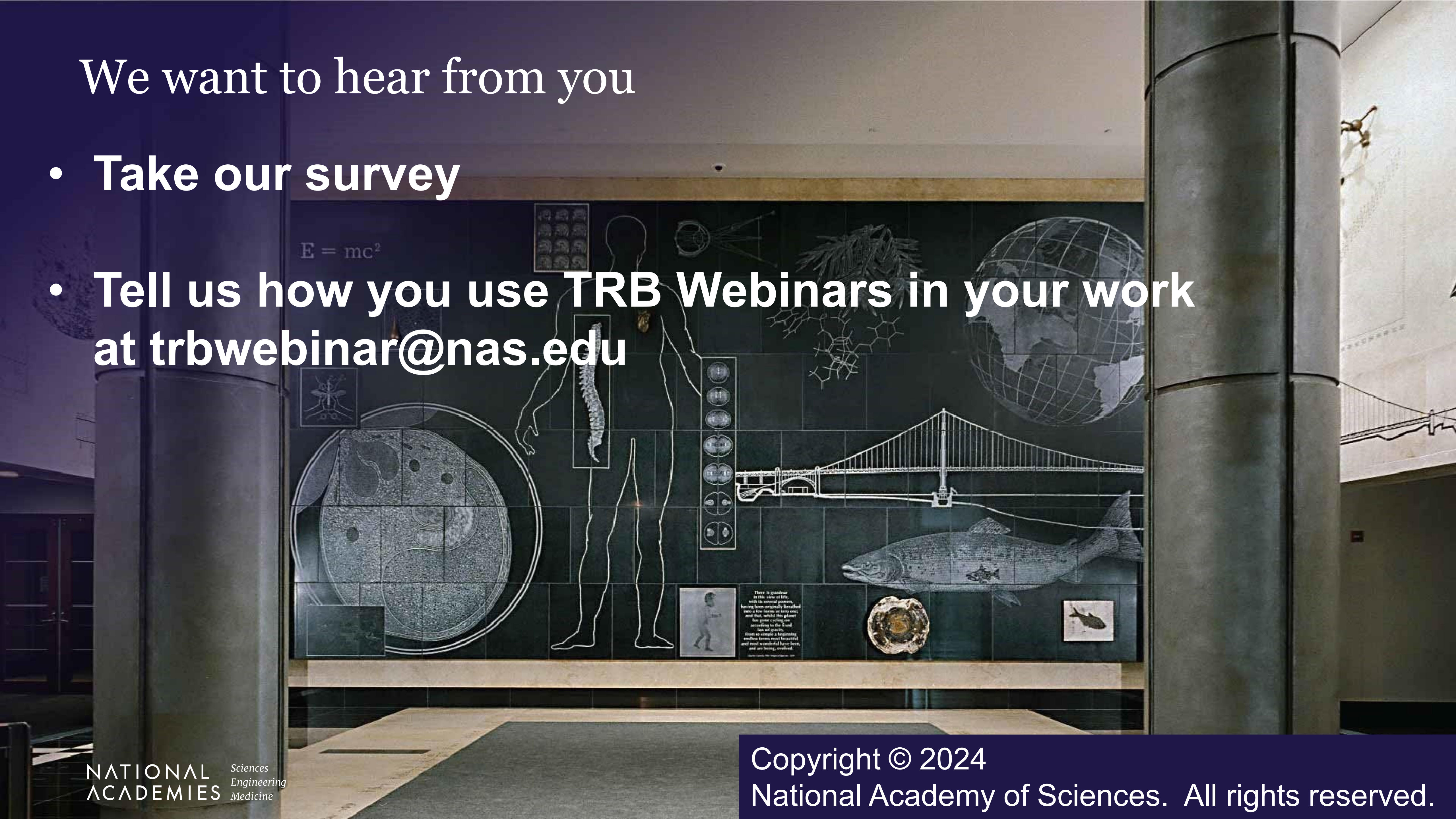

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