

Exogenous Disruptions of Visual Attention & Gaze Abnormality

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Background

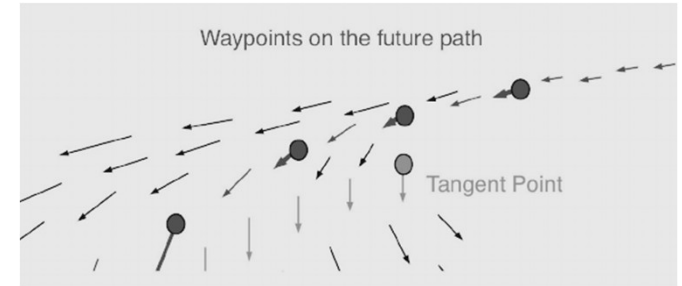
Expected gaze (Attention)

Environmental context and task demands dictate this expected patterns
(Hayhoe & Ballard, 2009).

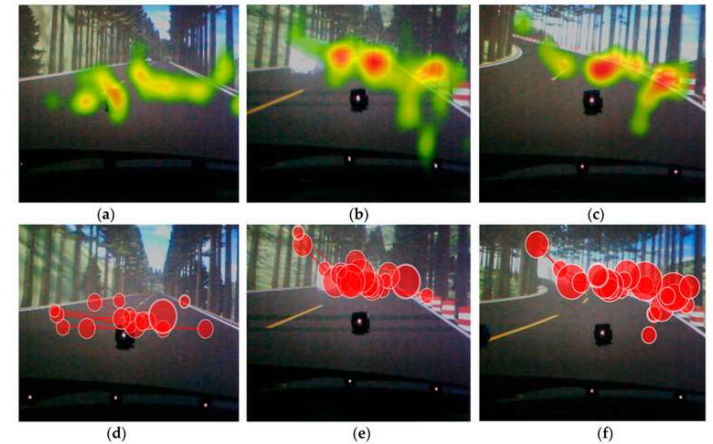


 Expected gaze patterns

Expectation is complex !!

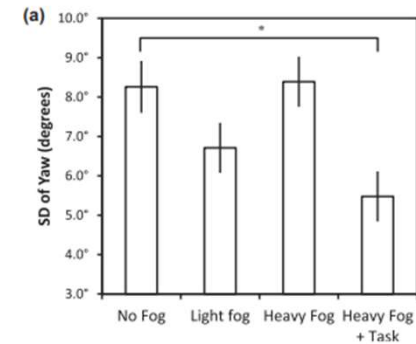


Curve negotiations focus attention on its tangent (Wilkie et al., 2003; Itkonen et al., 2015)



Method such as saliency map suggest that a situation's visual demand and expected pattern can be modelled (Borji & Itti, 2013)

Disruption



Cognitive load is associated with reduced gaze dispersion and peripheral hazards
(Louw & Merat, 2017; Engstrom et al., 2017)

Endogenous disruption

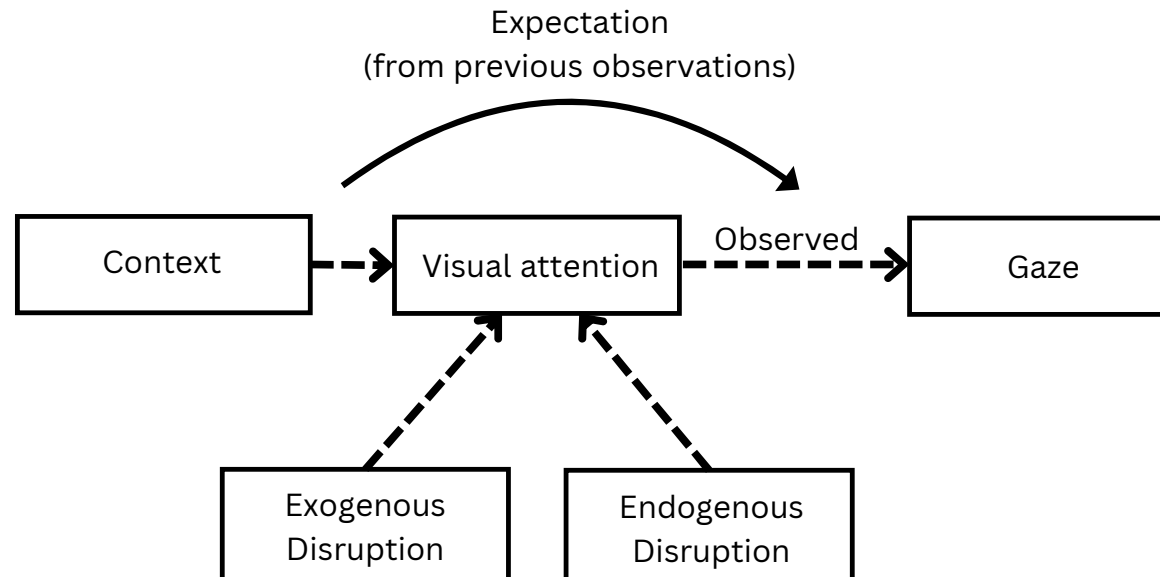


Looming of incoming stimuli is attributed to increased attention focus
(Franconeri & Simons, 2003)

Exogenous disruption

Gaze abnormality

Deviation in the driver's gaze under specific context when compared to previous observations from the same driver or from other drivers in similar conditions (Phan et al., 2025)



Different (expectation gaze, observed gaze) = score
by a self-supervised neural network

Validate the hypothesis*!

Operationalize the hypothesis with a neural network & an algorithm to examine whether it works in the simplest and controlled simulation.

Research question:

How do deviation and gaze abnormality manifest across drivers when exposed to the same exogenous disruptions?

**the wallaby is not used in this study. It is mainly included as an example to illustrate the concept.*

Method

Dataset & setup

Context:

Participants: 44 drivers (24 M, 20 F) → N=42 (data loss)

Age: 25–63 years (M = 40.23, SD = 11.19)

Eye tracking: Tobii Glasses 3, 50 Hz

Simulator: High-fidelity, motion-based driving simulator

Scenario: Urban UK road, manual driving, 30 mph, straight, unobstructed road

Events are fully counter-balanced

Baseline: 8 seconds (100 m) of free-lane driving, sparse road environment, no leading vehicles or hazards, 6 segments per participant

Exogenous* disruption: 8 seconds (100 m), pedestrian suddenly jaywalks into the road with left crossing: 0.75 m/s, TTC $\approx$ 2 s, and right crossing: 1.5 m/s, TTC $\approx$ 4 s



Maximizing deviation

Case 1:

Baseline & exogenous disruption left



B (n=6)



DL (n=1)

Case 2:

Baseline & exogenous disruption right



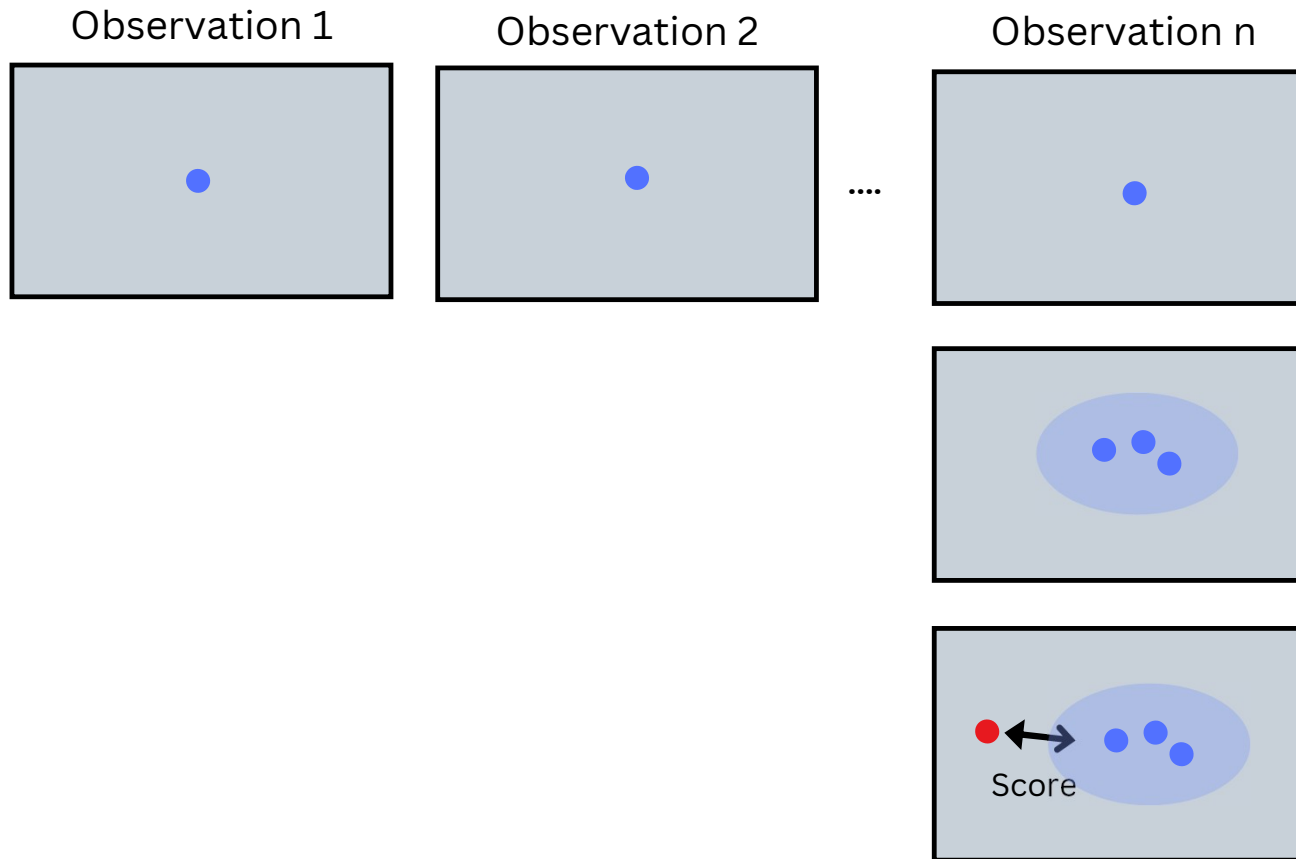
B (n=6)



DR (n=1)

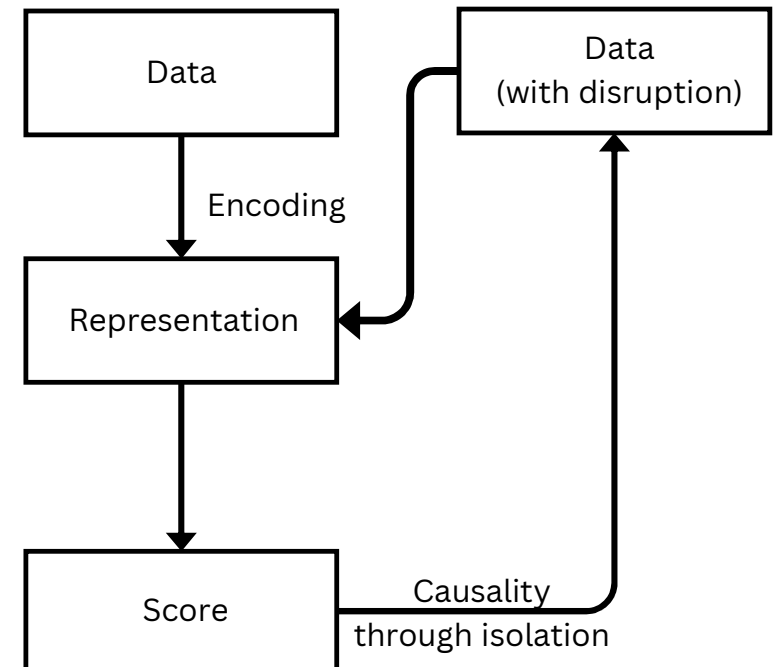
*exogenous disruption (represented by a pedestrian jaywalking) is the primary focus in this study. But the concept should also be applicable to endogenous disruptions.

Neural network



Contain majorly the
defined context

Non-accounted
variation of contexts



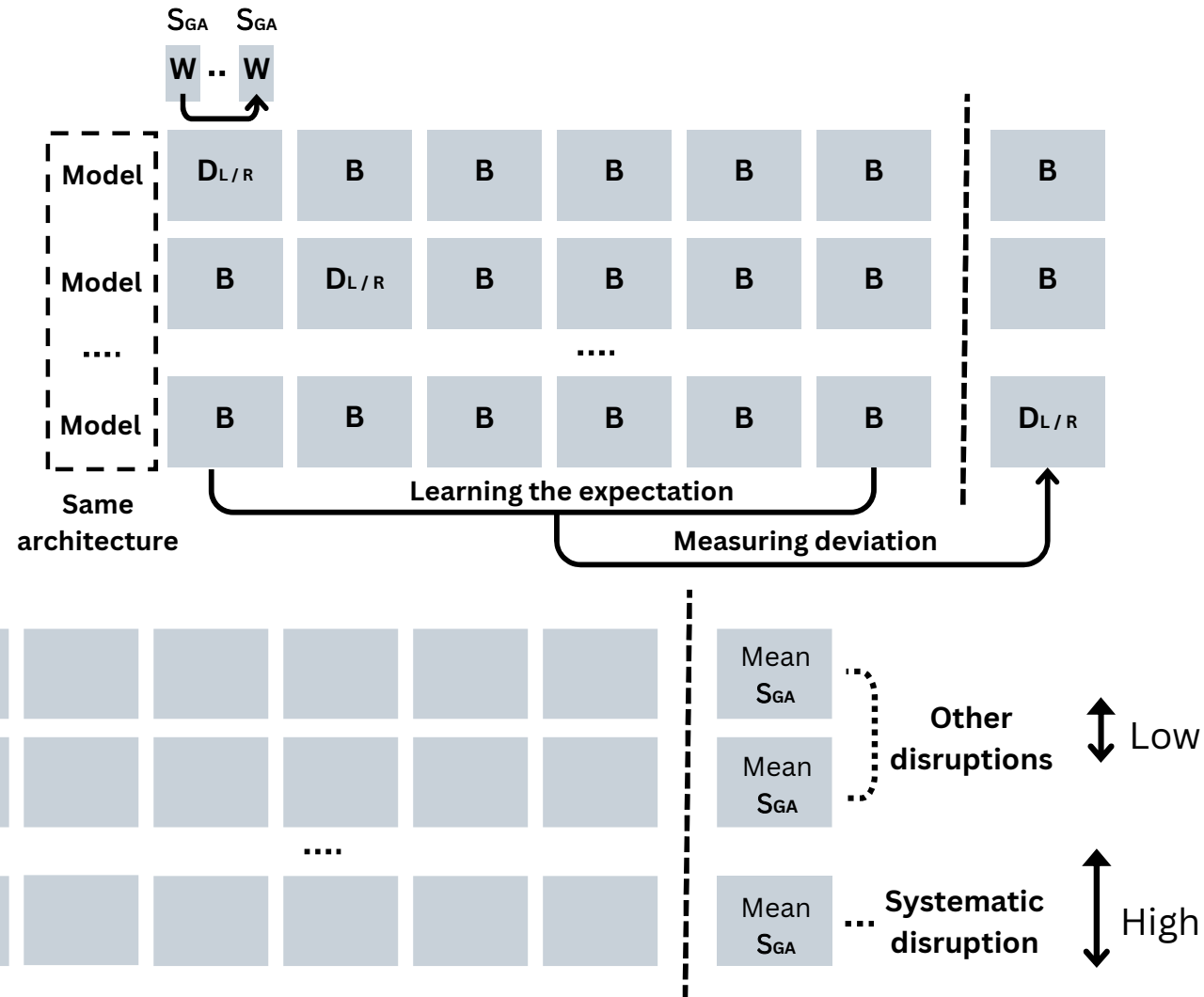
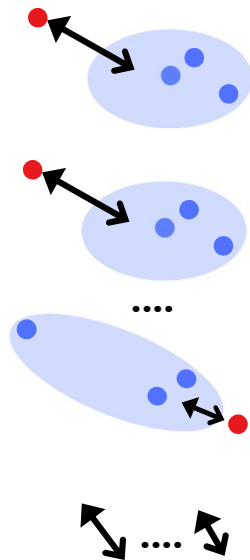
Algorithm

Why is this algorithm* important?

Single score not enough!

More combinations
= more scores

Cross comparison



Architecture: Anomaly Transformer, NCAD, and DIF

*Code would be made public for journal submission: <https://github.com/AI-for-Road-Safety/gaze-abnormality>

Post-hoc analysis!

Results

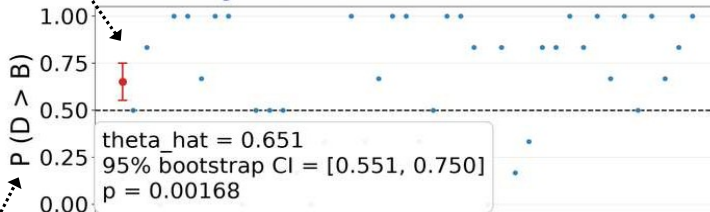
Deviation

Case 1: Maximizing L
(Rank-based test)

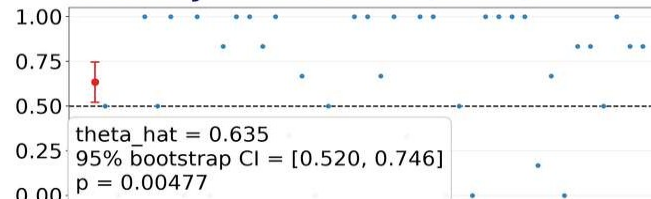
Case 2: Maximizing R
(Rank-based test)

Average

Anomaly Transformer (n=42): **

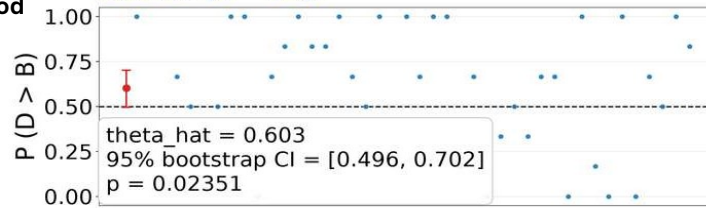


Anomaly Transformer (n=42): **

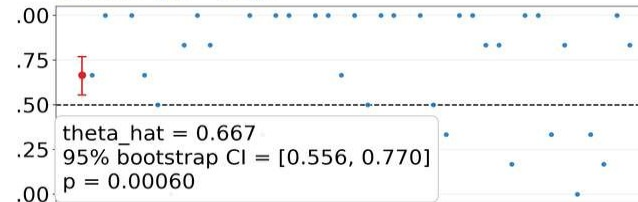


+ another robustness test

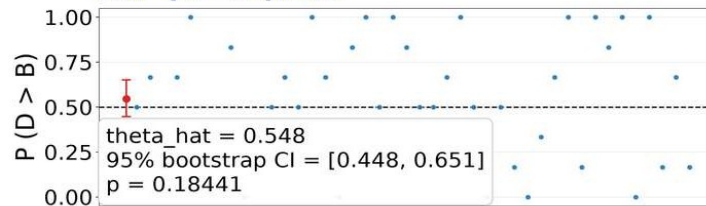
NCAD (n=42): *



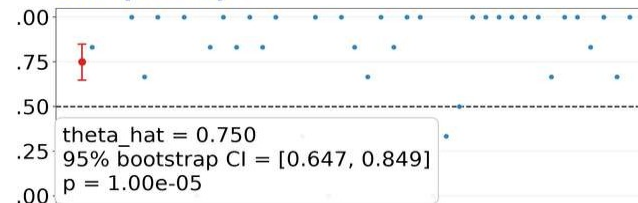
NCAD (n=42): **



DIF (n=42): NS



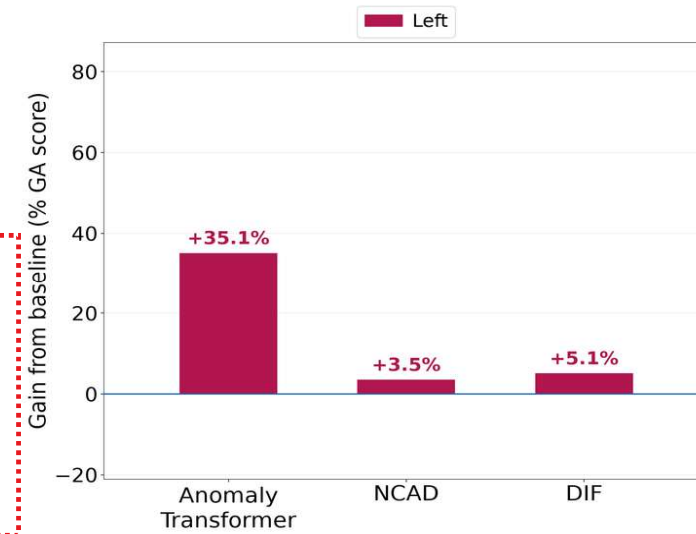
DIF (n=42): **



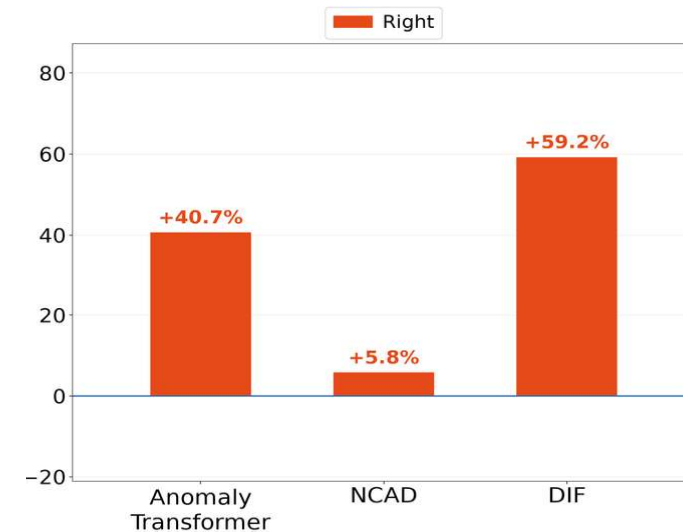
Exogenous Disruption Left

Exogenous Disruption Right

• Subject-level estimations
----- Null value ($H_0: \theta = 0.5$)
• Mean $\hat{\theta} \pm 95\% \text{ CI}$

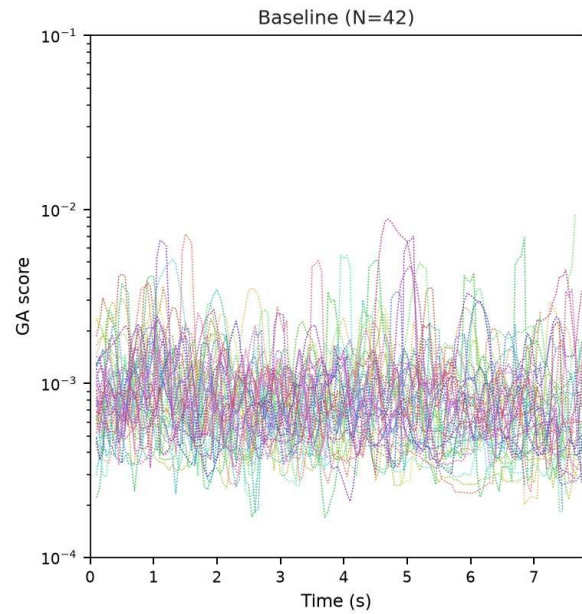


Gain of exogenous disruption left

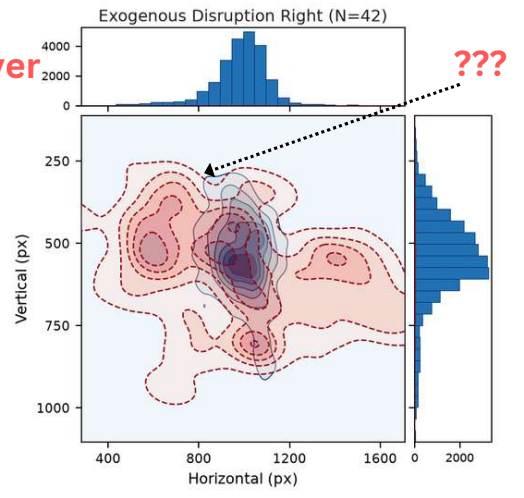
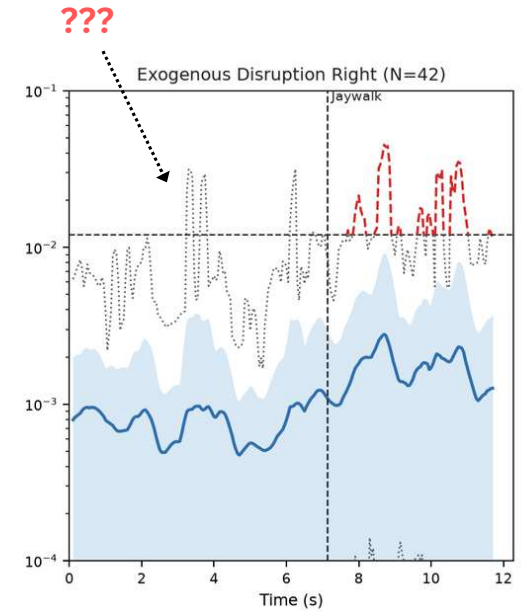
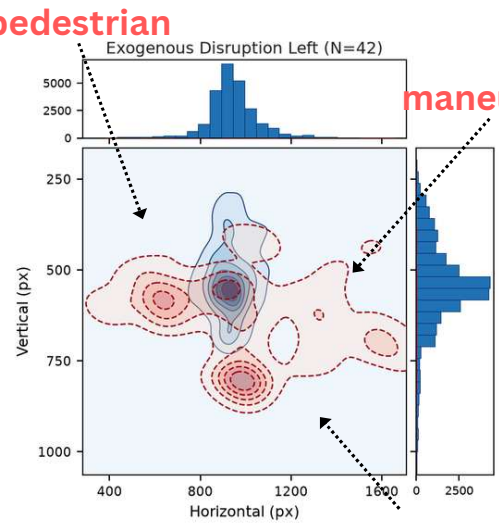
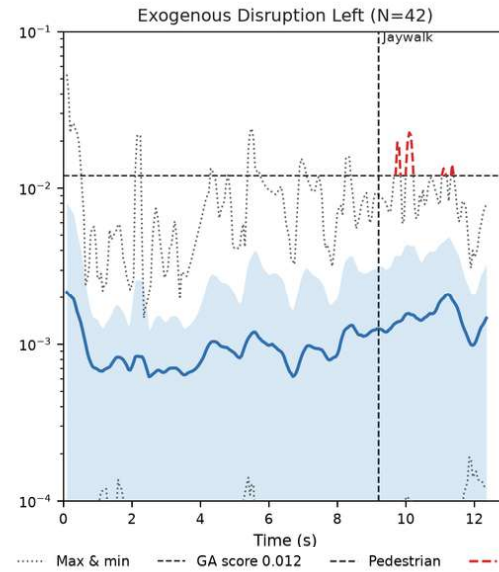
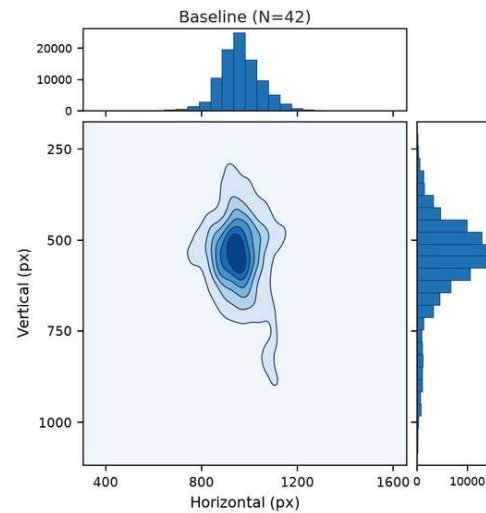
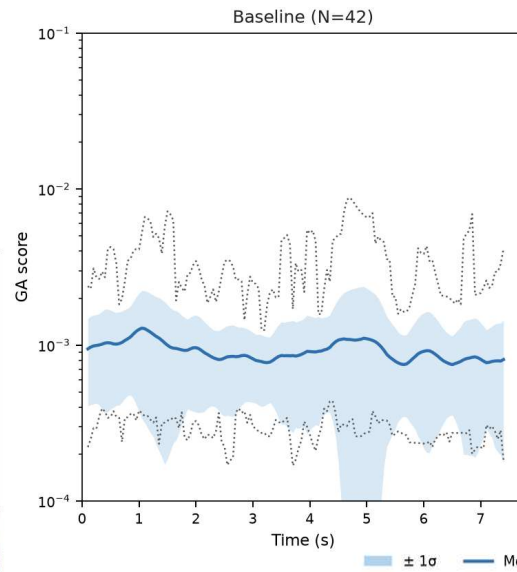


Gain of exogenous disruption right

Gaze abnormality



● S2 ● S9 ● S19 ● S32 ● S39 ● S47
 ● S3 ● S11 ● S22 ● S33 ● S40 ● S48
 ● S4 ● S12 ● S25 ● S34 ● S41 ● S49
 ● S5 ● S13 ● S26 ● S35 ● S43 ● S50
 ● S6 ● S15 ● S28 ● S36 ● S44 ● S51
 ● S7 ● S17 ● S29 ● S37 ● S45 ● S52
 ● S8 ● S18 ● S30 ● S38 ● S46 ● S53



■ Gaze ■ GA score > 0.012

Instrument cluster

Conclusion & Future-work

Conclusion

Theoretical framework was validated.

- Supporting theories on expected gaze patterns

(Hayhoe & Ballard, 2009; Borji & Itti, 2013).

New methodological tool

- Neural-network based metric encapsulating multiple complex elements of gaze.
- Find the changes in gaze and attribute the causality through isolation.

Future work

- Effect of endogenous disruption
- Exterior sensing for context understanding
- HMI intervention
- Safety outcomes
- Driver monitoring systems



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Q&A

Thank you

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