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Paper 157: Driver Classification Using Self-reported, Psychophysiological, and Performance Metrics within a Simulated Environment

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Outline

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Introduction

Research Need:

- Driver classification is essential for traffic and safety analytics.
- Very few studies incorporate physiological changes and environmental factors into driver classification.
- Can certain psychometric evaluators hint towards an individual's driving style?

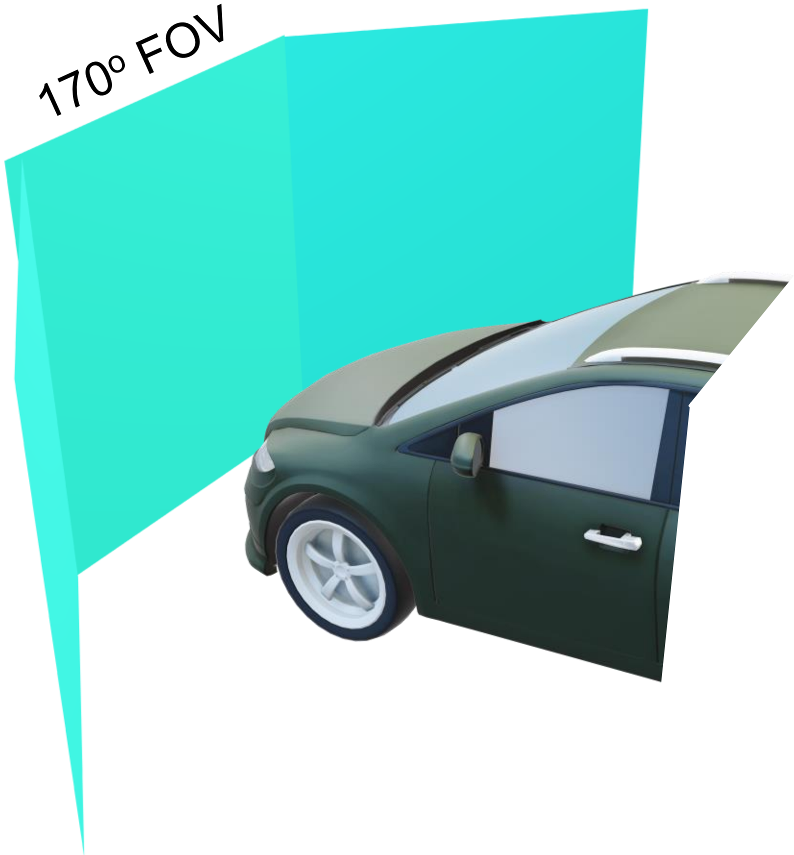
Main Objectives:

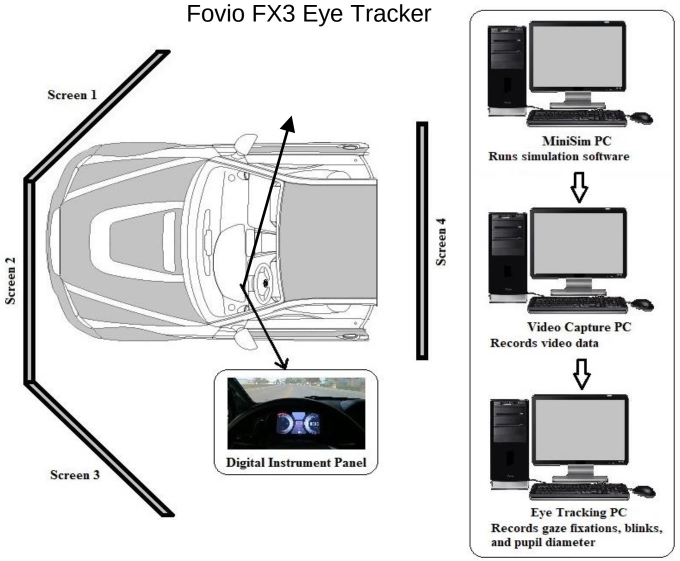
- Design simulated scenarios to capture changes in driving and cognition as a result of task complexity.
- Classify driving styles across a variety of scenarios by evaluating not only driving performance but also psychophysiological changes.
- Use various self-reported psychometric measures to identify any correlations to driving styles.

Psychometric Evaluators

Name	Description
Positive and Negative Affect Schedule (PANAS) *(Watson et al. 1988)*	Assess negative affect (i.e., distressed or nervous) and positive affect (i.e., excited or proud) on a scale of 1 to 5.
Cognitive Reflection Task (CRT) *(Frederick, 2005)*	3 questions designed to measure the ability to suppress an intuitive wrong answer in favor of a deliberative right answer.
Interpersonal Reactivity Index (IRI) *(Davis,1983)*	Measure individual differences in empathy across 4 subscales (perspective taking, fantasy, empathic concern, and personal distress).
Empathy Assessment Index (EAI) *(Lietz, 2011)*	50-item questionnaire with 5 sub-dimensions (i.e., affective response-AR, self-other awareness-SA, emotion regulation-ER, perspective taking-PT, and empathic attitudes-EA).
Psychological Entitlement Scale (PES) *(Campbell et al. 2004)*	9 self-reported measures to quantify the stable and pervasive sense that one deserves more than others.
Need for Cognition (NFC) *(Cacioppo et al. 1984)*	34 questions to assess the tendency to engage in and enjoy effortful cognitive endeavors.

Equipment and Participants





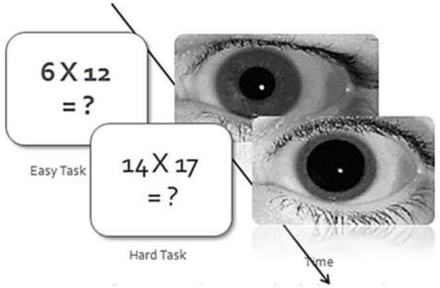
Participant Selection:

- 90 Participants
  - 45 M, 45 F
  - Aged 18 to 65 years
  - Mean 31.4 years; St dev 14.2 years
- IRB approval: 02/11/2019
- Participation incentive: $50

Physiological Measures

- Mental Workload (MW): The proportion of mental capacity required by an individual to perform a task *(Brookhuis et al., 1991)*

a) Index of cognitive activity (ICA): Estimates MW by tracking changes in pupillary response and disentangles artifacts from changing light.



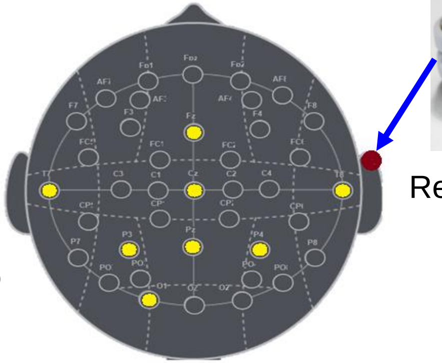
(Source: Hossain & Yeasin, 2014)

b) Heart rate (HR): Estimates MW by tracking variability in heartbeats per unit time.

Polar H10 chest strap

- Engagement Level (EL): Describes the driver's arousal state/ engagement before and during the drive *(Pope et al., 1995)*

Enobio 8-channel cap



Reference electrode

$\boldsymbol{\theta}: 4-8\ \mathrm{Hz}$

$\boldsymbol{\alpha}: 8-13\ \mathrm{Hz}$

Mental workload, Cognitive fatigue

$\boldsymbol{\beta}: 13-22\ \mathrm{Hz}$

Visual attention, Short-term memory

Power Spectral Density

$$\mathrm{EL} = \frac{\beta}{\alpha+\theta}$$

Simulator Task Configurations

Name	Composition	Work zone	Traffic Density
Task 1 (Baseline)	4-lane divided highway at 70 mph. 0% heavy vehicles.	None	25-28 pc/mi/ln (LOS B/C)
Task 2	4-lane divided highway at 70 mph. 0% heavy vehicles.	None	35-38 pc/mi/ln (LOS D/E)
Task 3	4-lane divided highway at 70 mph. 10% heavy vehicles.	Inactive: left shoulder closed	35-38 pc/mi/ln (LOS D/E)
Task 4	10-lane divided freeway at 70 mph. 20% heavy vehicles.	Active on both sides: 3 lanes closed	25-28 pc/mi/ln (LOS B/C)
Task 5	10-lane divided freeway at 70 mph. 20% heavy vehicles.	Active on both sides: 3 lanes closed	35-38 pc/mi/ln (LOS D/E)
Task 6 (Secondary task)	10-lane divided freeway at 70 mph. 20% heavy vehicles.	Active on both sides: 3 lanes closed	35-38 pc/mi/ln (LOS D/E)

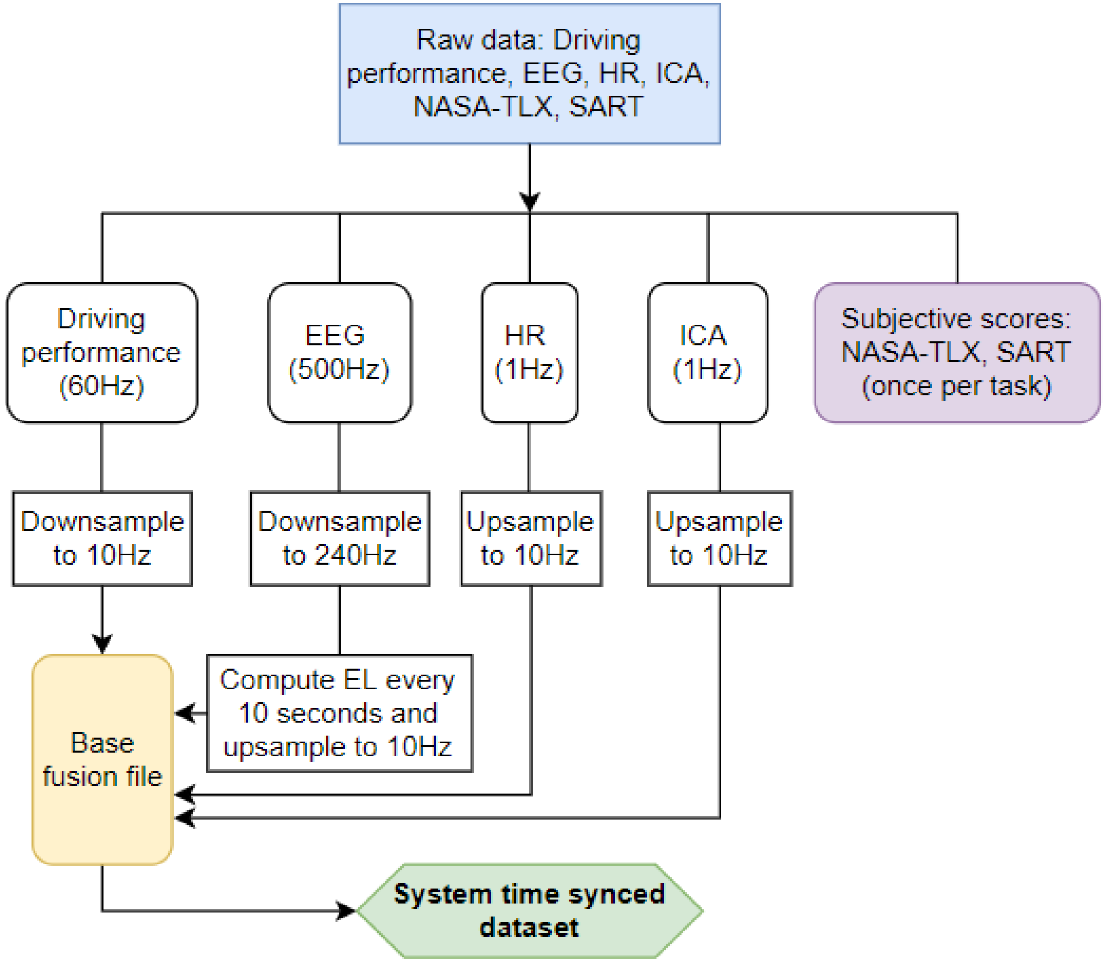
Task 1

Task 3

Task 5

Task 6

Data Fusion



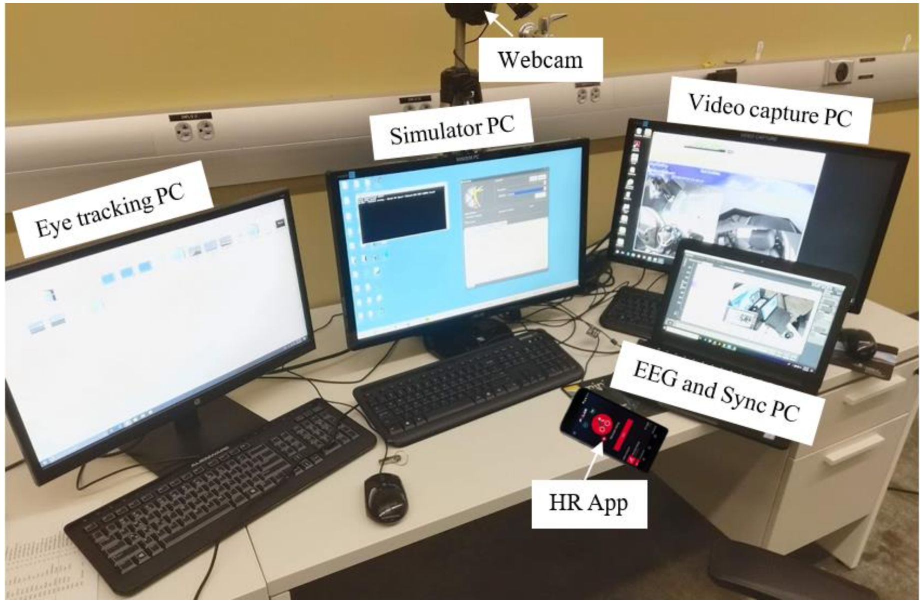
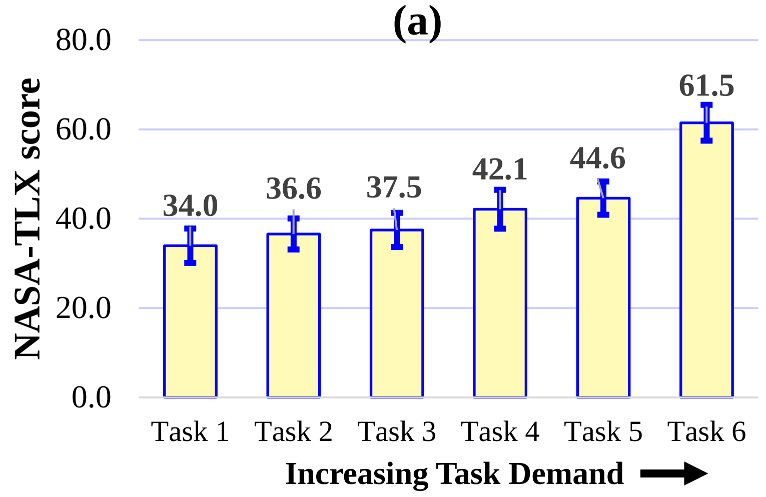
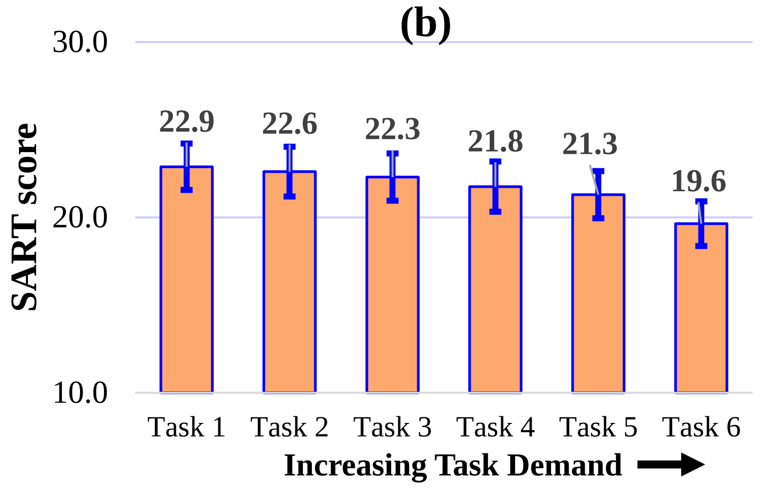


Figure shows the data collection setup

Results: NASA-TLX and SART Scores





Task 1: baseline	F	df	P-value	η_P^2
Task 3	4.087	83	0.046	0.047
Task 4	16.298	83	< 0.001	0.164
Task 5	35.230	83	< 0.001	0.298
Task 6	201.257	83	< 0.001	0.708

Task 1: baseline	F	df	P-value	η_P^2
Task 4	7.448	83	0.008	0.082
Task 5	7.840	83	0.006	0.086
Task 6	26.794	83	< 0.001	0.708

Dynamic Time Warping (DTW)

$$DTW(D1, D2) = \frac{1}{K}\sqrt{\sum_{k=1}^{K} d_k}$$

Where,

d_k is the distance in cell k in the shortest path

K is the total number of cells in the shortest path

Clustering variables

- Acceleration (m/s^2)
- Steering wheel angle (degrees)
- Headway (m)
- Index of Cognitive Activity
- Engagement Level

Table showing cluster output after DTW application and aggregation

	Clust ID	N	Age	License Age	Avg Headway (m)	Avg Speed (km/h)	Avg NASA-TLX	Avg SART
Task 1	1	72	29.8	12.9	88.2	118.2	34.6	22.7
	2	13	34.6	18.2	209.9	114.7	32.3	24.8
Task 2	1	60	29.9	13.4	91.6	115.2	36.9	22.6
	2	25	31.5	14.9	109.9	114.7	35.8	22.6
Task 3	1	40	29.7	12.7	96.0	114.4	37.9	22.0
	2	45	31.8	15.3	89.5	113.0	37.0	22.8
Task 4	1	27	31.4	15.1	78.6	114.4	41.6	22.4
	2	56	30.6	13.7	103.6	112.0	42.0	21.7
Task 5	1	43	29.6	13.2	68.4	114.0	43.5	20.8
	2	41	32.5	15.8	104.1	111.4	45.5	21.9
Task 6	1	47	30.1	13.4	85.5	110.7	57.5	20.6
	2	38	31.6	14.9	143.1	107.7	65.7	18.6

**Clust ID – 1: Moderate; 2: Conservative*

Binary Logistic Regression

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. Exp(B)	
							Lower	Upper
Annual mileage	.000	.000	4.367	1	.037*	1.000	1.000	1.000
Crash history	-3.412	1.209	7.967	1	.005**	.033	.003	.353
NFC total	-.095	.035	7.304	1	.007**	.909	.849	.974
EAI AR	-.209	.099	4.449	1	.035*	.812	.668	.985
EAI EA	.212	.114	3.447	1	.063	1.236	.988	1.546
Education level	-.467	.265	3.117	1	.077	.627	.373	1.053
Constant	9.985	2.994	11.125	1	.001**	21698.909		

**<0.05, **<0.01; Cox & Snell R^2 = 0.218; Nagelkerke R^2 = 0.331*

Confusion-Matrix	Conservative (0)	Moderate (1)	% correct
Conservative (0)	TP = 8	FP = 11	42.1%
Moderate (1)	FN = 3	TN = 61	95.3%

Classification accuracy 83.1%; Precision = 0.847; Recall = 0.727; F1 = 0.782

Conclusions

- Successful data fusion of psychophysiological and driving performance measures.
- Binary logistic regression results indicate that driving styles can be captured by knowing:
  - Annual mileage
  - Crash history
  - NFC total score
  - EAI affective response and empathic attitude; and
  - Education level

Limitations: The authors acknowledge that the data used was simulator-derived. However, testing complex physiological phenomenon and distracted driving is not feasible in the real-world.

Questions?

For further information, please refer to paper 157 or contact:

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