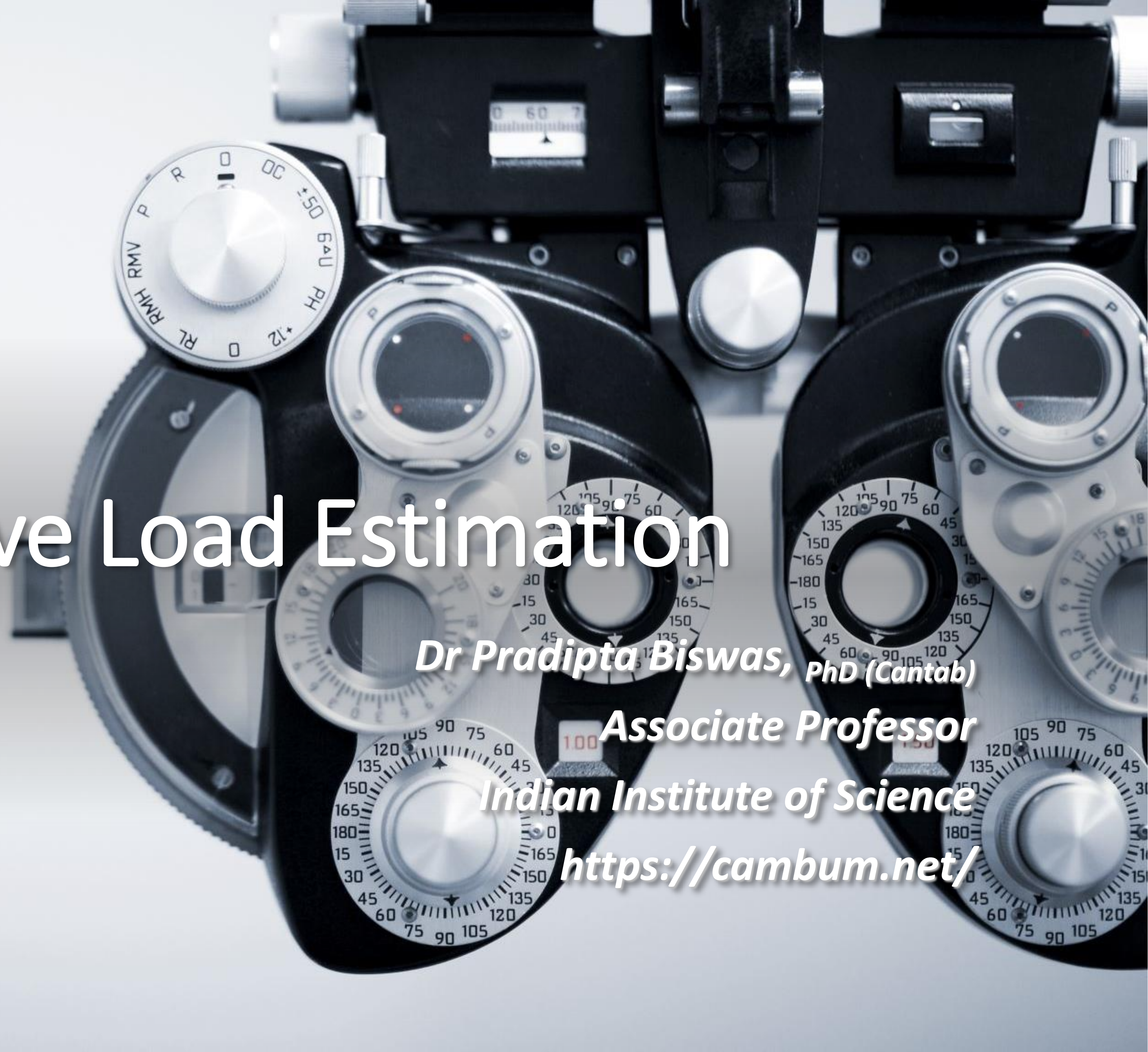
Cognitive Load Estimation



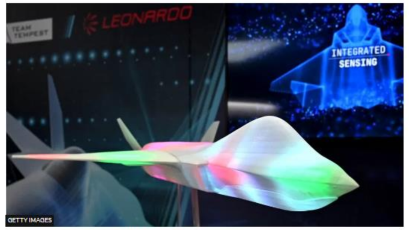
Dr Pradipta Biswas, ***PhD (Cantab)***
Associate Professor
Indian Institute of Science
https://cambum.net/

Why Cognitive Load Estimation

- Finite capacity of working memory
- Mental workload
- Stress / Distraction / Boredom

George Armitage Miller

John Sweller



BBC NEWS

Business | Market Data | New Economy | New Tech Economy | Companies | Entrepreneurship | Technology of Business | Global Education | Economy | CEO Secrets | Global Trade | Cost of living

A mind-reading combat jet for the future

26 July

A demonstrator model of the Tempest is due to fly in 2027

By Michael Dempsey
Technology of Business reporter

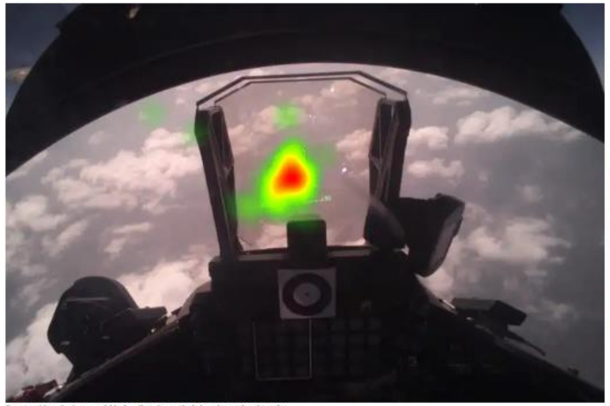
During World War II, Spitfire pilots described their plane as so responsive it felt like an extension of their limbs.

Top Stories

North Korea fires suspected long-range missile
1 hour ago

Can the US live in Xi Jinping's world?

Kim Jong-un wants America's attention
4 hours ago



NewScientist

Indian military tests eye-tracking tech to help pilots control planes

TECHNOLOGY 12 June 2020

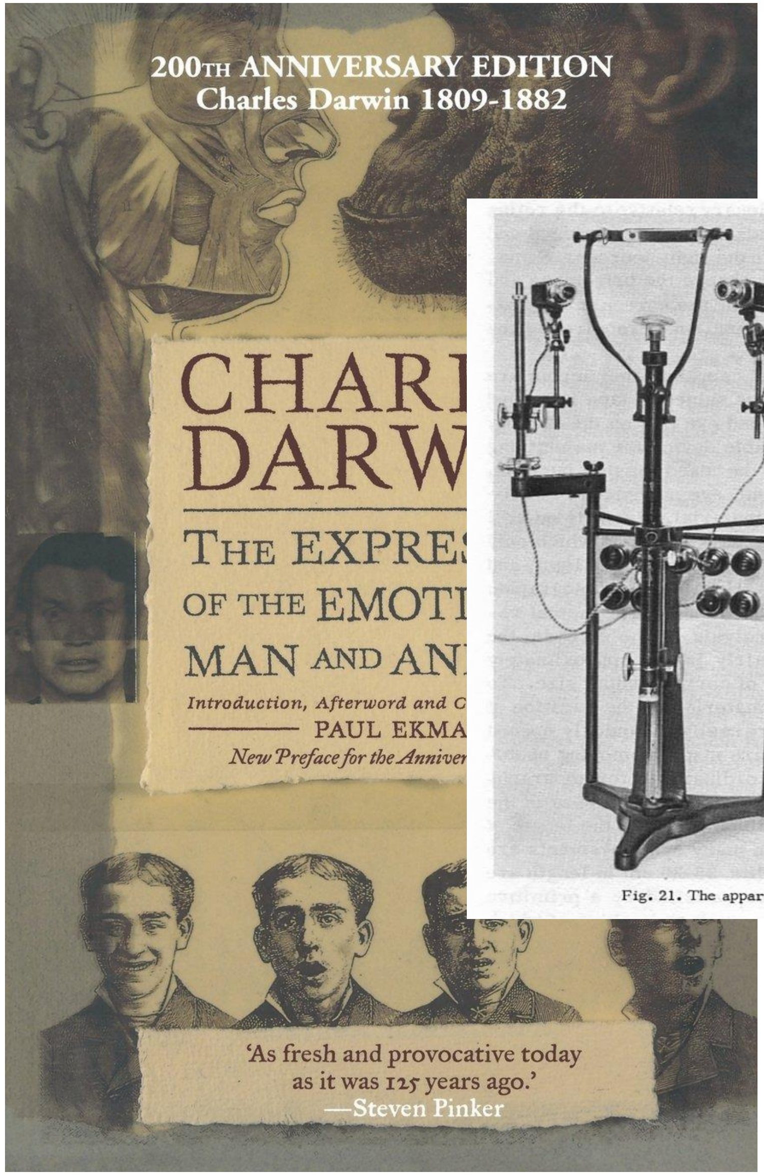
By Donna Lu

Eye-tracking devices could help pilots keep their hands on the throttle
Indian Institute of Science in Bangalore

Pilots in India are testing aircraft display systems that work by tracking and responding to eye movements and could let military pilots keep their hands on the plane's controls more often while flying.

Modern aircraft have electronic display systems that show information such as the plane's fuel level, imaging system or geographical position. Pilots can click the screen to the relevant page of

Cognitive Load from Ocular Parameters



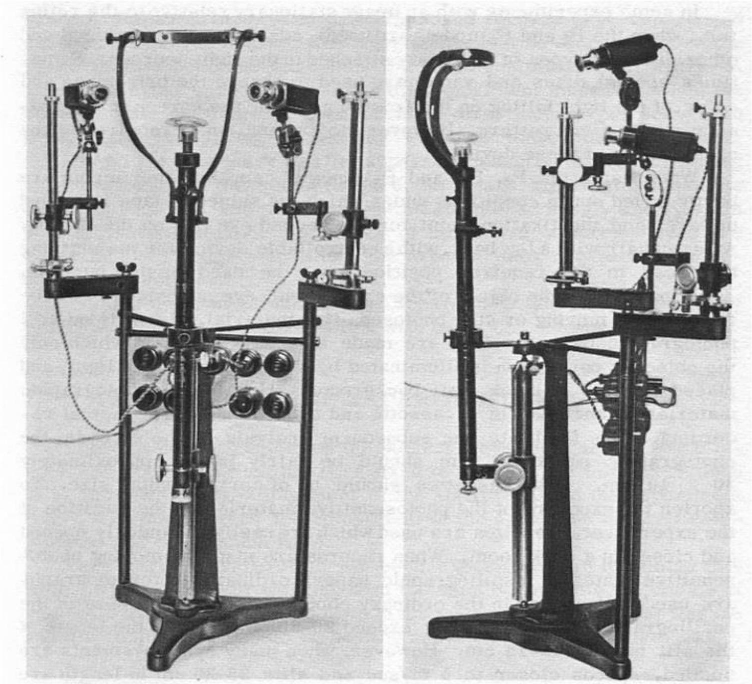
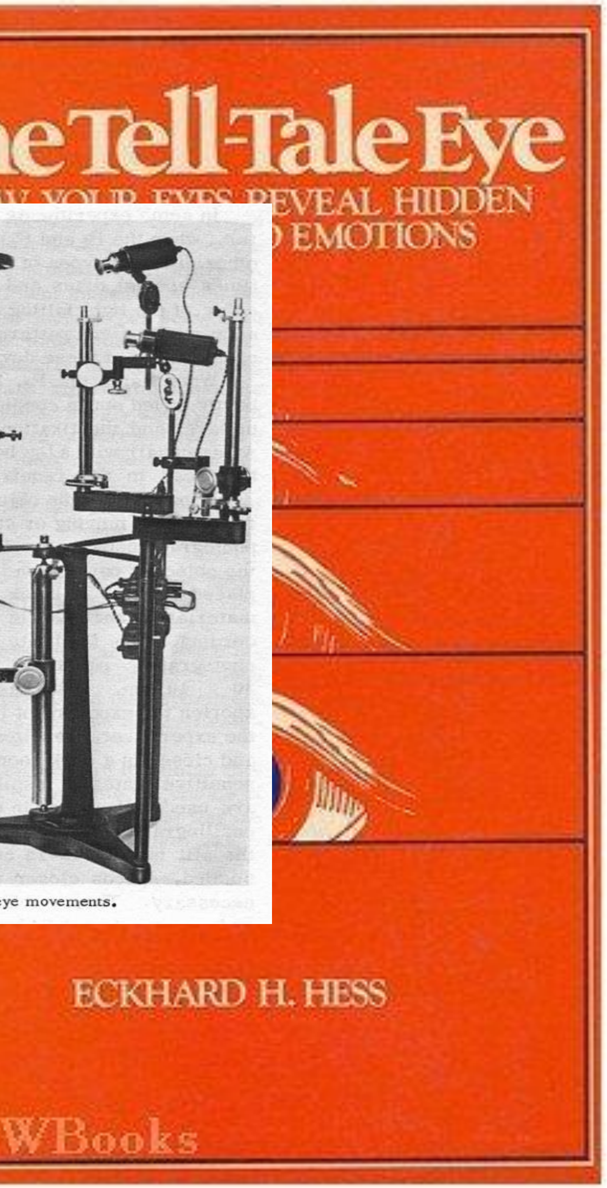


Fig. 21. The apparatus used in recording eye movements.



Cognitive Load Estimation

TIME SCALE OF HUMAN ACTION		
SCALE (sec)	SYSTEM	STRATUM
10^7 10^6 10^5		SOCIAL
10^4 10^3 10^2	Task Task Task	RATIONAL
10^1 10^0 10^{-1}	Unit Task Operations Deliberate Act	COGNITIVE
10^{-2} 10^{-3} 10^{-4}	Neural Circuit Neuron Organelle	BIOLOGICAL

A Newell, Unified Theories of Cognition

- Our research estimates cognitive load from ocular parameters
- Neural processing work at a faster level than cognitive processing
- Hike in Pupil Dilation is correlated to EEG output
- SI or SWJ are clinically used to diagnose neurological problems like Alzheimer’s Disease or Progressive Supranuclear Palsy

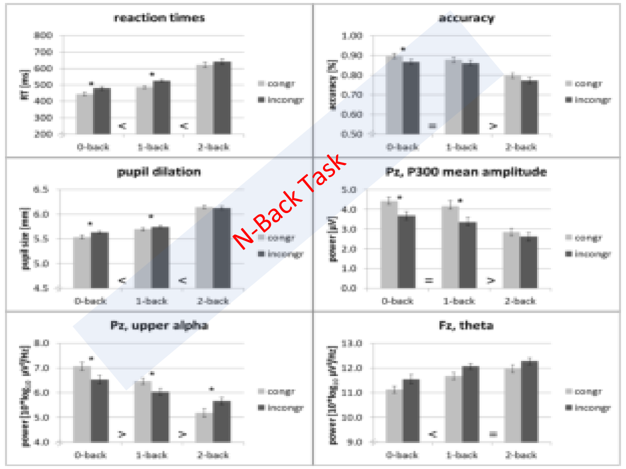


Figure 2. Mean values for reaction times, accuracy, pupil size (indicating pupil dilation), P300 amplitude at electrode Pz, upper alpha power (Pz), and theta power (Fz). Error bars: ± 1 SEM. The *, >, and < mark significant differences ($p < .05$). Light gray color symbolizes congruent trials, dark gray color incongruent trials.

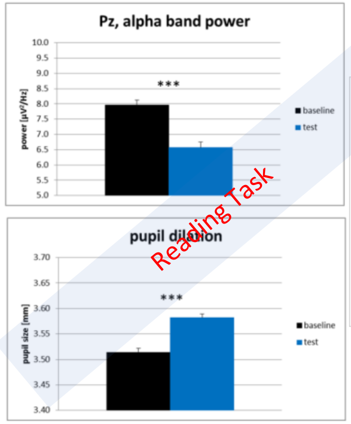
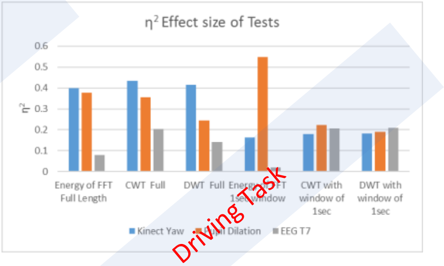


Fig 2. Mean alpha (8–13 Hz) frequency band power at electrode Pz and mean pupil dilation of Experiment 1. Note. *** indicate p < .001, black error bars indicate +1 standard error of the mean.

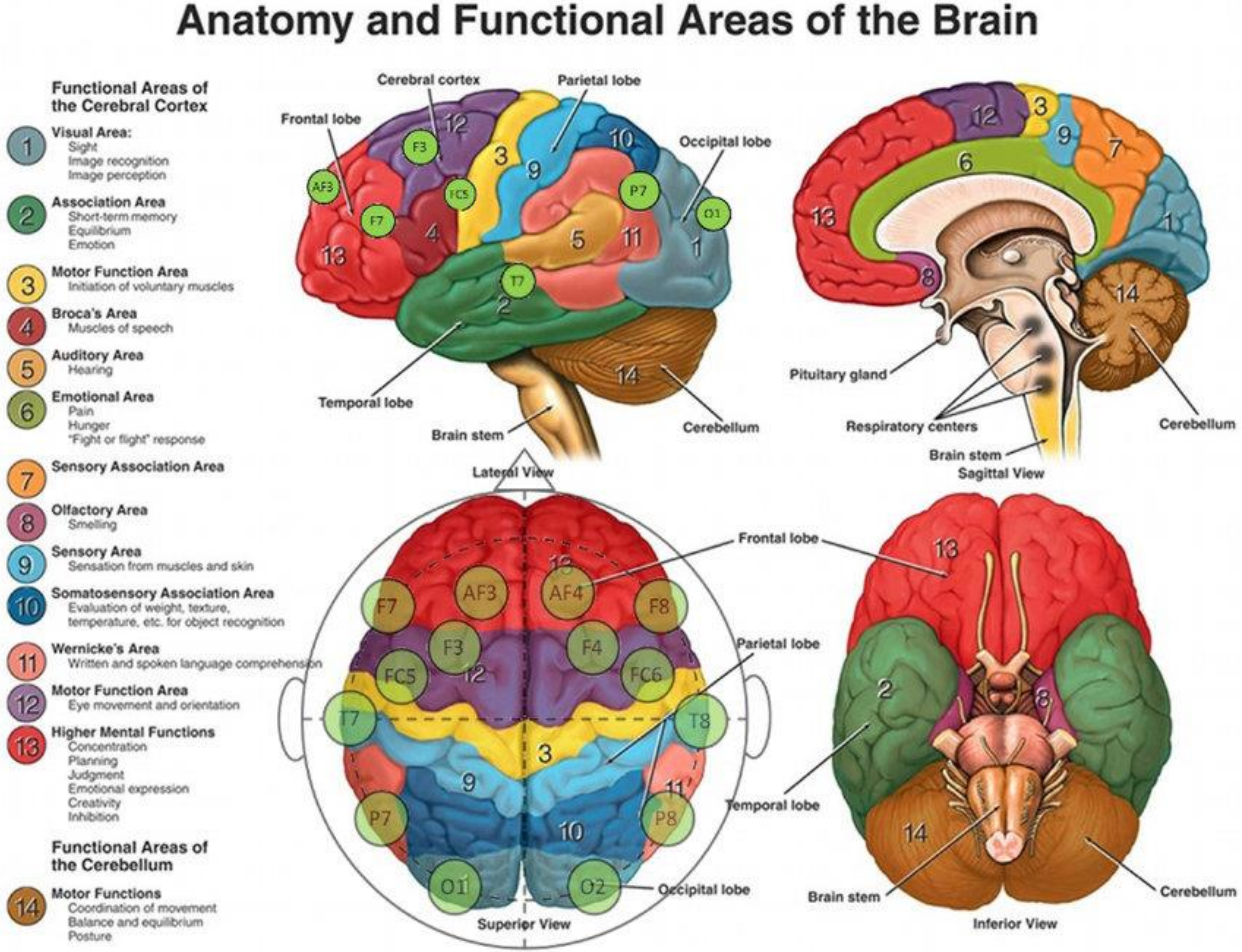


Effect size of each tests to find best performance for real-time implementation

Cognitive Load and Ocular Parameters

Indicator of Increased Cognitive Workload	
↑	Blink Duration
↑	Blink Interval
↑	Blink Frequency
↑	Saccade Rate
↑	Saccade Peak Velocity
↑	Saccade Amplitude
↑	Pupil Size
↑	Pupil Dilation
↑	Fixation Frequency
↑	Fixation Duration
↑	Horizontal Fixation
↑	Vertical Fixation
↑	Mean Dwell Time
↓	Saccade Extent
↓	Blink Rate
↓	Area of Visual Field

Cortical Topography

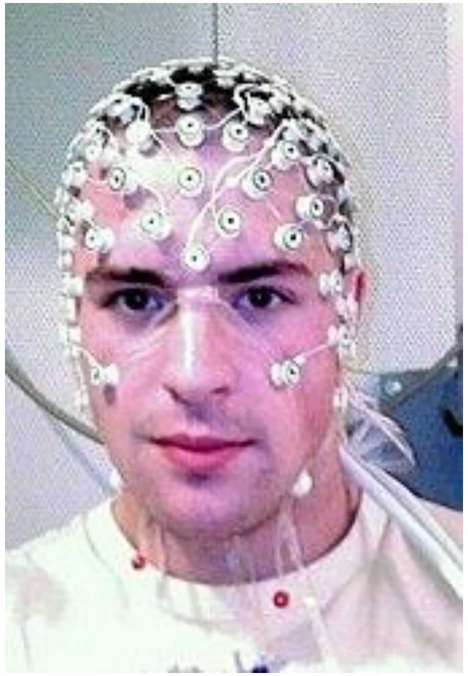


Adapted from Neuroanatomy - A Primer, by K. Sukel, 2011, http://www.dana.org/News/Details.aspx?id=43515

Cudlenco, Nicolae & Popescu, Nirvana & Leordeanu, Marius. (2019). Reading into the mind's eye: Boosting automatic visual recognition with EEG signals. Neurocomputing. 386. 10.1016/j.neucom.2019.12.076.

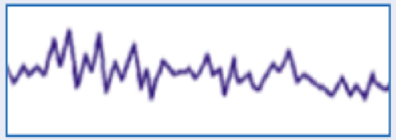
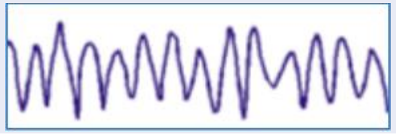
EEG

- Electroencephalography (1924)
- Hans Berger



From Wikimedia Commons

PSD Analysis: Frequency bandwidths

	Band	Frequency (hz)	Correlates
	Delta	<3	Slow wave sleep
	Theta	3-7	Memory Creation, Hypnagogia
	Alpha	8-13	Relaxation, Reflection Closed Eyes, Intrinsic Focus
	Beta	13-30	Active cognition, Intense concentration
	Gamma	30+	Multisensoring processing, Euphoria, High Focus
	Mu	8-12 (Over sensorimotor)	Suppression has been linked with empathy

Cognitive Load / Mental Workload

- Depletion of mental resources due to mental demands of a task
- High Workloads vs Low Workloads
- Individualized
- Limited Resources and Unlimited demands
- Importance in Occupations : ATCs and Healthcare
- Processing and Integration of Information
  Task-related knowledge, working memory, decision making, attention

Wrobel A 2000 MacPhee et al, 2017 Sauseng P et al, 2005 Friedman N. 2019

Cognitive Load Theory

- Sensory Memory → Relevancy → **Working Memory** → Processing → Long term theory (Schema)
- Limited Capacity (“Multitasking is a myth”)
- Intrinsic
- Extrinsic
- Germane (New Schema)

Assessment of Cognitive Load

- <u>Subjective Metrics</u>
  NASA-TLX, ATWIT
- <u>Objective Metrics:</u>
  Behavioral: Position of body, keystroke dynamics, mouse-tracking
  Physiological: Pupil dilation, blink frequency, duration, saccades; (ECG), heart rate and variability (HRV),
  Neuropsychological: EEG, fNIRS, fMRI
- EEG is most widely used for cognitive load estimation

Stein E.S. 1985
(Loft S, 2015; Debbie E, 2019
Mulder, L.1989

EEG for Estimation of Cognitive Load

- Theta band

  mental fatigue, mental workload, demands on cognitive resources, task difficulty, working memory, concentration, lower mental vigilance and alertness, a loss of cortical arousal

- Alpha band

  reduction in attention or alertness, cognitive fatigue, relaxed states, Lower mental vigilance, task difficulty,

  parietal and occipital areas

- Beta band

  Visual attention, short-term memory, working memory, mental workload, concentration.

  Arousal of the visual system during increased visual attention

EEG Indicators of Cognitive Load

Vidulich, M. A.,2012, Xie, J., 2016, Antonenko, P., 2010; Borghini, G., 2012, Parasuraman, R.,2002;Maior, H. A., 2014, Paus, T., 1997; Sterman, M., 1995

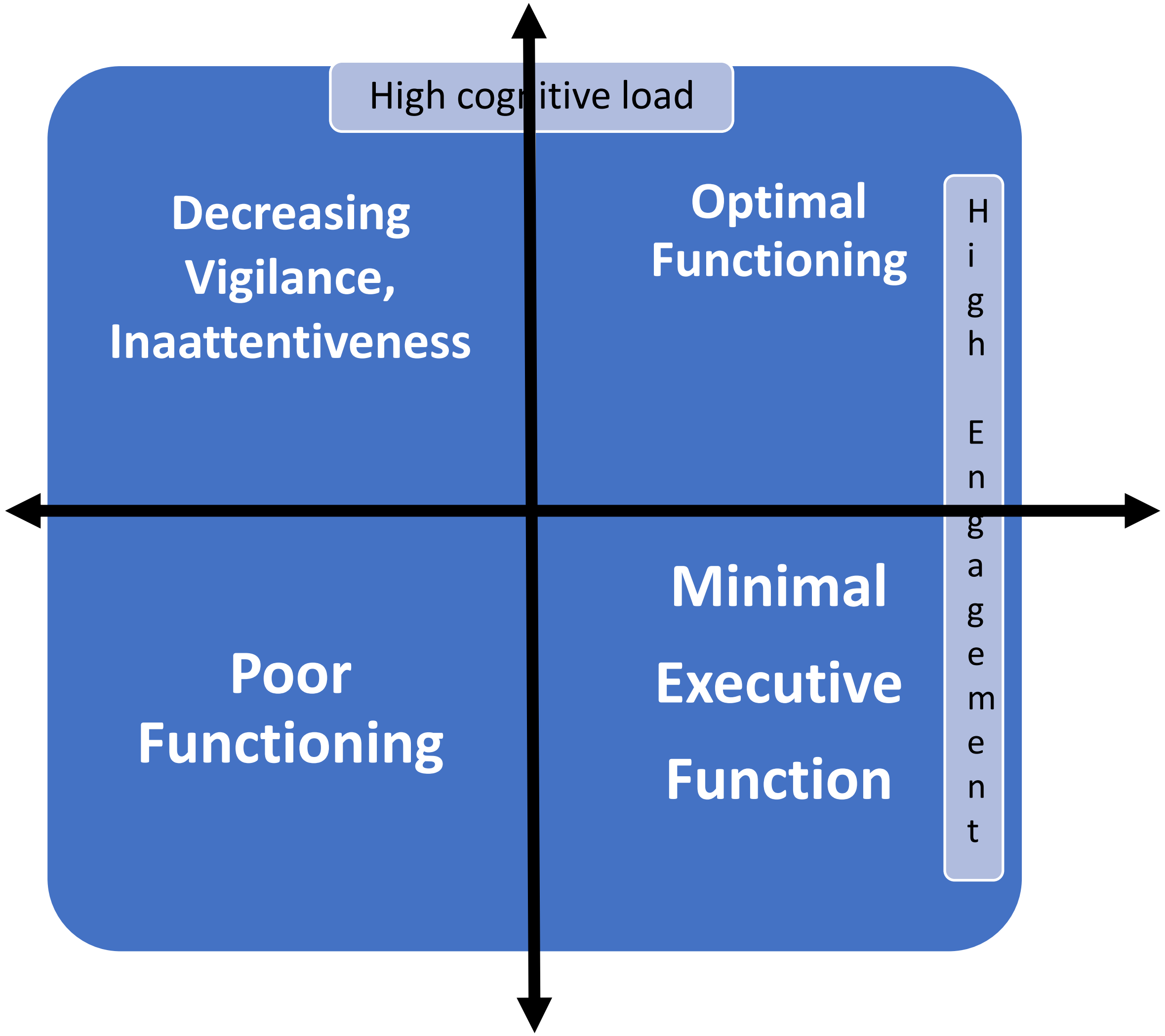
Antonenko, P., 2010, Puma, S., 2018, MacLean, M. H., 2012 Parasuraman, R., 2002 Maior, H. A 2014 Mazher, M., 2017, Xie, J.,2016, Wróbel, A. 2000,Sauseng P.,2005, Mazher, M.,2017

Tallon-Baudry, C., 1999; Palva, S., 2011, Spitzer, B., and Haegens, S. 2017; Coelli, S.,2015; Kakkos, I.,2019; Mapelli, I., and Özkurt, T. E. 2019; (Pope, A. T.,1995)

Fernandez **Rojas** R, Debie E, Fidock J, Barlow M, Kasmarik K, Anavatti S, Garratt M and Abbass H (2020) Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments. *Front. Neurosci.* 14:40. doi: 10.3389/fnins.2020.00040

Indicator	Type of cognitive behavior	Description
Theta	Workload, vigilance, and concentration.	Theta spectral power is thought to increase with increase cognitive resources demand.
		Theta increases in tasks requiring a sustained focus of concentration and vigilance.
Alpha	Workload, cognitive fatigue, and attention.	Alpha band increases in relaxed states with eyes closed and decreases when the eyes are open.
		An increase in alpha power is related to lower mental vigilance and alertness.
Beta	Workload, visual attention, and concentration.	An increase in beta power is associated with elevated mental workload levels during mental tasks and concentration.
		Beta band activity reflects an arousal of the visual system during increased visual attention.
$\frac{Beta}{Alpha + Theta}$	Mental Effort, vigilance, and attention.	It has been used to study alertness and task engagement, mental attentional investment, and mental effort.
$\frac{Theta}{Alpha}$	Workload, mental effort.	This index is based in the assumption that an increase of mental load is associated with a decrease in alpha power and an increase in theta power.
$\frac{Theta}{Beta}$	Working memory, attention, and sleepiness.	This index is based in the assumption that an increases in alertness and task engagement result in an increase in beta power and a decrease in theta power.

Cognitive Load and Task Engagement



Berka C (2007)
Advanced Brain Monitoring

Task Load Index

$$\frac{\theta}{\alpha}$$

- Ratio of the mean medial frontal theta power to the mean parietal alpha power.
- ‘Brainbeat’
- Frontal θ PSD ↑ and Parietal α PSD ↓ with task difficulty
- mental fatigue, mental workload, demands on cognitive resources, task difficulty, working memory, concentration, lower mental vigilance and alertness, a loss of cortical arousal

(Holm A., 2009; Hockey G., 2009; Gevins A et al, 2003; Bailey N.R. 2006; Prinzel L et al, 2003; Kamzanova AT, 2011); (Lansbergen et al)
Young M. S. 2005, Kathner I, 2014; Fairclough S, 2004
((Vidulich, M. A. 2012; Xie J, 2016; Antonenko, P 2010; Borghini 2012; Parsuram, 2002 ,Major H.A., 2014)
Ismail L et al, 2002)[69] Krause C. et al 200

Engagement Index

$$\frac{\beta}{\alpha+\theta} \quad \frac{\beta}{\alpha} \quad \frac{1}{\alpha}$$

- Introduction

  "sustained, engaged attention to a task requiring mental effort"

  "the extent for willingness to take on task, including amount of efforts and how long they persist

  Development

  Pope and his Adaptive System and further work by Freeman

- Importance and Factors

  information-gathering, visual processing, and allocation attention.

- Method of Calculation

  Multiple EEG indices and montages, Comparison studies

- Various Application : Education, Gaming, Automobile, Machinery to Missiles!

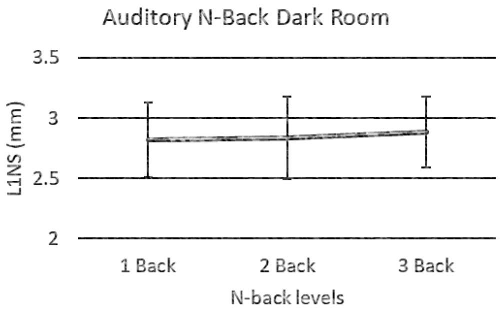
Pope AT, Bogart EH, Bartolome DS. Biocybernetic system evaluates indices of operator engagement in automated task. Biol Psychol. 1995 May 1;40(1):187–95.

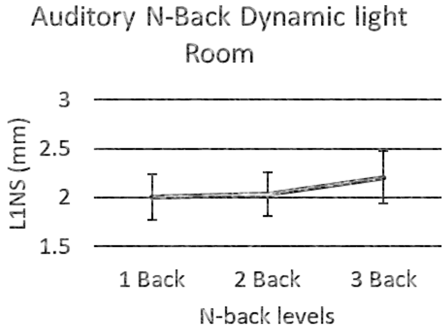
Freeman FG, Mikulka PJ, Prinzel LJ, Scerbo MW. Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. Biol Psychol. 1999 May 1;50(1):61–76.

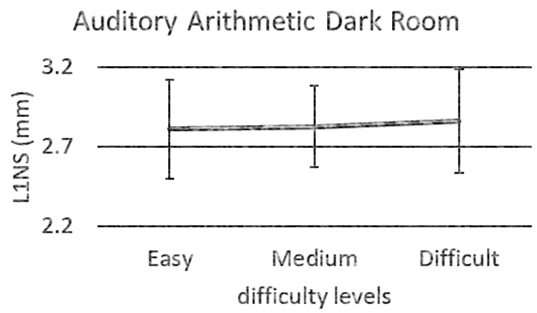
Coelli S, Barbieri R, Reni G, Zucca C, Bianchi AM. EEG indices correlate with sustained attention performance in patients affected by diffuse axonal injury. Med Biol Eng Comput. 2018 Jun 1;56(6):991–1001.

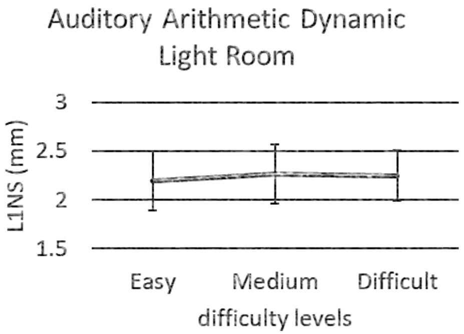
(Corno and Mandinach 1983)
, (Richardson and Newby 2006; Walker et al. 2006)
Pope et al(1995); Freeman (1999)
Berka C (2007)
Coelli S (2015,2018)

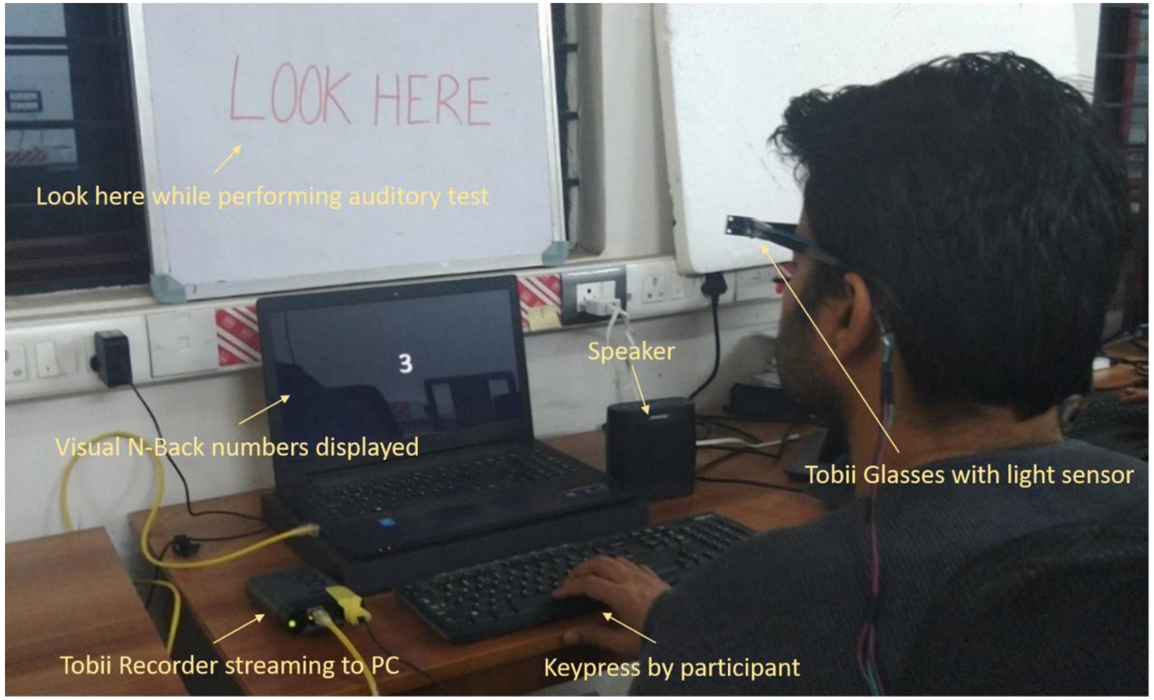
Laboratory Studies



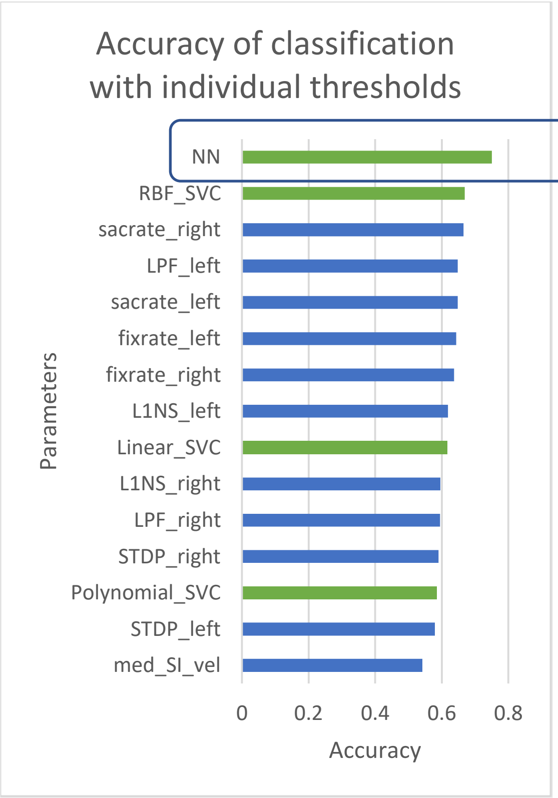


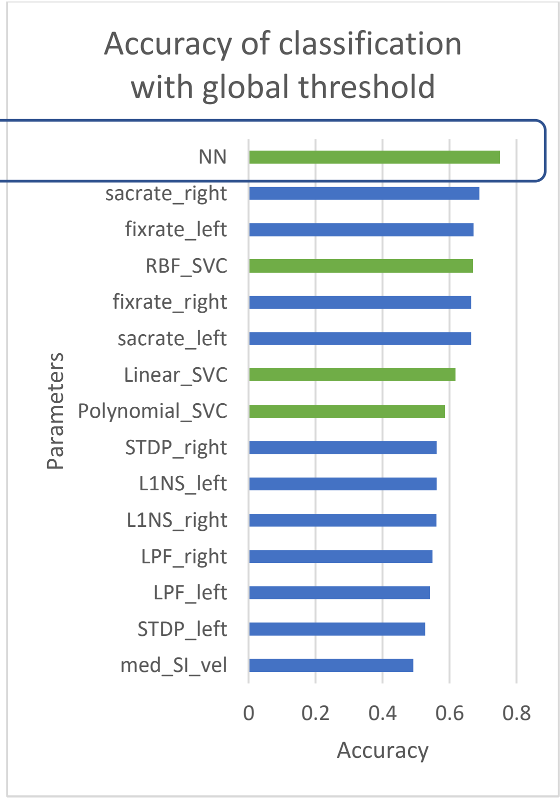


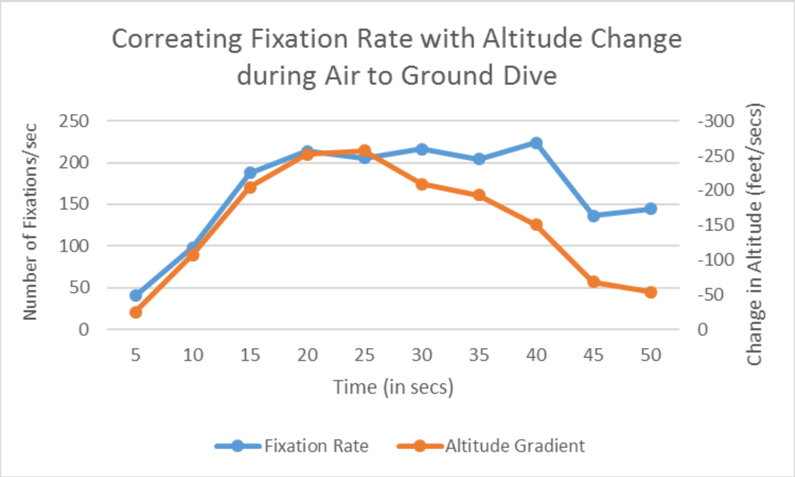


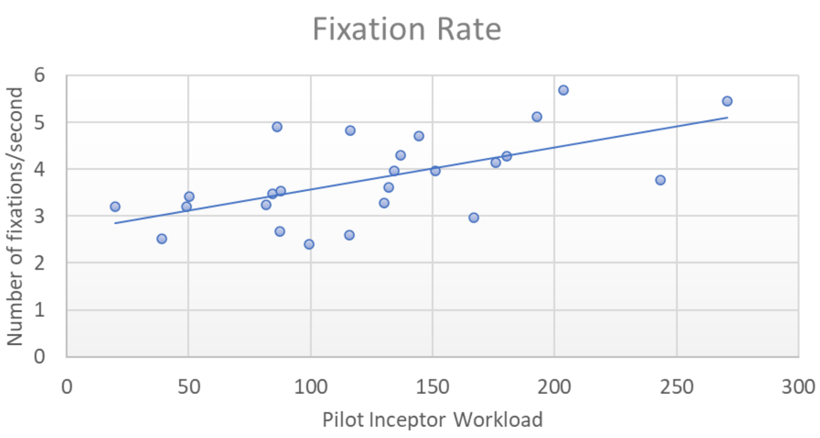


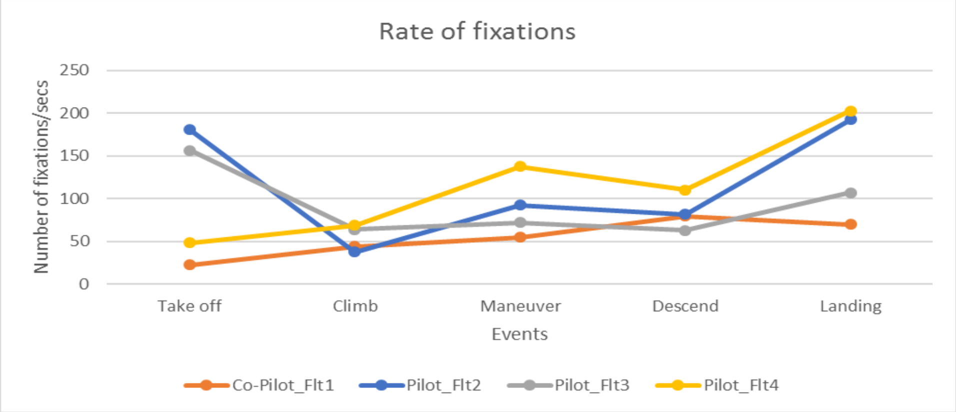
Automotive Study

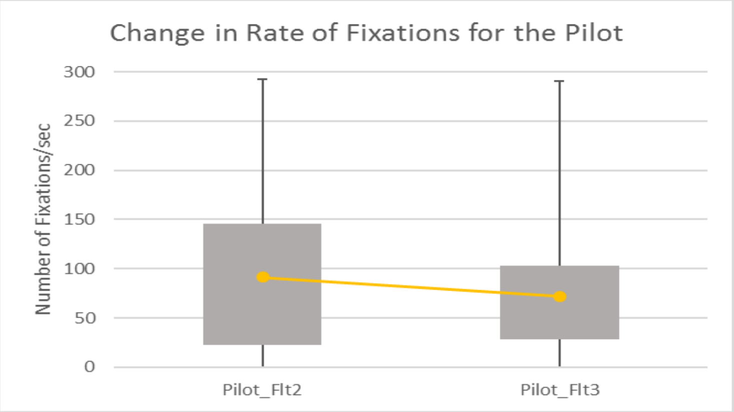












Aviation Study

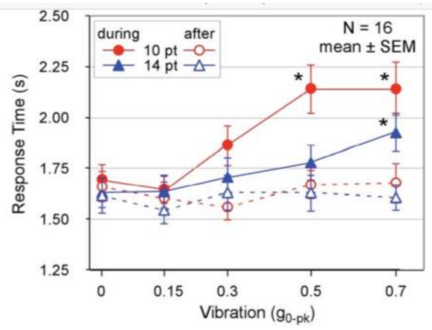


Figure 13. Mean response times (±SEM) of the general-population participants during (solid symbols and lines) and immediately after (open symbols and dashed lines) vibration at each of the 5 levels for 10-pt (red) and 14-pt (blue) font. Note the three points with significant ($p < 0.05$) increases over baseline. Note also the fact that performance after vibration (dashed lines) is

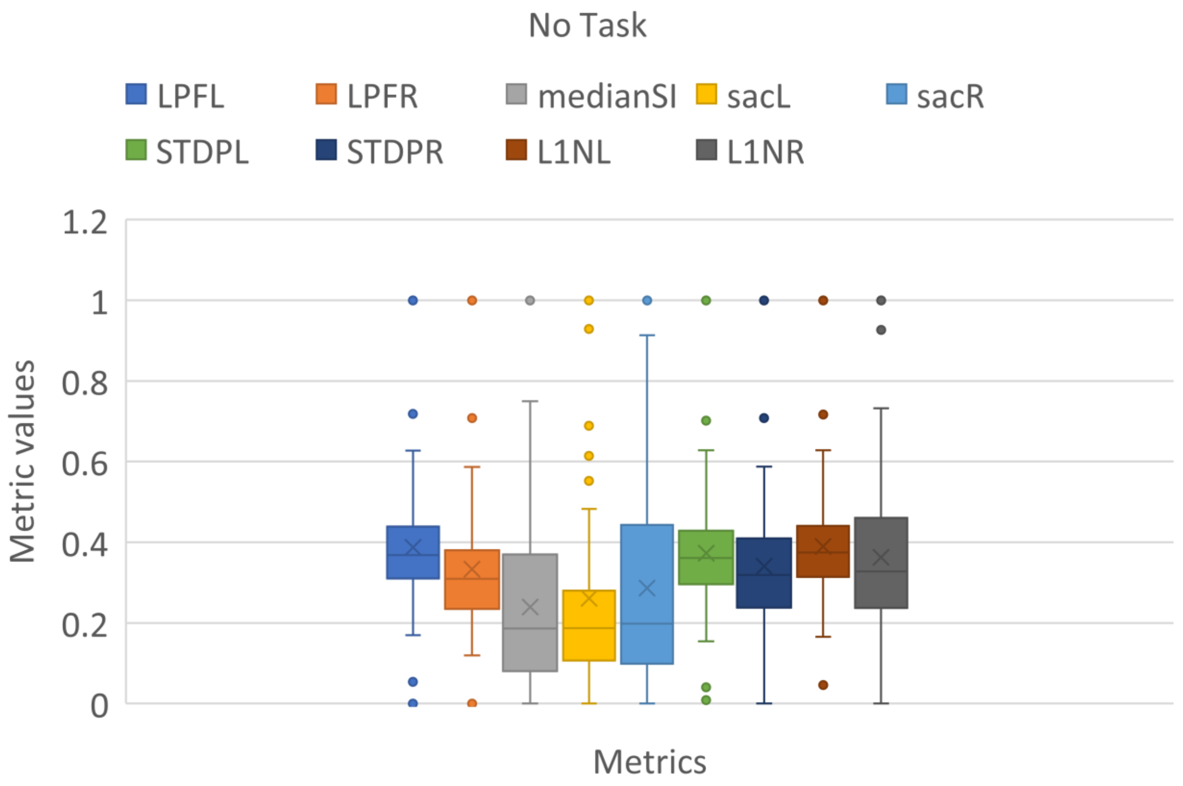
Human Space Flight Application

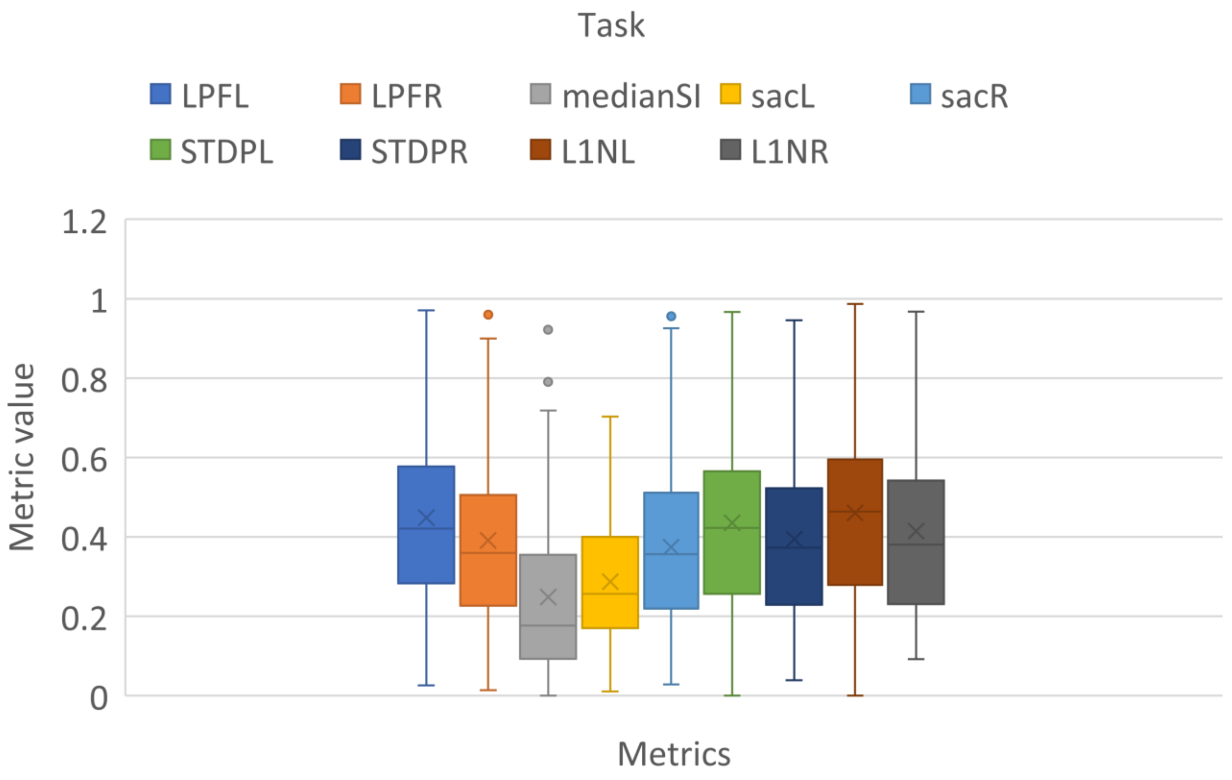
How it works - Cognitive Load Estimation from Ocular Parameters

Dataset preparation

- Analysed and measured ocular parameters and took average of each parameter in tagged time duration
- We have 6 features and 1 prediction vector, i.e., dataset dimension is (26×6)

Average value of parameter corresponding to an event





Training and Testing

STDPL	SMSSL	LPFL	MedianSI	sacl	sacr	Class
0.706459	1.137524	1.828027	49.3185	7.528443	5.505418	0
0.987355	1.530836	2.653351	8.010019	6.559692	7.233281	0
1.05791	1.684927	2.832962	20.94228	41.93676	23.30592	0
1.364831	2.120465	3.673532	5.846828	6.214595	3.726455	0
0.952527	1.495051	2.561194	12.53268	14.98782	5.575253	0
1.004906	1.581594	2.685834	14.80185	12.73494	4.306997	0
1.155556	1.794817	3.104505	7.088327	11.33383	9.864231	0
1.068594	1.672585	2.871536	17.12084	25.50885	29.48941	0
0.997523	1.554821	2.762956	7.757654	8.026166	7.050217	0
0.866554	1.349139	2.350035	18.08792	7.976758	6.305152	0
0.90166	1.403927	2.439939	9.771493	10.49378	9.735114	0
0.90389	1.403503	2.425858	4.601533	2.775808	3.795692	0
1.063928	1.655209	2.866627	10.89931	16.40668	20.90531	0
0.700745	1.091478	1.906794	57.6819	26.58492	12.54121	1
1.146462	1.811556	3.081482	14.24862	16.74549	15.16804	1
1.254093	2.001666	3.385174	30.20105	34.23355	23.86729	1
1.401125	2.194649	3.784753	7.342054	10.08158	7.269943	1
1.040266	1.637844	2.801202	13.30015	19.27478	14.13997	1
1.081412	1.68687	2.910298	17.16687	15.67151	7.225739	1
1.243439	1.93863	3.351217	12.71217	17.34932	14.89335	1
1.072975	1.708304	2.939804	20.14046	28.33814	30.513	1

Training Data (26 × 6)

STDPL	SMSSL	LPFL	MedianSI	sacl	sacr	Class
0.706459	1.137524	1.828027	48.4645	5.961252	5.826803	0
0.702569	1.107083	1.889691	38.65474	26.72293	13.261	1
0.698922	1.075874	1.923896	27.969	20.62204	18.13298	1
1.00639	1.557407	2.668574	6.824375	6.772009	3.762227	0
1.01435	1.572846	2.678924	6.879444	6.090487	8.12065	0
0.981585	1.518262	2.643635	5.218889	6.337558	9.006004	0
0.947095	1.474827	2.622272	13.11737	7.038713	8.044243	0
1.022034	1.681122	2.742683	28.75488	38.64873	25.47953	1
1.111368	1.762064	3.064896	30.21846	30.45515	22.7577	1
1.263466	1.991384	3.372473	18.605	18.54446	17.14362	1
0.943755	1.482271	2.522211	4.28744	5.055612	13.14459	1
1.286281	2.018722	3.426783	4.154595	7.432819	6.003431	1
1.25368	1.971348	3.553604	4.87398	11.33995	9.338781	1
1.140585	1.790685	3.063587	12.22103	12.06637	15.58572	1
1.214173	1.902103	3.288128	4.102436	12.65823	15.30422	1
1.082814	1.704302	2.876858	9.116888	10.02004	9.733753	1
1.072113	1.687796	2.878466	26.00818	54.86076	32.34951	0
1.156814	1.836831	3.117295	18.97778	51.02551	23.67851	0
1.050196	1.649141	2.80376	16.90274	38.69246	22.84857	0
1.043542	1.655777	2.795555	21.90934	27.01621	20.11207	0
0.966884	1.59509	2.569736	20.91336	38.08887	17.54093	0

Test Data (128 × 6)

Sample Prediction

IPython console

Console 1/A

```
[0.361334214380169, 0.36801489488426997, 0.3561004541979096, 0.11060374493385947, 0.09445010278782445, 0.20094260571898273] => 0 (expected 0)
[0.7019738603303165, 0.7166484199694302, 0.7184630006357013, 0.08036529680365295, 0.11775416305363998, 0.10984961972201632] => 0 (expected 0)
[0.5864920140647172, 0.6039534474640601, 0.598568646743004, 0.15580462609476753, 0.153888900109501, 0.13346826990047744] => 0 (expected 0)
[0.352215120513522, 0.3565815839745744, 0.3517689286445165, 0.10942596216568817, 0.10710436746321106, 0.08208151932064538] => 0 (expected 0)
[0.30695937411626373, 0.3844861880204743, 0.31040512042961543, 0.4107526226300086, 0.6885852598827314, 0.4578485480922916] => 1 (expected 0)
[0.040487219162712695, 0.04964323865859199, 0.053615692405943105, 0.23777784906911337, 0.17876877065674457, 0.22848846193076078] => 0 (expected 0)
[0.39475180157067435, 0.40602872799064615, 0.4066277937481979, 0.08104432538791398, 0.16744377810805178, 0.19812603238554605] => 0 (expected 0)
[0.38376671106404325, 0.3979733153764139, 0.3948705437610669, 0.21004566210045664, 0.17644148162218906, 0.08590265467936653] => 0 (expected 0)
[0.3176415075937593, 0.3403111699386895, 0.33740715057248694, 0.37068642862489704, 0.37891069921460324, 0.582483145904518] => 1 (expected 0)
[0.23710345349064776, 0.27296114836915997, 0.24581259492100194, 0.3592085164629516, 0.40404244049274407, 0.06134554075204082] => 0 (expected 0)
[0.3528791864488703, 0.36087990724197405, 0.3709515891904833, 0.10410522601135672, 0.1692080364696452, 0.19777357292374864] => 0 (expected 0)
[0.2964732174132261, 0.3200188418923765, 0.3080828646483533, 0.19074304107450302, 0.14872398558724934, 0.06141728102846576] => 0 (expected 0)
[0.3870269838410225, 0.4001656707929947, 0.41226296690461184, 0.4956673403697882, 0.5520086359008187, 0.9132820058501251] => 1 (expected 0)
[0.30946449956662403, 0.31638447192573016, 0.32531836331396646, 0.05866596088244414, 0.10096674042965886, 0.13953329557477695] => 0 (expected 0)
[0.427502924078085, 0.4531363980302542, 0.4396085854411429, 0.5197177290857956, 1.0, 0.8617019730401331] => 0 (expected 0)
[0.32380018818920653, 0.327594719431323, 0.3413317214113323, 0.07508878979393238, 0.09903763550725467, 0.22508762197382517] => 0 (expected 0)
[0.4720022825356347, 0.4792792100953035, 0.4924732086845418, 0.12229501780501106, 0.11143517959759786, 0.1568779700778709] => 0 (expected 0)
[0.3751316636439159, 0.3950364084279526, 0.3861607114832599, 0.18132272518259493, 0.2879347739283329, 0.37518140096880714] => 1 (expected 0)
[0.43134743741411663, 0.4307880749469458, 0.4389197346543421, 0.0366334520334071, 0.19886142269971183, 0.43782558308999375] => 1 (expected 0)
[0.19246272699971945, 0.19799158562197994, 0.22445989452966253, 0.3919766021836536, 0.21220317038667738, 0.28571758857591995] => 1 (expected 0)
[0.40209660908665534, 0.4098843063750487, 0.41336696956292296, 0.219747585897148, 0.25593580506266717, 0.4797922164493394] => 1 (expected 0)
[0.19480382804949536, 0.2144069988680778, 0.21847743888123272, 0.0667289253900527, 0.21545697635647199, 0.3096639067638501] => 0 (expected 0)
[1.0, 1.0, 1.0, 0.0293864168618267, 0.018620411034722957, 0.0] => 0 (expected 0)
[0.5978668861882079, 0.6158348623530373, 0.6101617175569485, 0.13307240704500978, 0.27706291583080783, 0.34004143844003226] => 1 (expected 0)
[0.45204244916571246, 0.4946636226703568, 0.4589428609571846, 0.4566210045662101, 0.6141409176522841, 1.0] => 1 (expected 0)
[0.3947736743927712, 0.429426229870684, 0.40491034268024895, 0.4320542170607295, 0.48299179699367656, 0.5279675672542585] => 1 (expected 0)
```

[Input vector => Prediction:0/1 (Actual (0/1))]

Calculation of Accuracy

We took Task region as positive and No_task region as negative

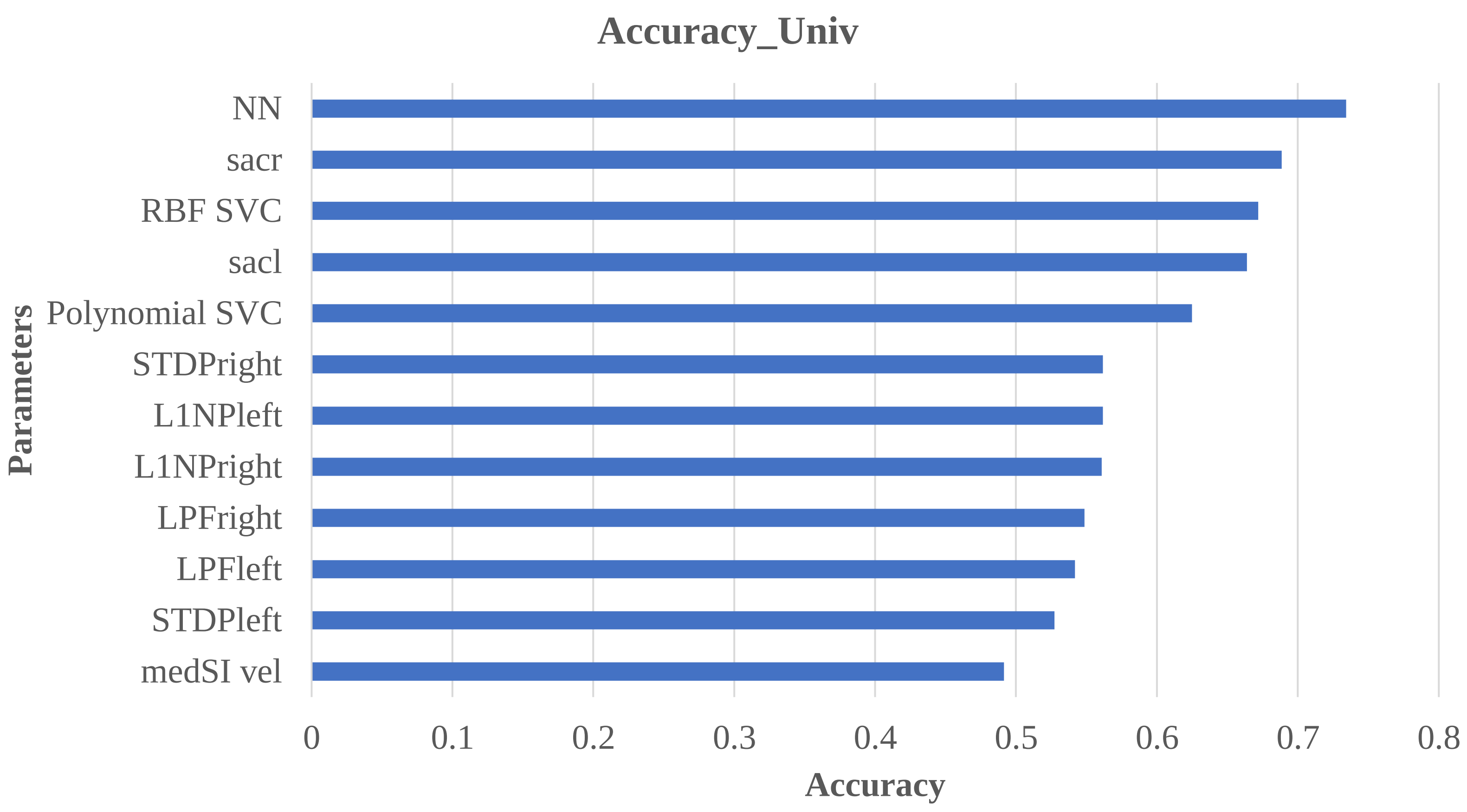
We counted True positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) as follows:

- TP= If parameter > threshold and lies in Task region
- FP= If parameter>threshold and lies in No_task region
- FN=If parameter<threshold and lies in Task region
- TN=If parameter<threshold and lies in No_task region
- Accuracy=(TP+TN)/(TP+FP+TN+FN)

Results - Individual threshold

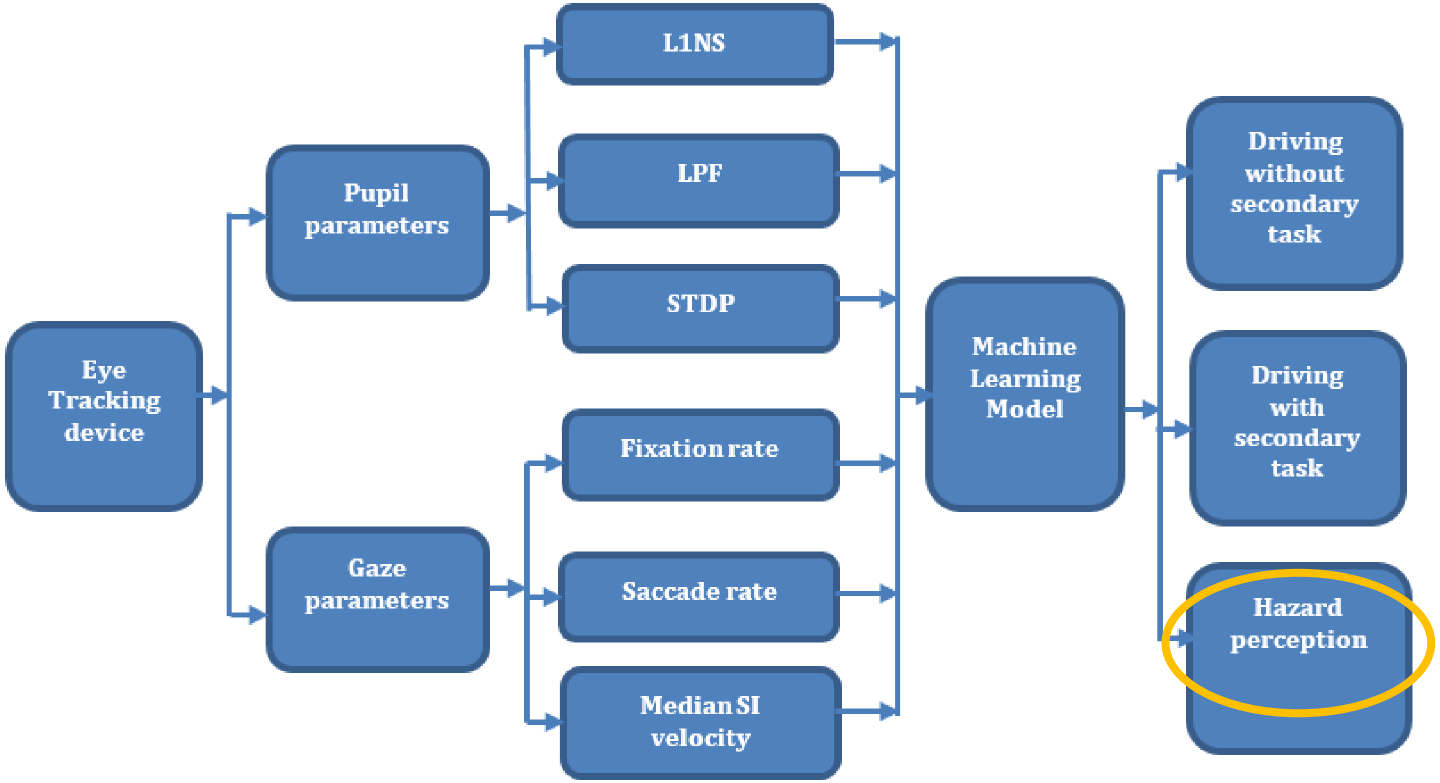
- Calculated accuracy of each parameter by choosing individual threshold corresponding to No_task of each driver
- Compared accuracy individual parameters against that of Neural network model to classify

Results - Universal threshold



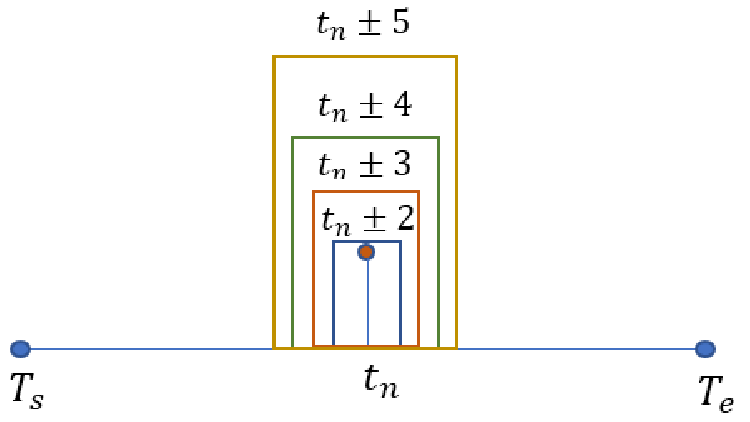
- Calculated accuracy of each parameter by choosing universal threshold which is the average of thresholds corresponding to No_task of each driver
- Compared accuracy individual parameters against that of Neural network model to classify

Architecture of proposed model



- **Model structure**: 8 – 160 – 80 – 3
- **Activation function in hidden layers**: ReLU
- **Activation function in output layer**: ‘Softmax’
- **Optimizer**: ‘Adam’
- **Loss function**: ‘categorical cross entropy’

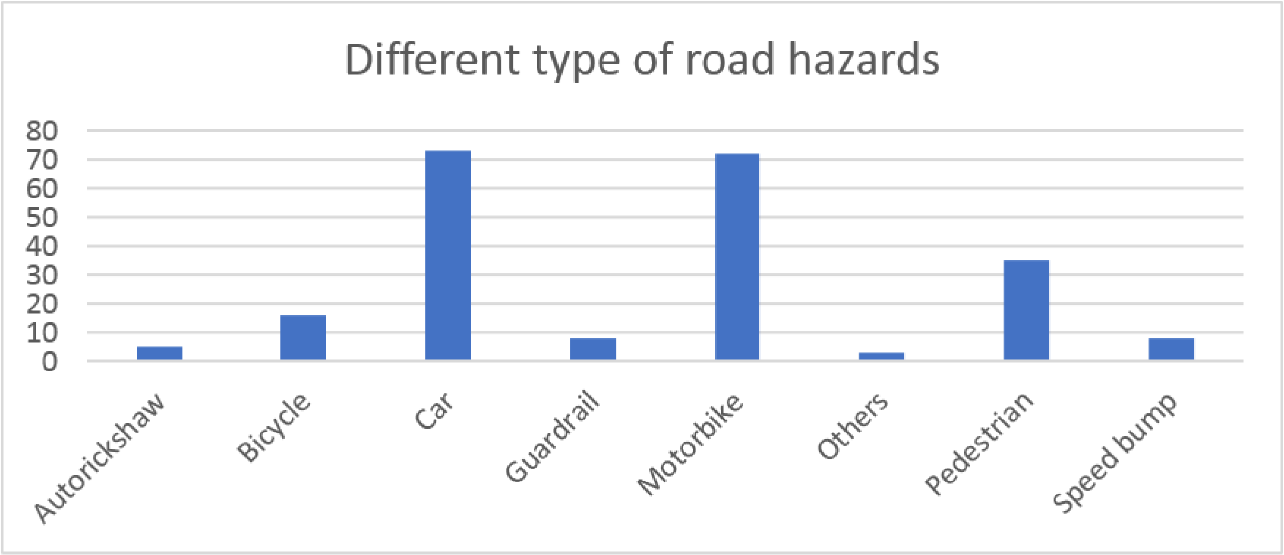
Dataset preparation



T_s : Starting time from when driver stared driving

T_e : End time when driver stopped driving

t_n : event timestamp



- **Followed the guideline of Driver and Vehicle Standards Agency (DVSA), UK to identify developing road hazard**
- **Calculated L1NS, STDP, LPF, saccade rate, fixation rate and median SI velocity in time window duration of ± 2 secs, ± 3 secs, ± 4 secs, and ± 5 secs around the instances of each developing hazard and secondary tasks**
- **Comparative chart between different type of road hazards for the set of driving samples used in our system**

Results and analysis

Predicted / True	A	B	C
A	T_A	E_{AB}	E_{AC}
B	E_{BA}	T_B	E_{BC}
C	E_{CA}	E_{CB}	T_C

- **Accuracy : ($T_A + T_B + T_C$)/# of test samples.**

	± 2 secs	± 3 secs	± 4 secs	± 5 secs
Training	91.95%	94.62	92.47	84.52%
Test	71.15%	72.44%	70.50%	70.51%

- We found that our model was abled to classify 28 events out of 39 test events correctly
- Accuracy is 72.44 % with ± 3 secs of time window corresponding to road hazards

Conclusion & Acknowledgement

- Cognitive load is estimated through correlation – not measured with unit
- Physiological parameters can be measured and combinations of different parameters results better accuracy than individual parameter
- Cognitive load depends and varies among situation, application and individual – a common minimum trend is useful