# Workload estimation using brain- and bio- signals for adaptive training system

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# Agenda

- Hardware Experimental Setup
- Adaptive Training System
- Brain- and bio-signal scoring
- Conclusions and future work

# Collaborators

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# Adaptive Training System

Hardware experimental system

EEG

Eye Tracking

EEG Feature Extraction

Eye-Tracking Feature Extraction

Cognitive Score

Score (0 – 100)

Adaptive Training System

Learning Process Model

Trial Difficulty Level

Trials Library

**Adaptive Trial Difficulty Level**


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**Adaptive Trial Difficulty Level**


# Hardware experimental system

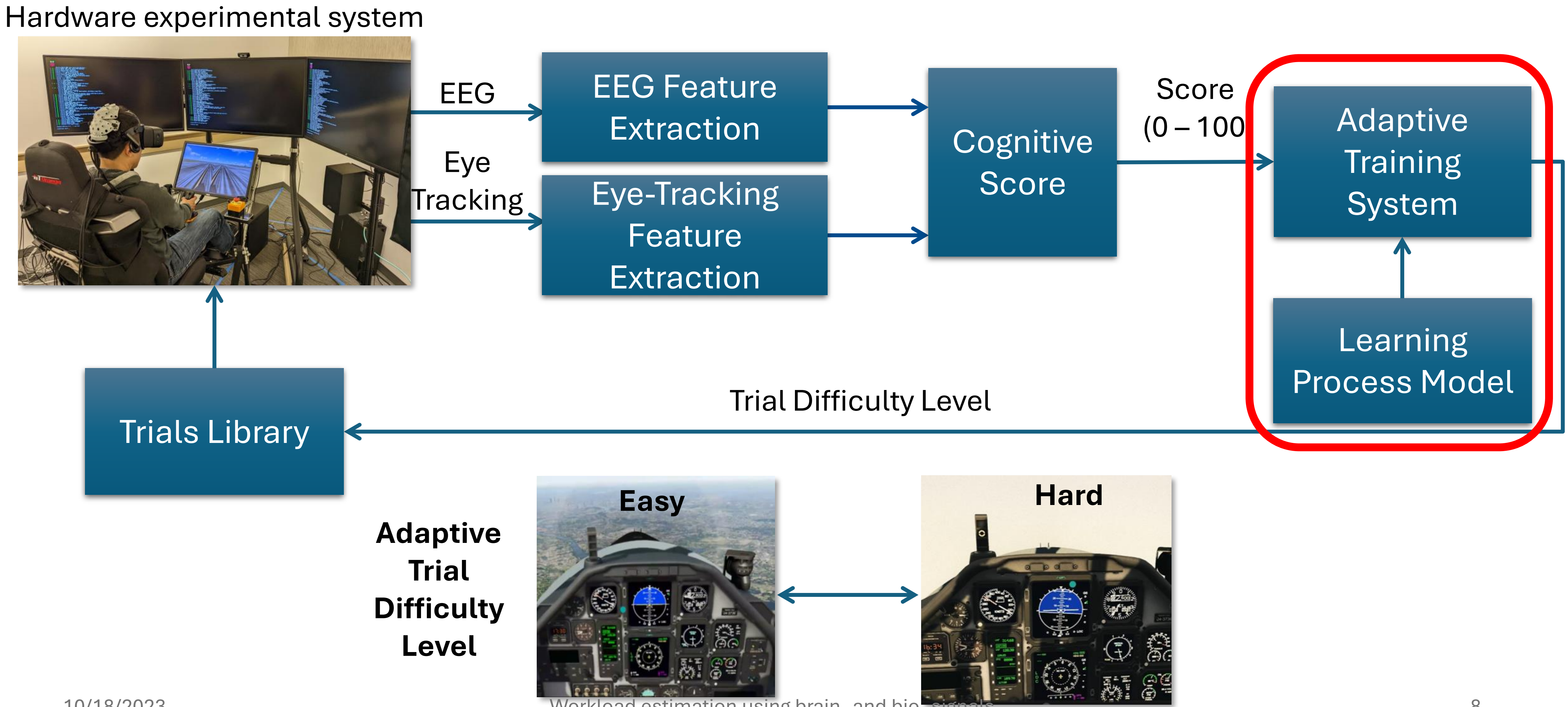
- Flight simulator
  - Prepar 3D software with T6A Texan II plugin
  - 6 DoF motion platform
  - Works in both 3+1+1 monitors setup and in VR
  - 5.1 surround sound
- VR glasses Varjo VR3 retrofitted with EEG electrodes
  - 32 EEG channels plus ground and reference
    - Custom electrodes with Ag/AgCl tips and spring
    - Three 3D printed plates for flexible shape
  - BrainVision LiveAmp pre-amplifier (24 bits, up to 1,000 Hz)
  - Gaze tracking integrated into Varjo VR3
- Auxiliary bio-signal collection
  - Electrocardiographic
  - Galvanic Skin Resistance
  - Breathing

# Trials library

- General scenario is straight line flight with two flavors:
  - Straight-and-level: maintain course, altitude, and speed
  - Glideslope: maintain speed and course, approach the runway
- Difficulty variability
  - Visibility: clouds, fog
  - Disruptions: wind, gusts, thermals
- In the final set are 11 scenarios
  - One straight-and-level with full visibility (easiest)
  - 10 glideslope scenarios
    - Starting with full visibility
    - Ending with practically zero visibility, wind gusts, and thermals (most difficult)
- Data collection with N=16 subjects
  - Experience vary from novice to licensed pilots
  - Aim is to estimate the scenario difficulties (see the training process model later)

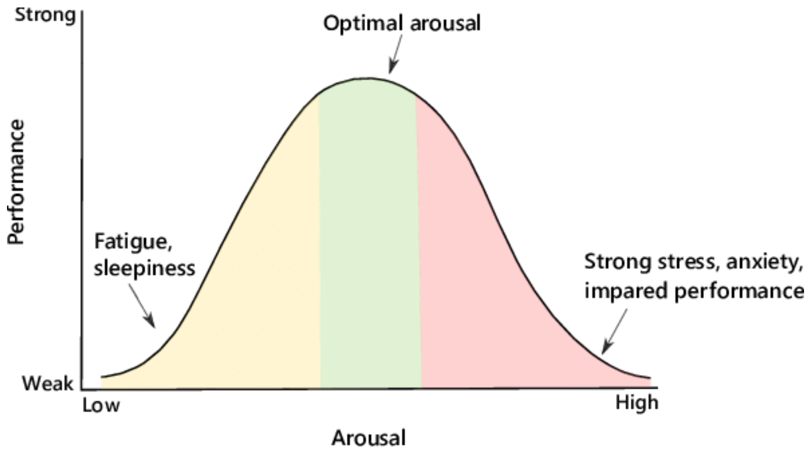
| Name | Difficulty | Limitation |
|---|---|---|
| Straight-and-Level Sc Diff 0 | 1.00 | 95.00 |
| Glideslope Sc Diff 1 | 2.86 | 77.14 |
| Glideslope Th2 Diff 2 | 4.52 | 82.83 |
| Glideslope Th2 Diff 3 | 6.59 | 92.20 |
| Glideslope Th2 Diff 4 | 8.53 | 93.34 |
| Glideslope Th2 Diff 5 | 10.36 | 100.00 |
| Glideslope Th2 Diff 6 | 12.36 | 100.00 |
| Glideslope Th2 Diff 7 | 14.24 | 99.75 |
| Glideslope Th2 Diff 8 | 16.23 | 100.00 |
| Glideslope Th2 Diff 9 | 18.16 | 82.71 |
| Glideslope Th2 Diff 10 | 20.07 | 100.00 |

# Adaptive Training System

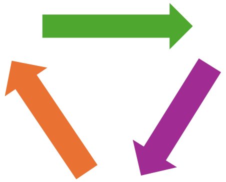


# Theories of Learning Optimization

- Hypotheses
  - Yerkes-Dodson Law valid in pilot training
  - Keeping optimal arousal increases learning speed (cognitive load theory)
- Adaptive Simulation Training
  - Keep the trainee in optimal cognitive and performance state during training




**1. Performance Measurement**
- RMS Deviation
- Kinematics of Controls
- GSR, HRV, RSA
- Gaze & Pupillometry
- EEG / MEG
- Learning-Styles, Self-Report



**2. Adaptive Logic**
- Rule-based Heuristics
- Fuzzy Logic
- Decision Trees
- KNN, SVM (Supervised Learning)
- Reinforcement Learning
- State-Control Regulators

**3. Adaptive Variable**
- Wind Speed
- Wind Direction
- Visibility
- Control of Aircraft
- Controller Sensitivity
- Task Difficulty

RM Yerkes, JD Dodson, "The relation of strength of stimulus to rapidity of habit-formation". Journal of Comparative Neurology and Psychology, 1908/18 (5): 459–482.
M. Zahabi, AM Abudl Razak, “Adaptive virtual reality-based training: a systematic literature review and framework.” Virtual Reality, 2020/24 (4), 725–752.

# Model of the scenarios and trainees

- Each scenario $l$ is characterized by: a) scenario difficulty $d_l$; b) maximum achievable score $M_l$.
- Each trainee $k$ is characterized by: a) initial absolute skill $S^0{}_k$; b) learning rate $\mu_k$.
- At each training step $n$ with scenario with difficulty $d_l$, every trainee $k$ is modelled as:

$$S_k^{(n-1)} = \exp\left(-\frac{\left(t_k^{(n)} - t_k^{(n-1)}\right)}{\tau}\right) S_k^{(n-1)}$$

Account for the absolute skill deterioration

$$\hat{Q}_k^{(n)} = M_l \left(1 - \exp\left(-\frac{\left(S_k^{(n-1)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)\right) + \mathrm{N}\left(0, \left(c_1 \exp\left(\left(-\frac{d_l^{(n)}}{c_2}\right)^{c_4} + c_3\right)\right)^2\right)$$

Compute the score, second part is random performance variation, interpolated with the difficulty of the scenario

$$S_k^{(n)} = S_k^{(n-1)} + \mu_k \frac{S_k^{(n-1)}}{\left(d_l^{(n)}\right)^2} \exp\left(-\frac{\left(S_k^{(n-1)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)$$

Compute the increase in the absolute skill

Ivan J. Tashev, R. Michael Winters, Yu-Te Wang, David Johnston, Nathaniel Bridges. “Adaptive Training System", IEEE RAPiD 2023, September 2023

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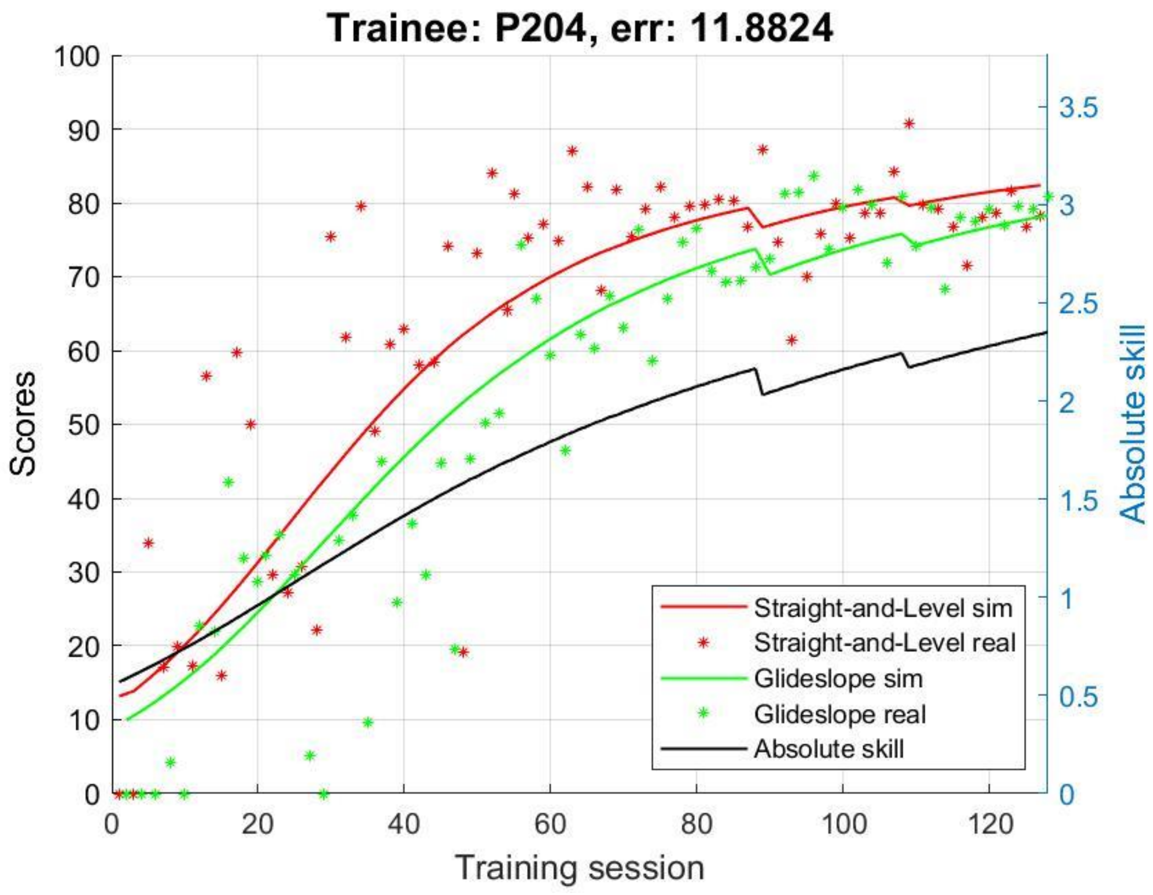


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Compute the increase in the absolute skill

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# Adaptive Training System – the math

- Absolute skill increase at $n$-th run of scenario with difficulty $d_l$:

$$S_k^{(n+1)} = S_k^{(n)} + \mu_k \frac{S_k^{(n)}}{\left(d_l^{(n)}\right)^2} \exp\left( -\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2} \right)$$

- The absolute skill increase depends on:

$$\frac{S_k^{(n)}}{\left(d_l^{(n)}\right)^2} \exp\left( -\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2} \right)$$

- After taking the first derivative, assigning to zero, and solving for $d_l$ the highest increase of the absolute skill is at: $d_l^{(n)} = S_k^{(n)}$
- Given the training history (scores, dates, difficulties) we can estimate the initial absolute skill and the learning rate – lead to the current skill, hence the recommended difficulty

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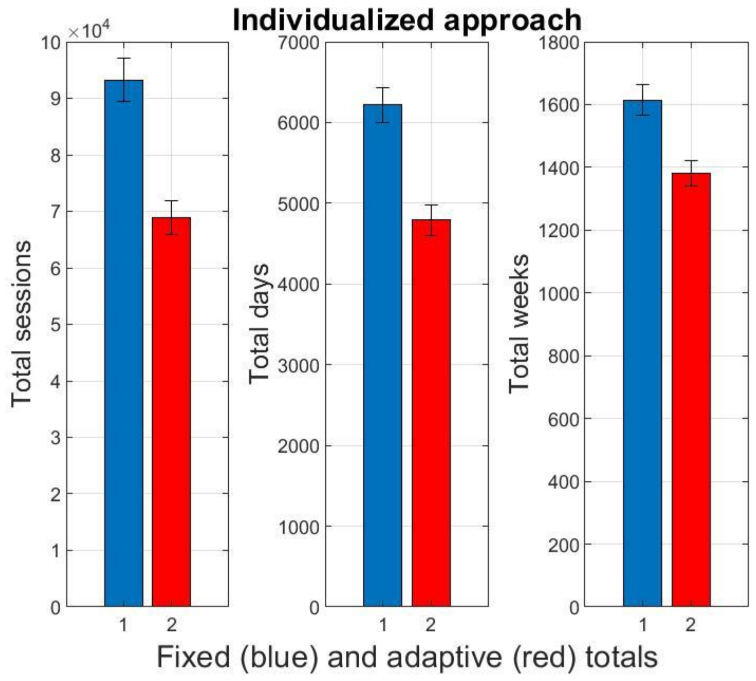
# Adaptive Training System – the

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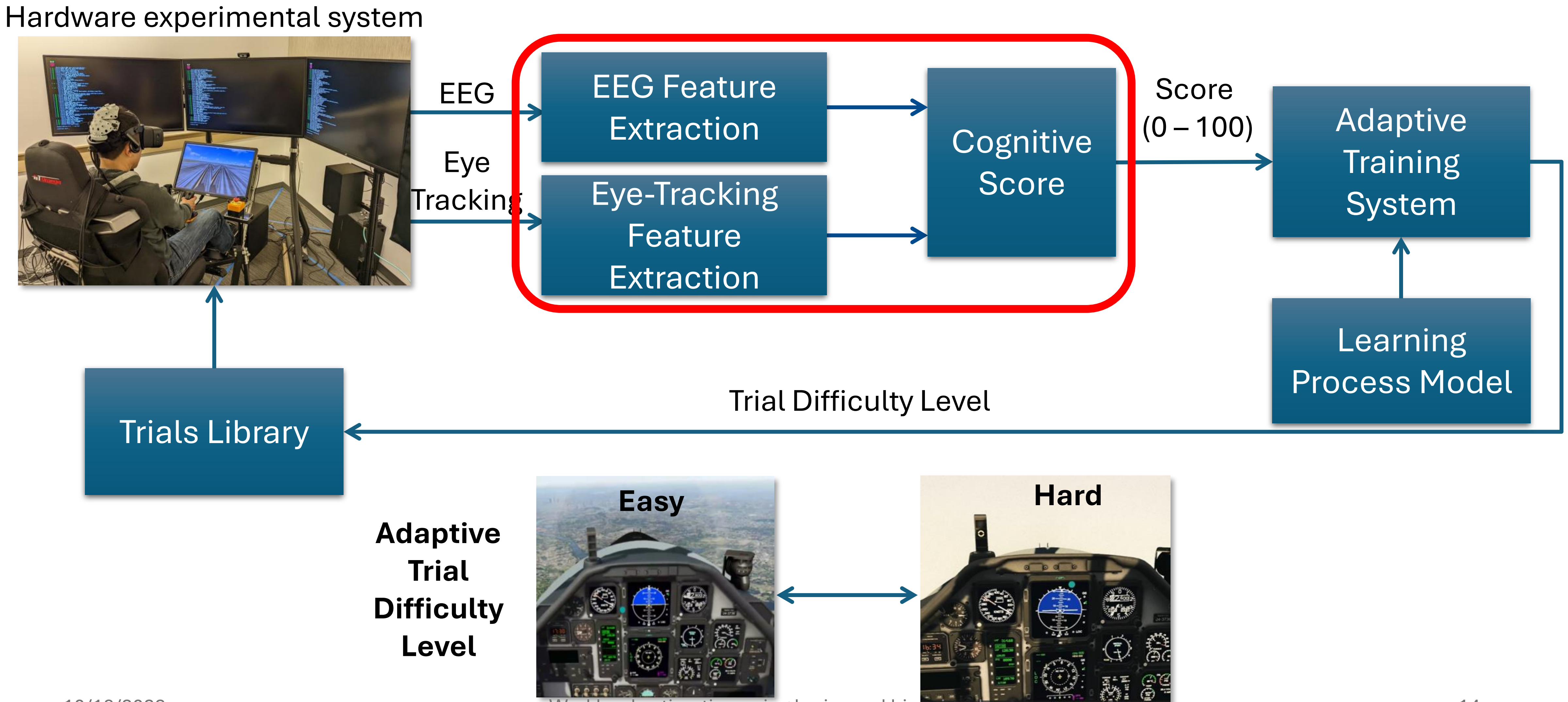
# Adaptive Training System



# EEG and Eye-tracking Preprocessing and Feature Extraction Pipeline

- 32 channel dry EEG
  - Only F5, C3, P5, F6, C4, P6, Pz channels used (frontal, central, parietal; left and right)
  - Process in 5 seconds frames
  - Data cleaning, artifact removal, frames rejection
  - Feature calculation – spectral power in delta, theta, alpha, beta, and gamma bands*
  - Variable length vector for the session

- Eye tracking
  - Convert raw gaze data to PyTrack format
  - Oculomotor feature extraction
  - Statistical measures calculation
  - Variable length vector for the session

- Dealing with the variable length vectors for each session
  - Statistics across the timeline: mean, deviation, min, max
  - One fixed set of features for each session
    - EEG: 5 bands x 4 stats x 6 channel = 120
    - EYE: 39 eye features x 4 stats = 156

* Delta: 1-4 Hz, Theta: 4-8 Hz, Alpha: 8-12 Hz, Beta: 12-30 Hz, Gamma: 30-60 Hz

# Workload vs. scoring

| Workload (WL, 0-1) | Situation | Expected score 100*(1-WL) | Skill (S) and Difficulty (d) | Simulated Score mean and deviation |
|---|---|---|---|---|
| High | Skill below difficulty | 25 | $S/d < 0.9$ | $11.57 \pm 9.31$ |
| Medium | Skill adequate to difficulty | 50 | $0.9 < S/d < 1.1$ | $37.56 \pm 3.48$ |
| Low | Skill above difficulty | 75 | $S/d > 1.1$ | $70.51 \pm 18.75$ |
| None | Calibration | 100 | N/A | 100 (assigned) |

Conclusions: 1. Simulated score is highly correlated to the workload.
2. Correlation with simulated score is a good evaluation parameter.

# Using the simulation scores as labels

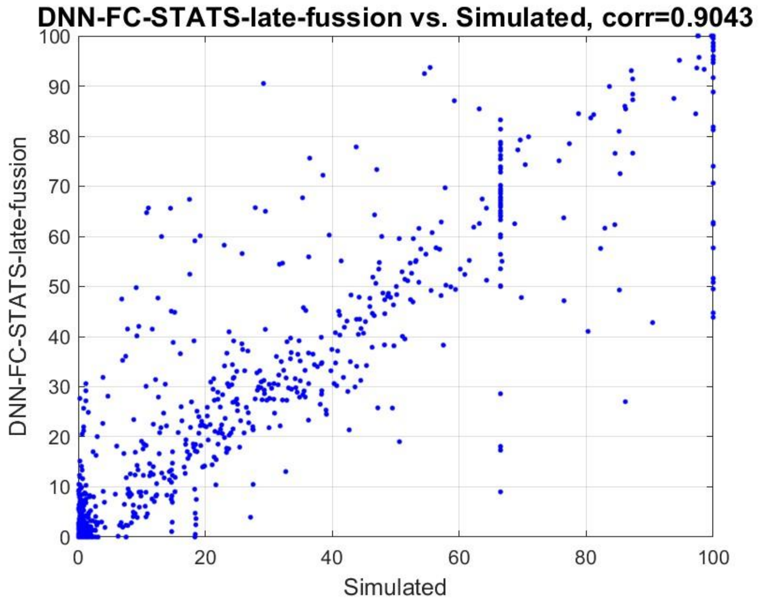
- Treat the problem as a machine learning problem:
  - Set of feature vectors with variable length as input
  - The simulated score as label – one per session
- Evaluation criterion: correlation with the simulated scores
- Try to create one scoring model for all persons and sessions
  - Take one subject for test, one for validation, train on the rest
  - Exercise all possible combinations for subjects with scores > 90, average the results
- Features: all bands (alpha, delta, theta, beta) and timeline statistics (mean, deviation, min, max)
- Fusion of the two feature sets:
  - Early – all features in one classifier
  - Late – two classifiers (for EEG and EYE), third for final score estimation
- Dataset: 20 subjects, 1223 points
- Classifiers: linear, SVM, ELM, DNN, LSTM

Ivan Tashev, R. Michael Winters, Yu-Te Wang, David Johnston, Justin Estepp, Nathaniel Bridges. “Towards Better Scoring", IEEE RAPiD 2023, September 2023

# Results

| Features | | Validation | | | | | Test | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | LIN | SVM | ELM | DNN | LSTM | LIN | SVM | ELM | DNN | LSTM |
| mean of the feature set | EEG | 0.1471 | 0.1204 | 0.1469 | 0.1375 | | **0.1471** | 0.1204 | 0.1381 | 0.1332 | |
| | EYE | 0.4592 | 0.1615 | 0.2509 | 0.4816 | | 0.4592 | 0.1615 | 0.2437 | **0.4693** | |
| | Fusion | 0.7207 | 0.724 | 0.7359 | 0.7560 | | 0.7207 | 0.724 | 0.7331 | **0.7403** | |
| | Early fusion | 0.4391 | 0.1596 | 0.1488 | 0.4814 | | 0.4391 | 0.1596 | 0.1414 | **0.4511** | |
| mean, max, min, std of the feature set | EEG | 0.1143 | 0.1250 | 0.1182 | 0.1290 | | 0.1143 | **0.125** | 0.1058 | 0.1186 | |
| | EYE | 0.4233 | 0.3262 | 0.2909 | 0.5449 | | 0.4233 | 0.3262 | 0.279 | **0.5417** | |
| | Fusion | 0.8093 | 0.8073 | 0.8394 | **0.8402** | | 0.8093 | 0.8073 | **0.8397** | 0.8376 | |
| | Early fusion | 0.2816 | 0.3417 | 0.3399 | 0.4688 | | 0.3786 | 0.3253 | 0.2743 | **0.5087** | |
| Sequence | EEG | | | | | 0.3173 | | | | | 0.2986 |
| | EYE | | | | | 0.5613 | | | | | 0.5499 |
| | Fusion | 0.839 | 0.8464 | 0.8384 | 0.8489 | | 0.839 | **0.8464** | 0.8384 | 0.8371 | |

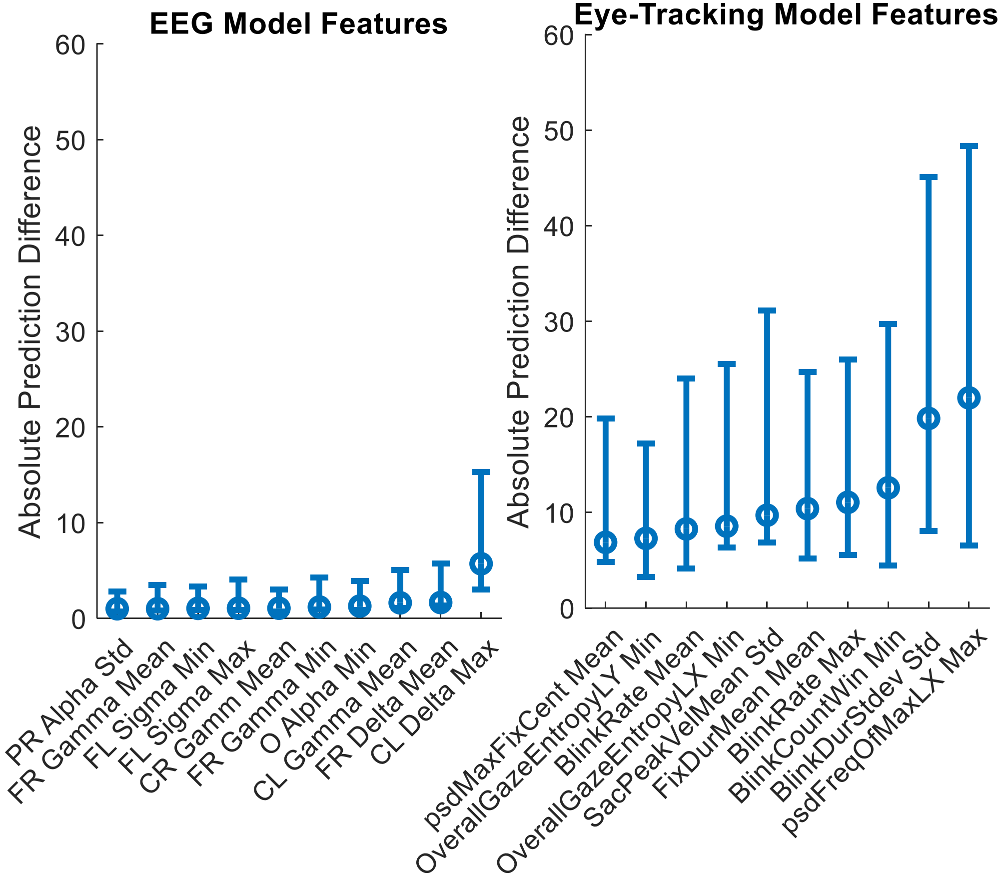
- Recommended:
  - Late fusion structure
  - DNN for EEG features + stats
  - DNN for EYE features + stats
  - DNN for late fusion




**Note:** correlation in the figure is for all data (test + validation + train)

# Ablation Study

FR: Frontal Right
FL: Frontal Left
CR: Central Right
CL: Central Left
PR: Parietal Right
O: Occipital




- Systematically "removed" each feature to identify the primary drivers of the model.
- For EEG, the primary feature is in the Delta band, which may be associated with attention [1].
- For Eye-Tracking, the primary features are related to the frequency of eye-movements and blinking, which could be associated with attention and fatigue [2]

**For predicting performance, the eye-tracking measures have a larger effect on the prediction compared to the EEG.**


[1] Liang (2022)
[2] Huette S (2016)

# EEG ablation study per feature groups

- Bands group:
  - Most useful: Alpha and Theta
  - Mostly noise: Beta, Delta
- Electrodes group:
  - Most useful: CL, FR, FL
  - Mostly noise: PR, CR, O
- Processing group:
  - Most useful: Std, Max
  - Mostly noise: Min, Mean

| **Algorithm** | **Baseline** | **Bands** | | | | | **Electrodes groups** | | | | | | | **Feature groups** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Delta | Theta | Alpha | Beta | Gamma | FL_ | CL_ | PL_ | FR_ | CR_ | PR_ | O_ | Mean | Std | Min | Max |
| LIN | 0.0544 | 0.0285 | 0.0321 | 0.0216 | 0.0607 | 0.0644 | 0.0628 | 0.0288 | 0.0494 | 0.0448 | 0.0999 | 0.1142 | 0.0733 | 0.0747 | 0.0559 | 0.0737 | 0.0304 |
| SVM | 0.1078 | 0.1480 | 0.0754 | 0.0995 | 0.1204 | 0.1155 | 0.1023 | 0.1111 | 0.1174 | 0.1024 | 0.1083 | 0.1214 | 0.1245 | 0.1274 | 0.1149 | 0.1128 | 0.0896 |
| ELM, 64 | 0.0724 | 0.0603 | 0.0610 | 0.0659 | 0.0983 | 0.0558 | 0.0787 | 0.0348 | 0.0963 | 0.0749 | 0.1234 | 0.1391 | 0.0978 | 0.1000 | 0.0896 | 0.0576 | 0.0212 |
| DNN-FC | 0.0920 | 0.1094 | 0.0848 | 0.0708 | 0.1112 | 0.1087 | 0.0567 | 0.0726 | 0.0720 | 0.0556 | 0.0832 | 0.1264 | 0.0414 | 0.0929 | 0.0953 | 0.0709 | 0.0583 |

# Conclusions and future work

- Conclusions:
  - Created a model for predicting simulated scoring based on brain- and gaze-signals
  - The model is person independent and session independent
  - The correlation with the simulated scores is above 0.84

- Future work:
  - Continue to refine the model based on feature set analysis to identify key features across participants
  - Exploring more sophisticated classifiers: CNN, LSTM, for example (while being careful of limited number of labels)
  - Adding other bio-signals collected: ECG, GSR, respiration
  - Evaluation how the model will work outside of the specific scenario

# Finally…

# Questions?

## Thank you for your attention!

BCI Project in MSR: https://www.microsoft.com/en-us/research/project/brain-computer-interfaces/

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