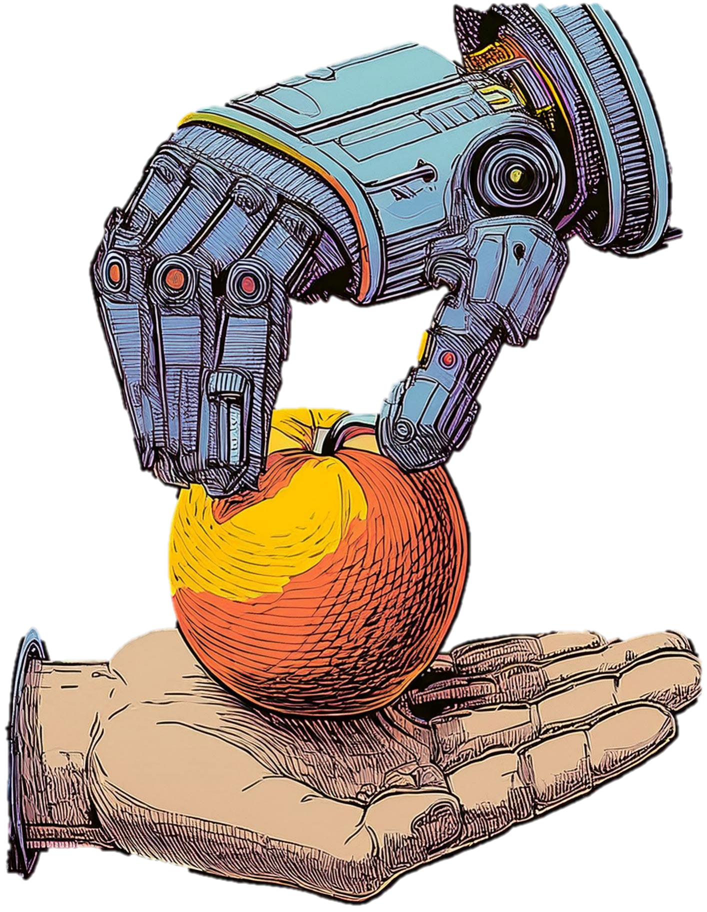
Brain-computer interfaces: methods and applications



Arnau Dillen

Introduction

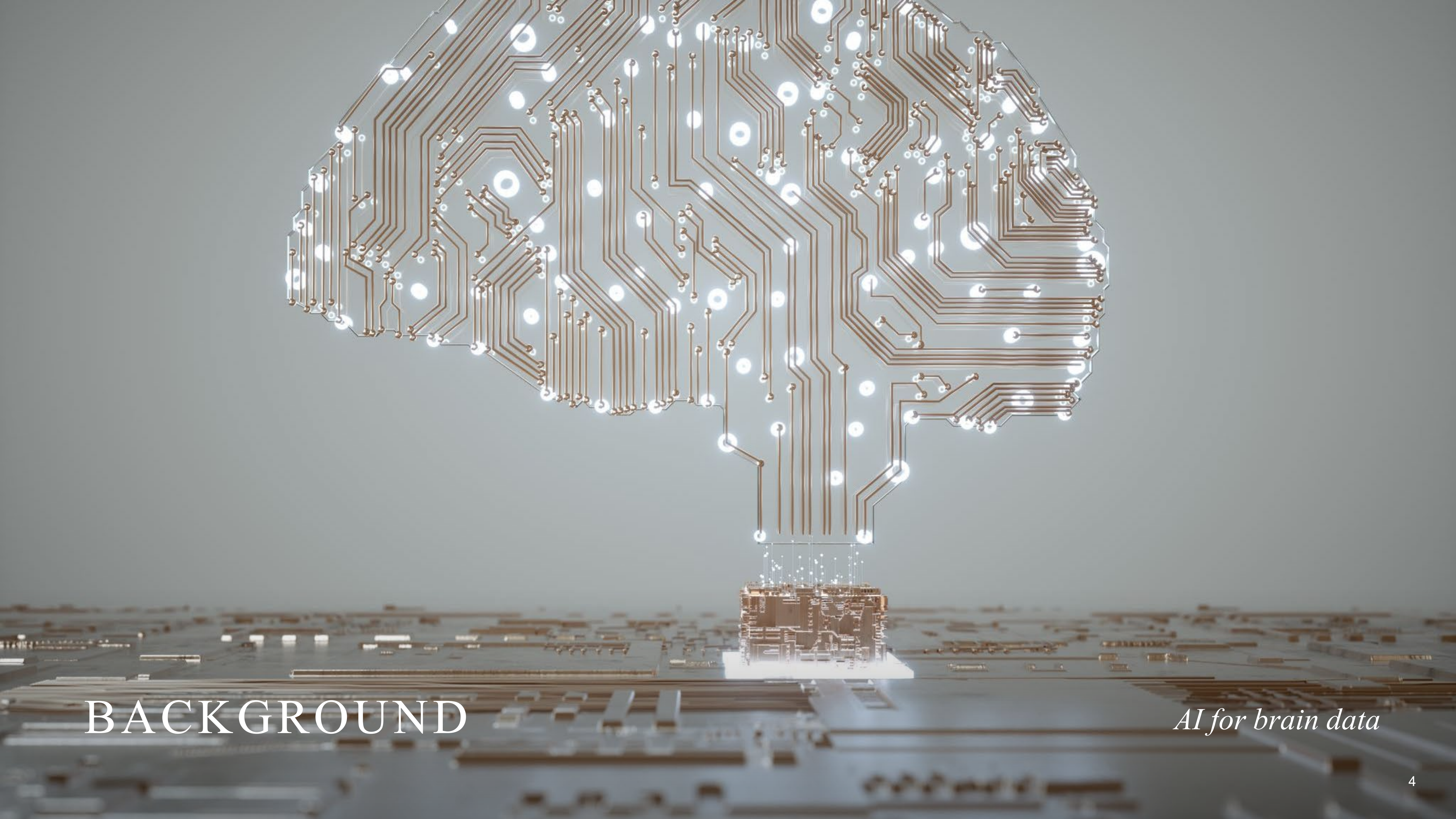
"Unless in communicating with it one says exactly what one means, trouble is bound to result.“ (Alan Turing, 1945)

Mouse + keyboard and touchscreens are the standard interaction modalities today

- **But excludes people with physical disabilities!**
- **Inefficient for certain applications and use cases!**

➔ Alternatives are necessary.

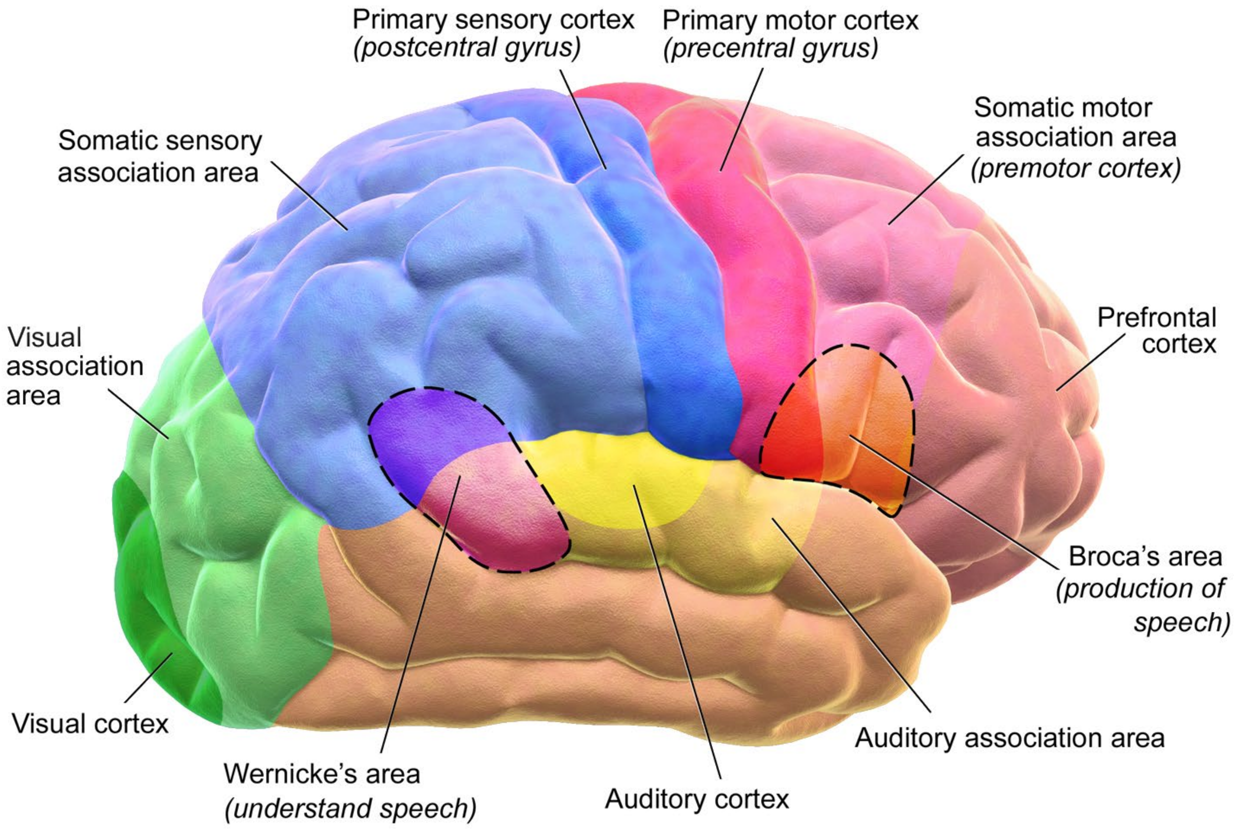
Possible alternative: Brain-computer interface



BACKGROUND

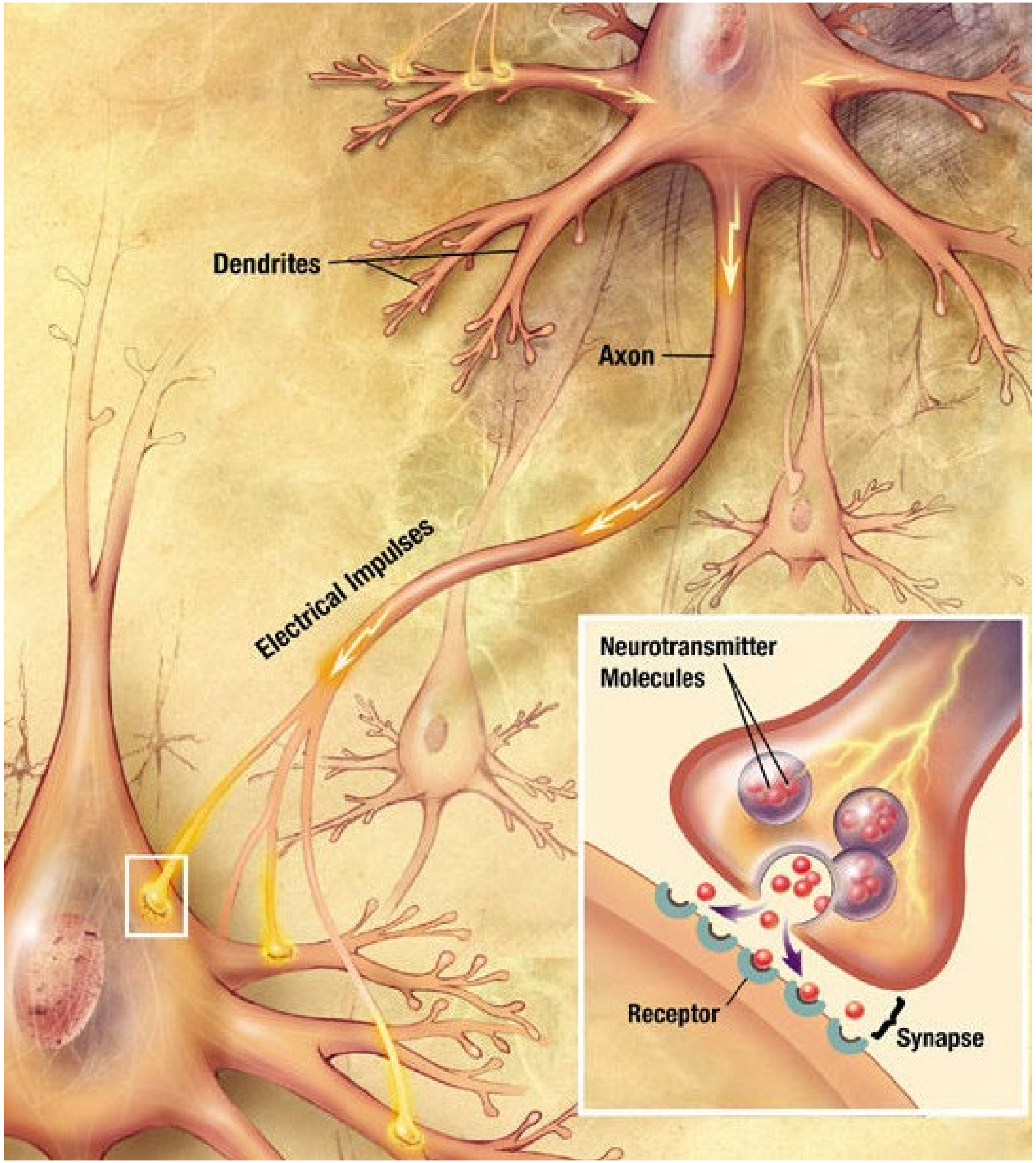
AI for brain data

THE BRAIN

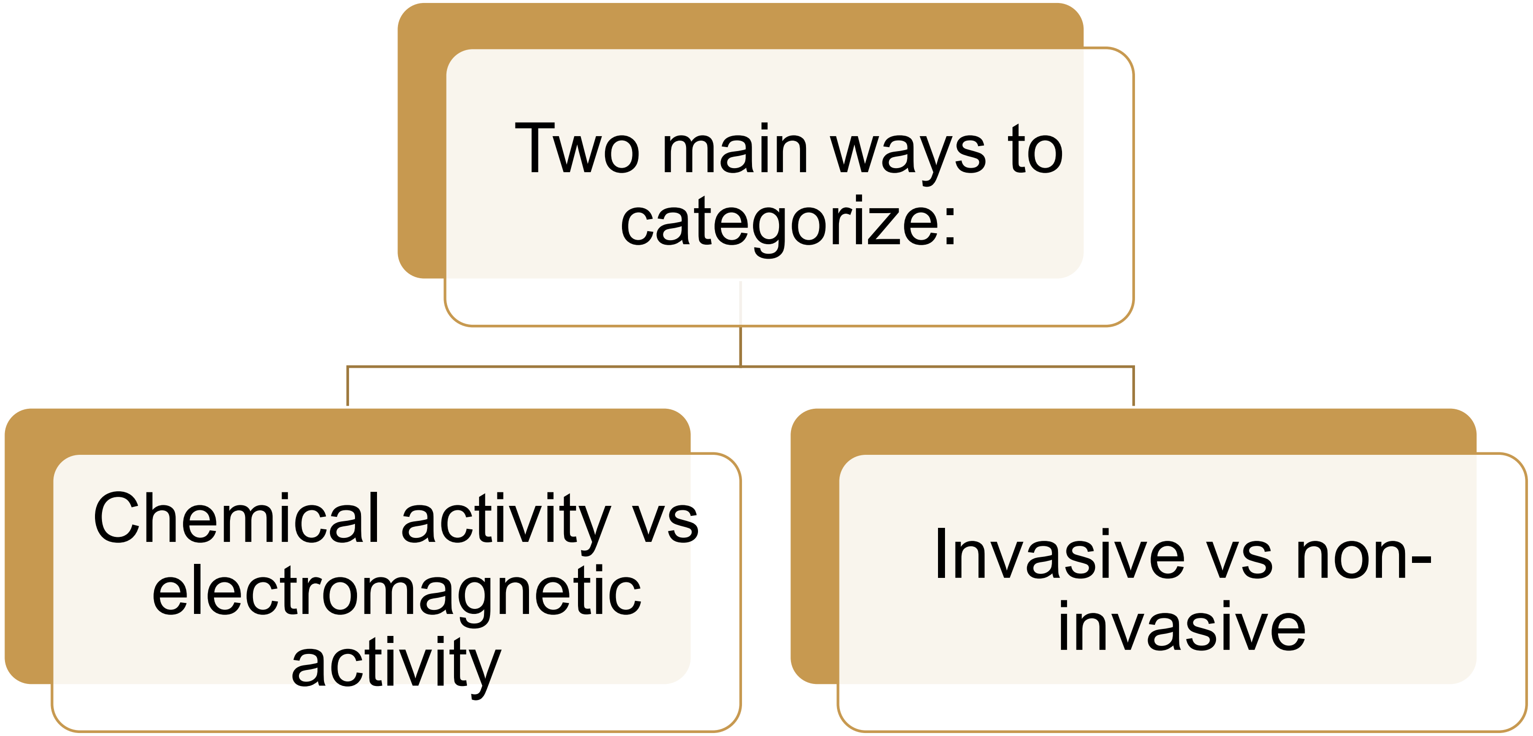


Blausen.com staff (2014). "Medical gallery of Blausen Medical 2014". WikiJournal of Medicine 1 (2). DOI:10.15347/wjm/2014.010. ISSN 2002-4436. - Own work, CC BY 3.0, https://commons.wikimedia.org/w/index.php?curid=60100749

NEURONS


Dendrites
Axon
Electrical Impulses
Neurotransmitter Molecules
Receptor
Synapse

Measuring neural activity



Two main ways to categorize:

Chemical activity vs electromagnetic activity

Invasive vs non-invasive

Electromagnetic brain activity: non-invasive

Electroencephalogram (EEG)

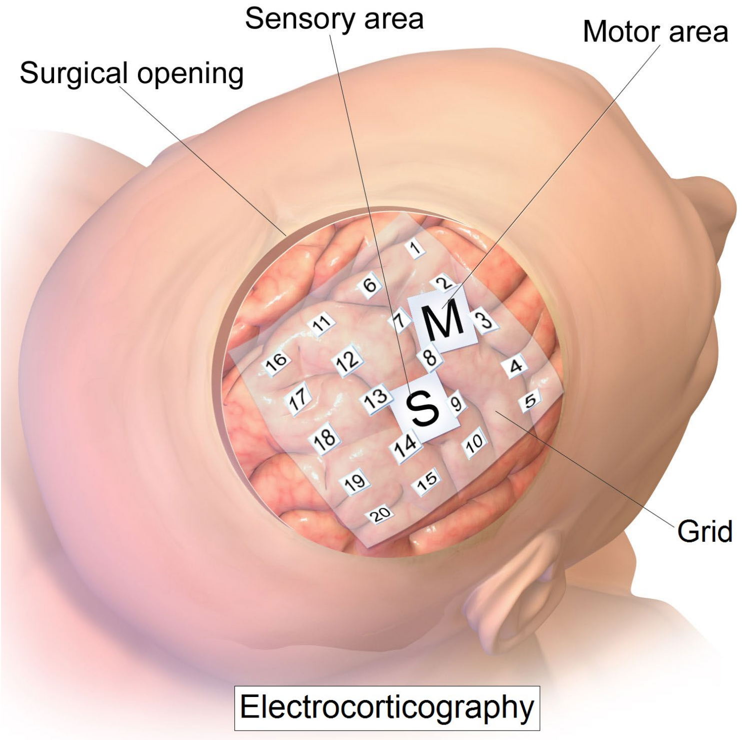
By mBrainTrain. https://mbraintrain.com/smarting-pro-line/

Magnetoencephalogram (MEG)

By Unknown NIMH author - NIMH Image library,
http://infocenter.nimh.nih.gov/il/public_il/image_details.cfm?id=80, Public Domain,
https://commons.wikimedia.org/w/index.php?curid=11909237

Electromagnetic brain activity: invasive

Electrocorticogram (ECoG)



Blausen.com staff (2014). "Medical gallery of Blausen Medical 2014". WikiJournal of Medicine 1 (2). DOI:10.15347/wjm/2014.010. ISSN 2002-4436. - Own work, CC BY 3.0, https://commons.wikimedia.org/w/index.php?curid=31574255

Local field potentials (LFP)

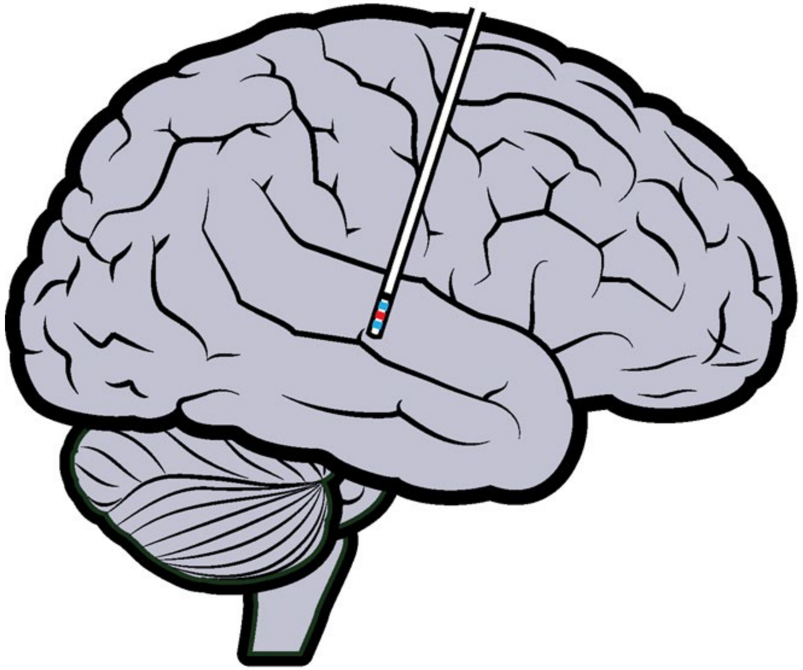


Image from: MRC Brain Network Dynamics Unit. https://www.mrcbndu.ox.ac.uk/groups/tan-group

Chemical brain activity: invasive

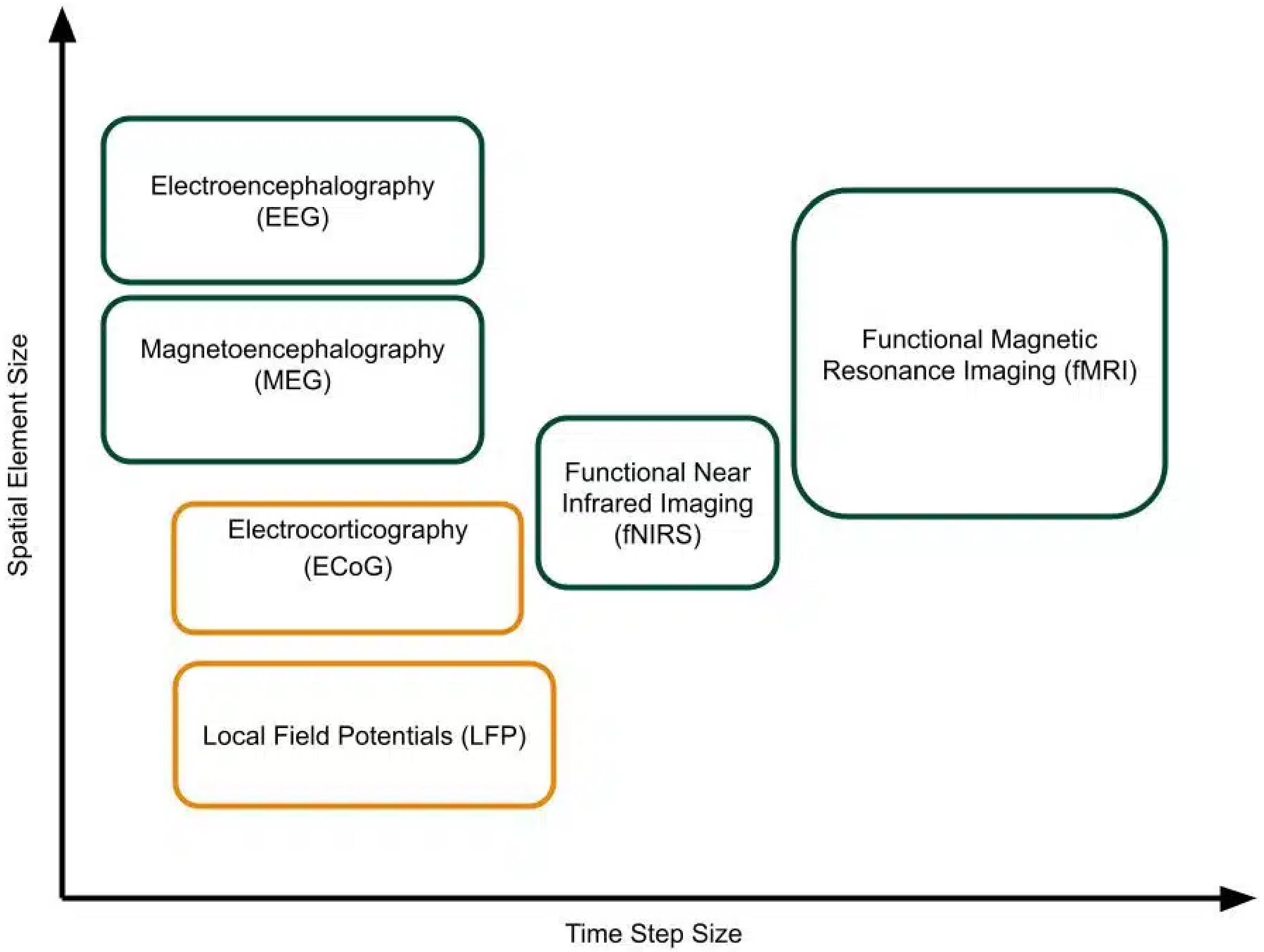
Functional magnetic resonance imaging (fMRI)

Functional near-infrared spectroscopy (fNIRS)

Image from: Salford PsyTech.
https://hub.salford.ac.uk/psytech/psytechsalford/equipment-resources/functional-near-infrared-spectroscopy-fnirs/

Neural signal comparison

Spatial resolution



Temporal resolution

Image from: Brainaccess. https://www.brainaccess.ai/methods-of-brain-activity-measurements/

Our choice: EEG

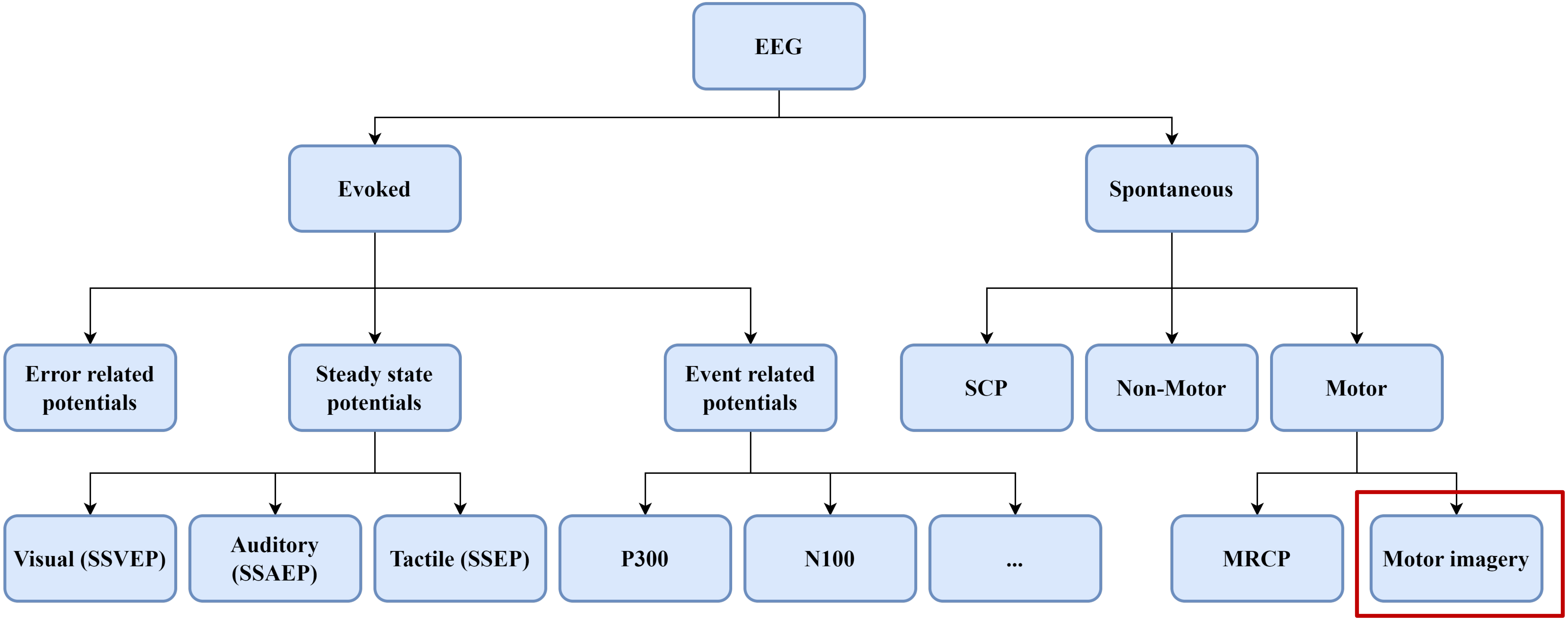
Pros

- Non-invasive
- Portable
- High temporal resolution
- Well-known

Cons

- Noisy
- Low spatial resolution

EEG modalities



- EEG
  - Evoked
    - Error related potentials
    - Steady state potentials
      - Visual (SSVEP)
      - Auditory (SSAEP)
      - Tactile (SSEP)
    - Event related potentials
      - P300
      - N100
      - ...
  - Spontaneous
    - SCP
    - Non-Motor
    - Motor
      - MRCP
      - Motor imagery

AI applications using neural activity

Brain-computer interfaces (BCI)

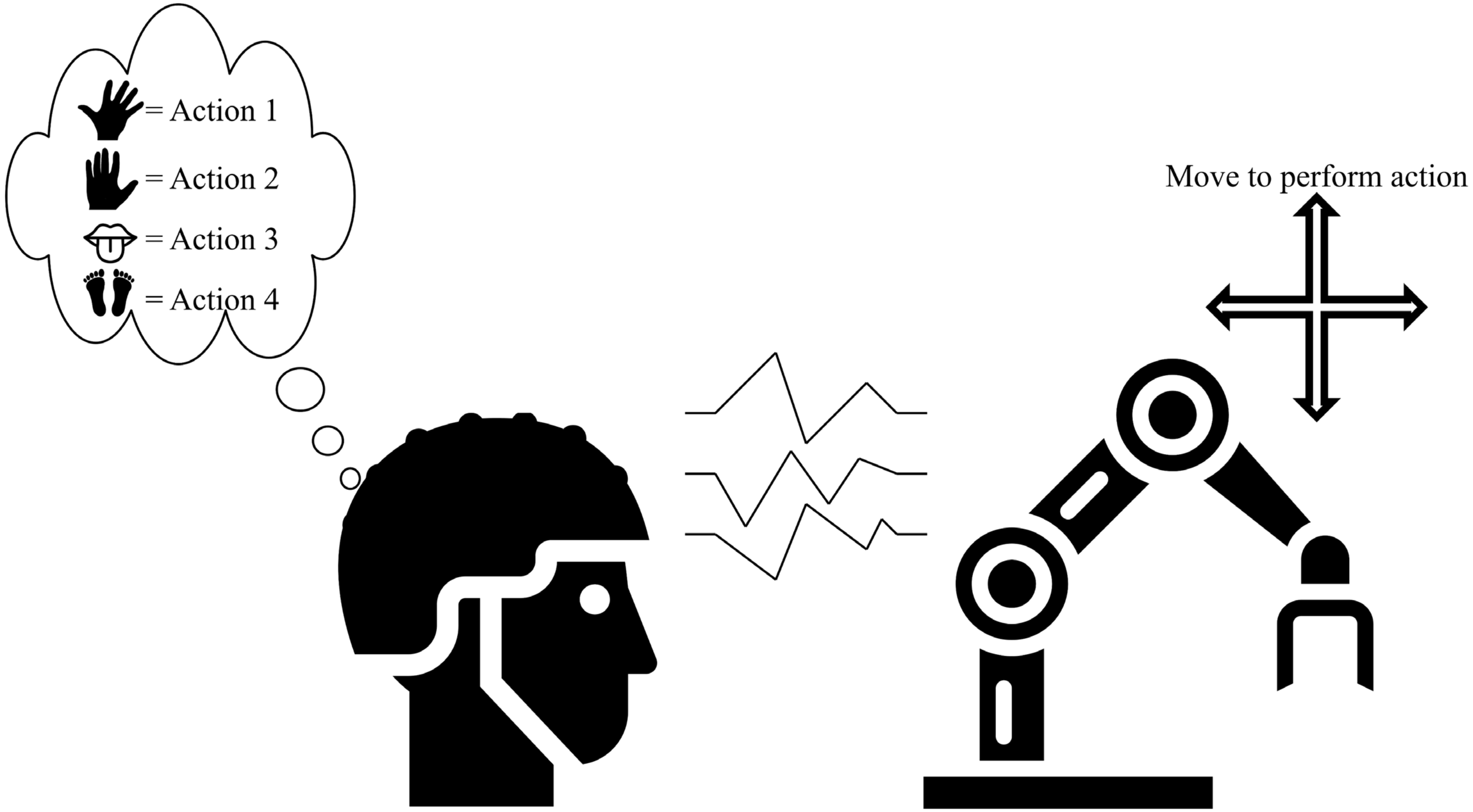
- Control
- Monitoring
- Human-in-the-loop

Neuroscience

- Epileptic seizure prediction
- Early onset Alzheimer detection
- Brain activity modelling

Brain-computer interfaces for control

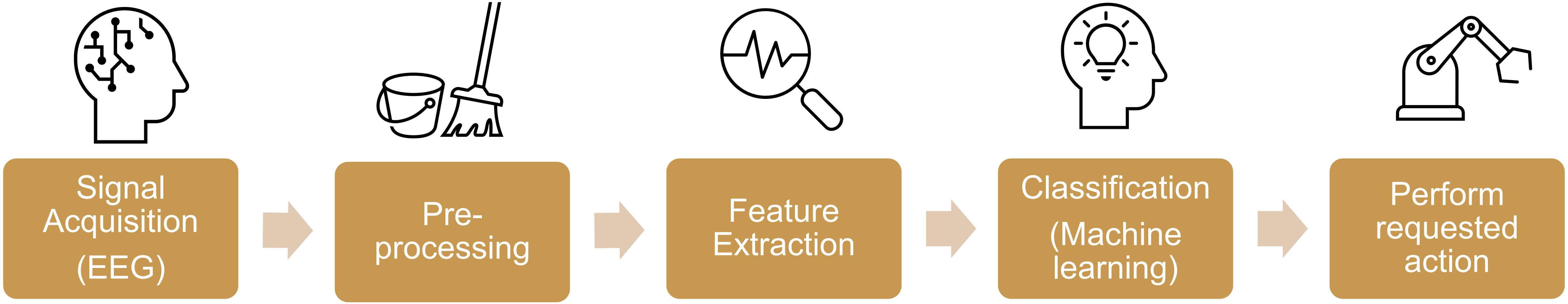
Motor imagery (MI) BCI: Mapping imagined movement to device action


= Action 1
= Action 2
= Action 3
= Action 4

Move to perform action

Robotic Arm by Smalllike from NounProject.com

BCI decoding pipeline



Signal Acquisition (EEG)

Pre-processing

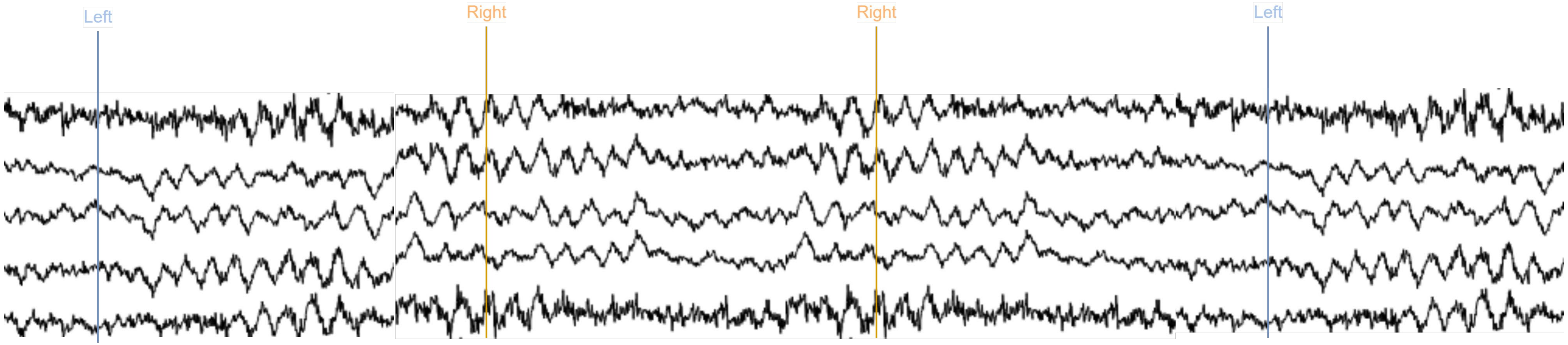
Feature Extraction

Classification (Machine learning)

Perform requested action

Getting training data from EEG

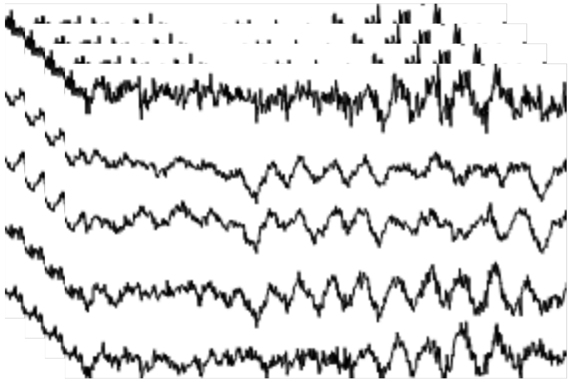
Continuous
recording of EEG
with event markers



Extract windows

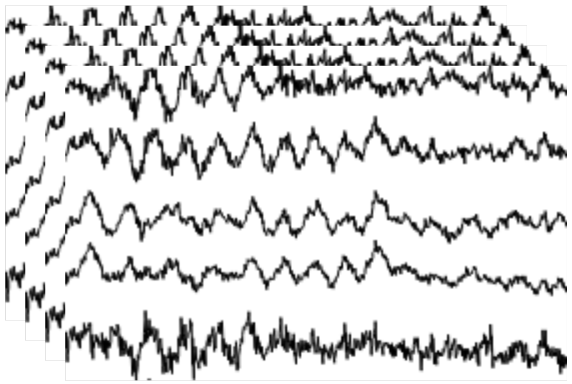
Labelled dataset
of EEG windows

Left hand



•••

Right hand



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Issues

Noisy EEG (artifacts, inter- and intraindividual variability, …)

More MI classes harder to classify

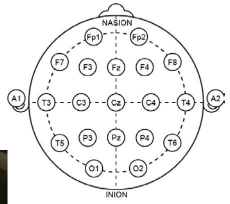
User training necessary

Hard to gather machine learning training data

Lack of standardised evaluation for BCI prototypes

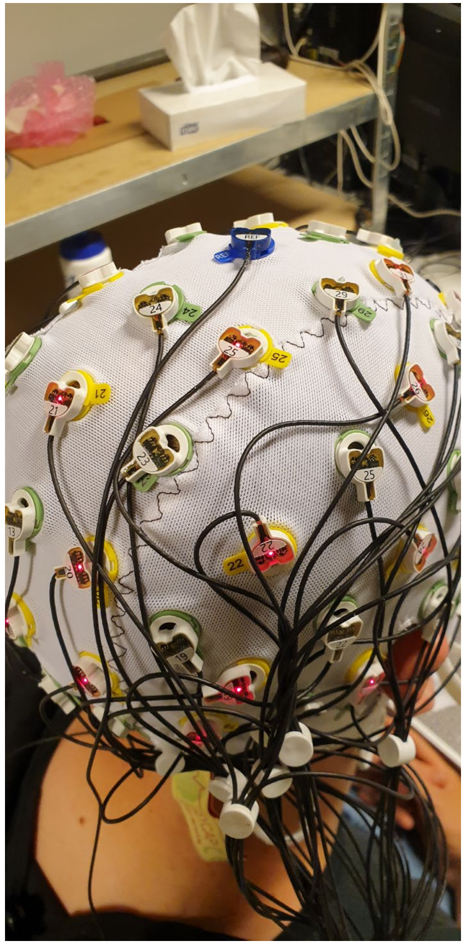
Data acquisition

Acquiring MI data



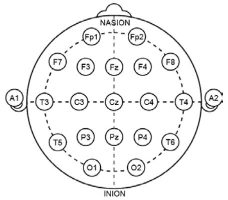
15 participants

- 14 male, 1 female
- Aged between 18 and 50 years (mean 28 ± 7).
- No prior BCI experience
- 5 sessions each

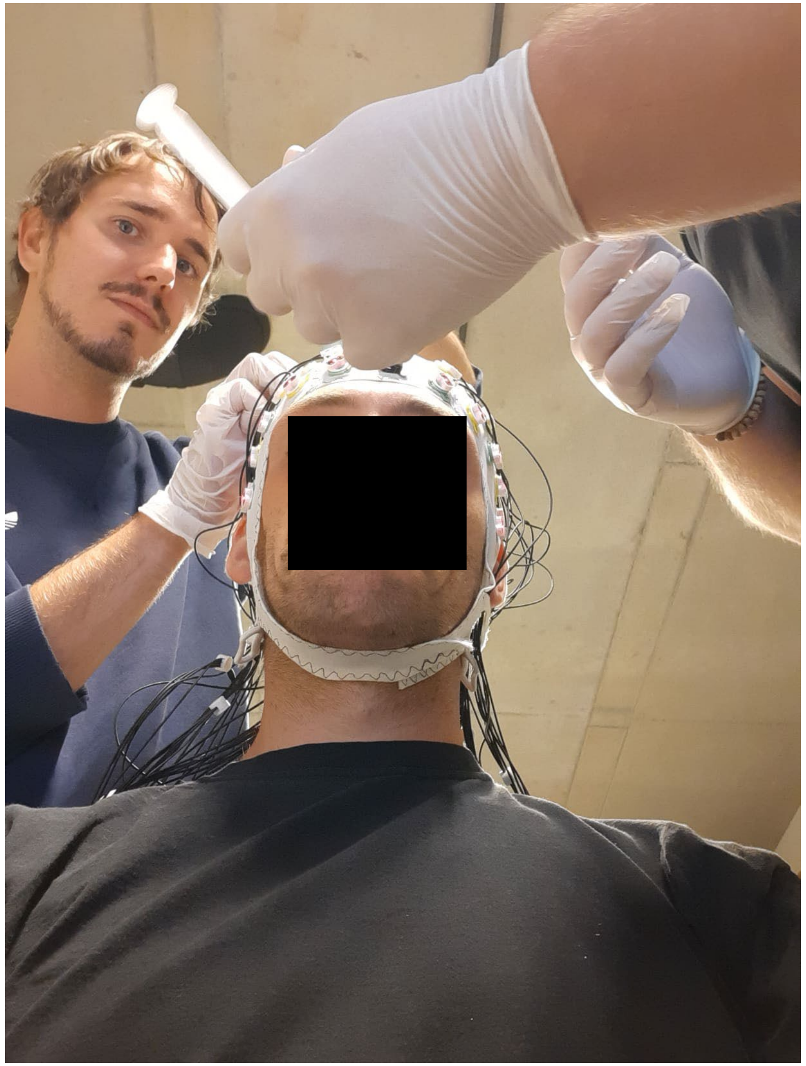


64 channel LiveAmp (Brain Products) with active wet electrodes for EEG recording

Preparing the EEG cap



1. Connect all the cables
2. Initiate the connection to the PC
3. Start impedance check
4. Add gel to every single electrode
5. Start streaming the data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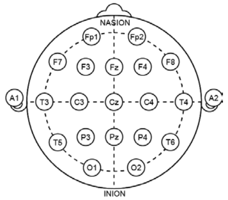


MI acquisition procedure

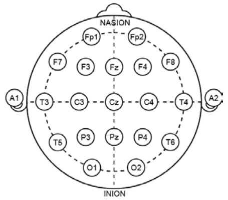
First 2 sessions: Familiarization

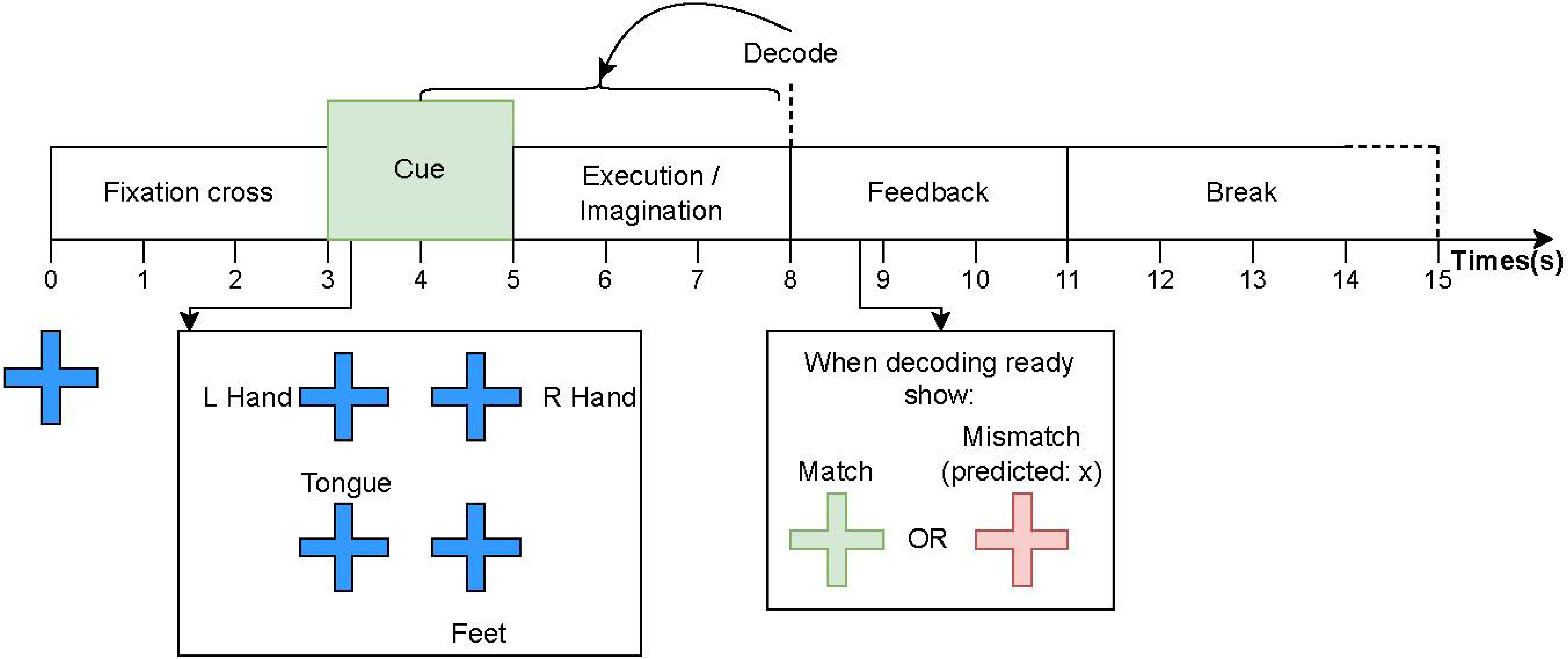
- Alternating executed and imagined movement
- No feedback

Sessions 3-5: Data acquisition

- First MI run without feedback (calibration)
- 3+ feedback runs

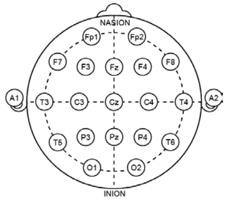
Acquiring motor imagery data

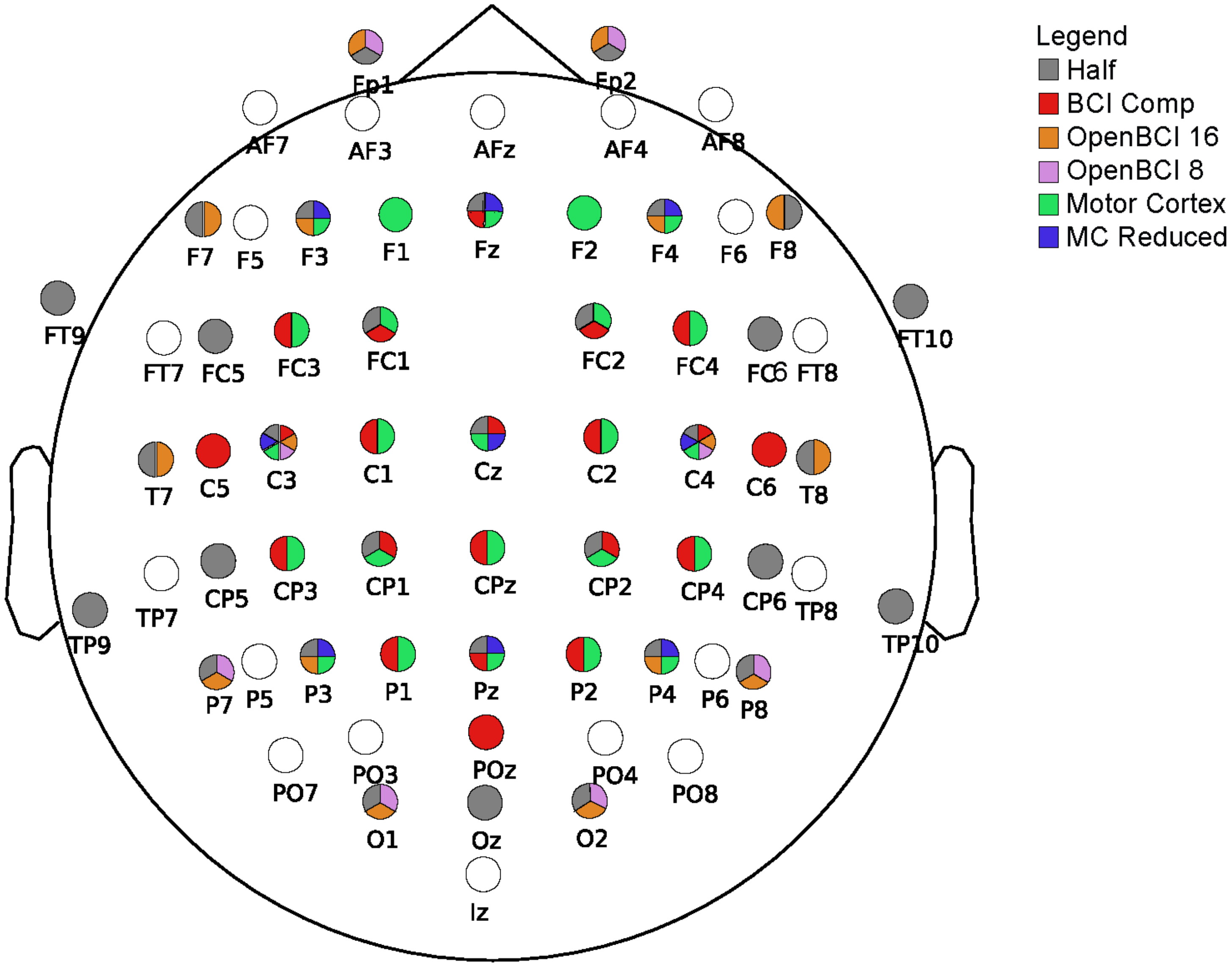




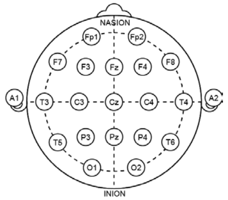
Study: optimal set of sensors for MI decoding

Evaluate accuracy of fixed decoding pipeline





The ML pipeline

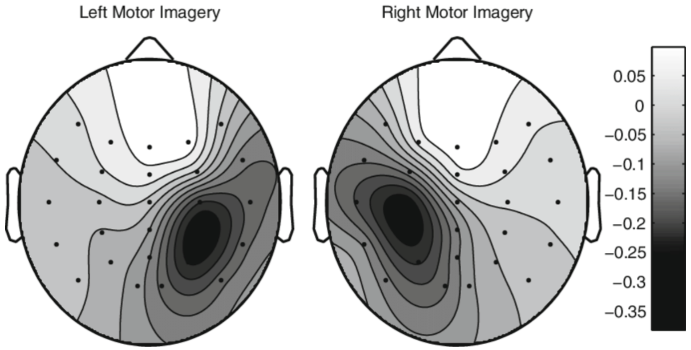


Signal Acquisition (EEG) → Pre-processing → Feature Extraction → Classification (Machine learning)

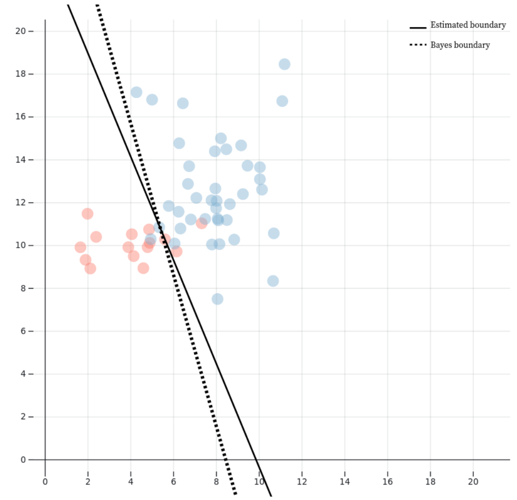
4-class MI data:
- Stored in XDF format
- Read in Python with the MNE library

- Filtering between 8-35 Hz
- Cleaning using PREP pipeline
  - Drop bad data
  - Sensor interpolation
  - …

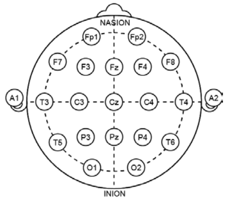
Common spatial patterns

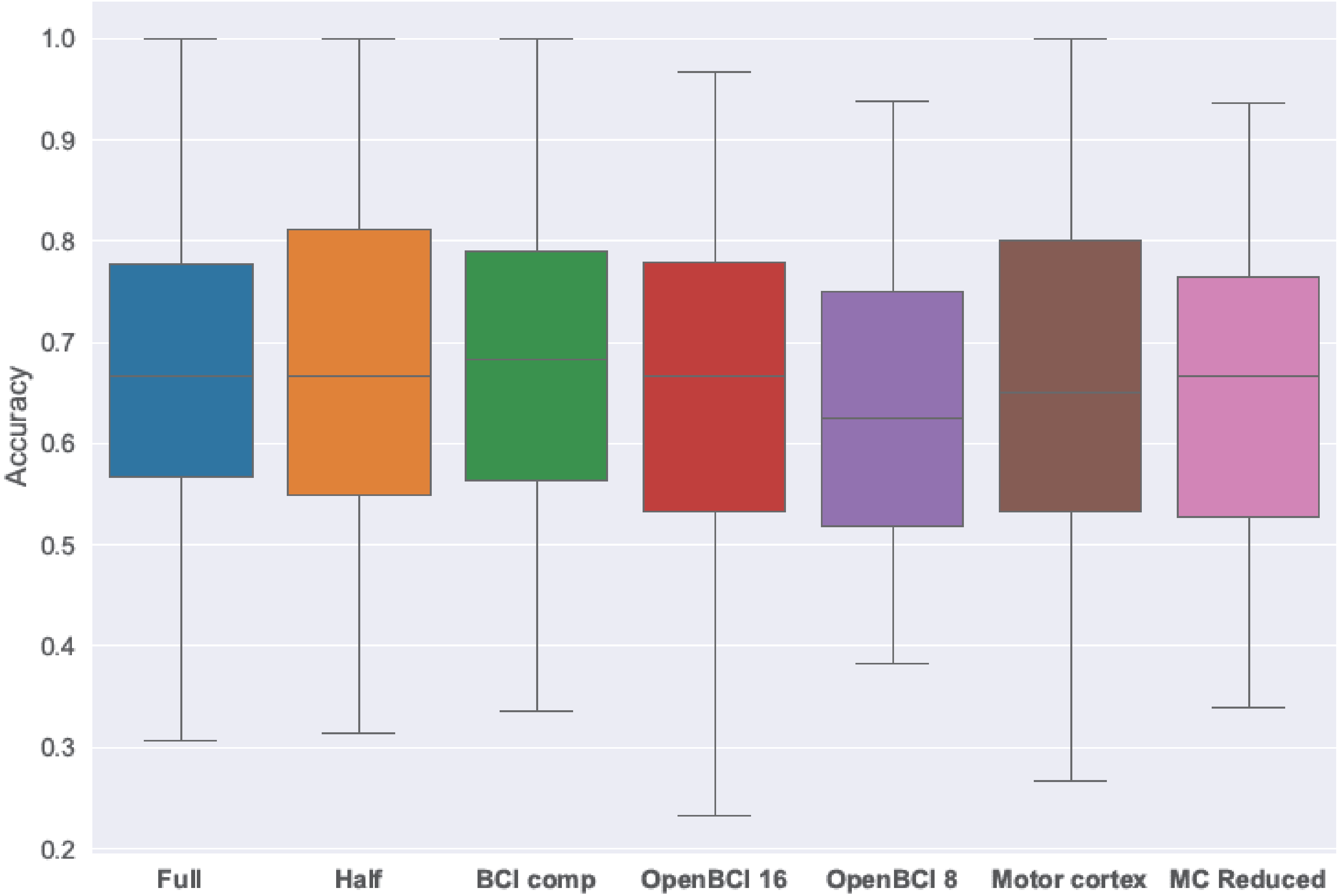


Linear discriminant analysis

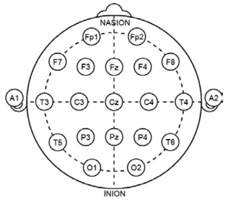


Optimal sensor set for MI decoding
Results





Optimal subset conclusions



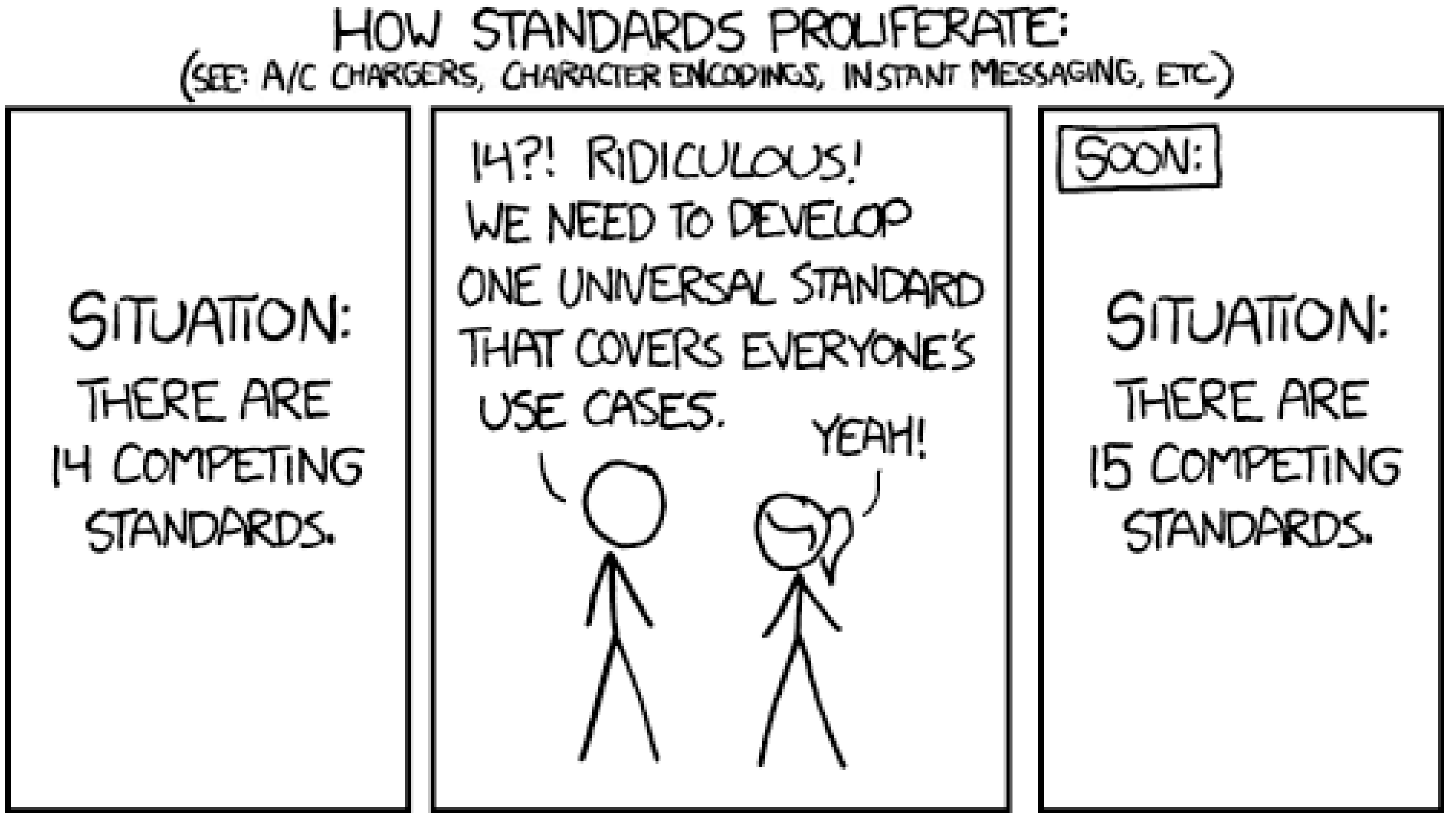
Eight sensors sufficient to achieve adequate decoding performance

Often "classic" methods are sufficient and easier to use

-> We will use standard methods for now

A standardized user evaluation procedure for BCI prototypes

Avoid just making another standard



Avoid just making another standard

- Reuse existing knowledge and formalize it
- Modular procedure
- Share with a stand-alone publication: *Dillen, A. et al. Evaluating the real-world usability of BCI control systems with augmented reality: A user study protocol. Front. Hum. Neurosci. 18, (2024).*

Usability

Efficiency

Effectiveness

User experience

Performance measures

Completion time:
Time it took to complete a single run of the evaluation task

Success rate:
Successful completion of a task within a given time

Fatigue:
Visual analogue scale before and after evaluation task

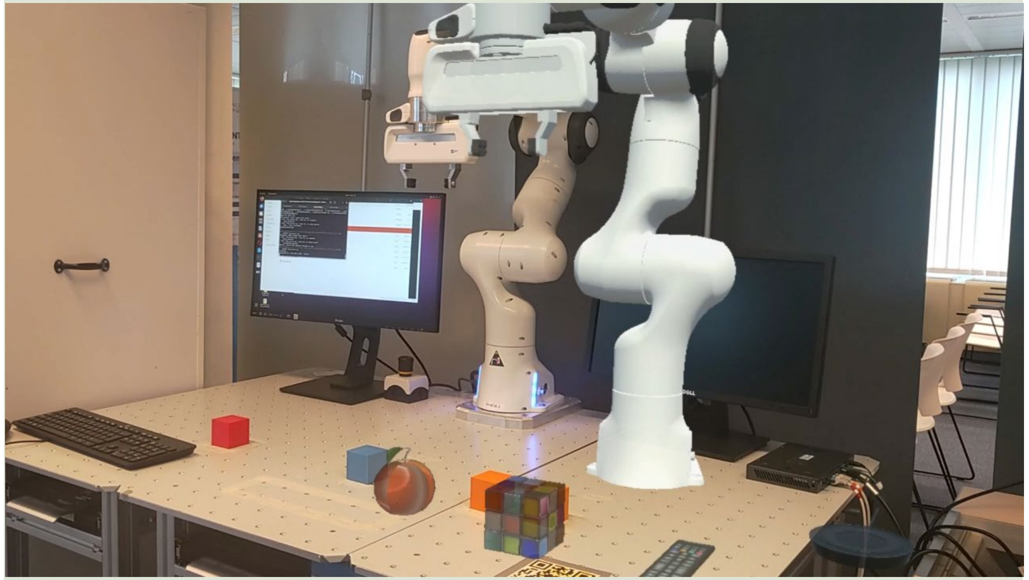
User experience:
User experience questionnaire and interview

Evaluation tasks

Sorting task

- 10 repetitions to complete
- 15 minutes cutoff

Pick-and-place task



- Complete predetermined sequence of object actions
- 15 minutes cutoff

User study design

Phase 1

- 3 participants (2 sessions each)
- Perform sorting task
- OpenBCI used for EEG

Phase 2

- 5 participants (3 sessions each)
- Simulated robot and environment in augmented reality
- Final session:
  - Performance assessment on sorting task
  - Comparison with eye tracking

Phase 3

- 12 participants (3 sessions each)
- Real robot reproduces virtual movement
- Final session
  - Performance assessment on pick-and-place task
  - Comparison with eye tracking

Design of our MI-BCI control system

A shared control approach to MI BCI

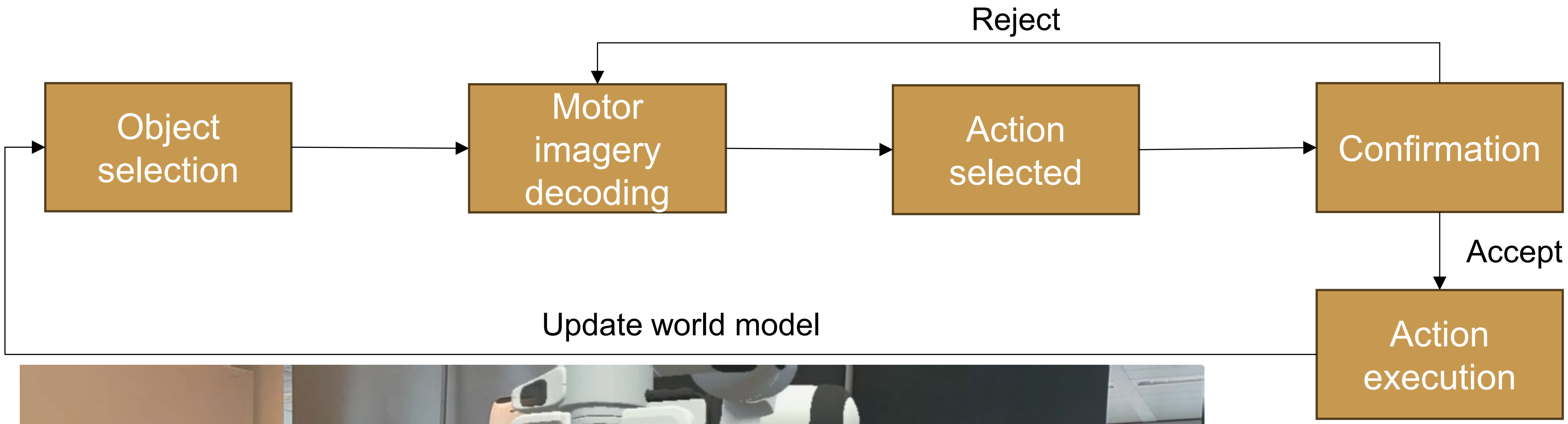
Shared control: Semi-autonomous robot with environment awareness. User gives high-level commands to robot.

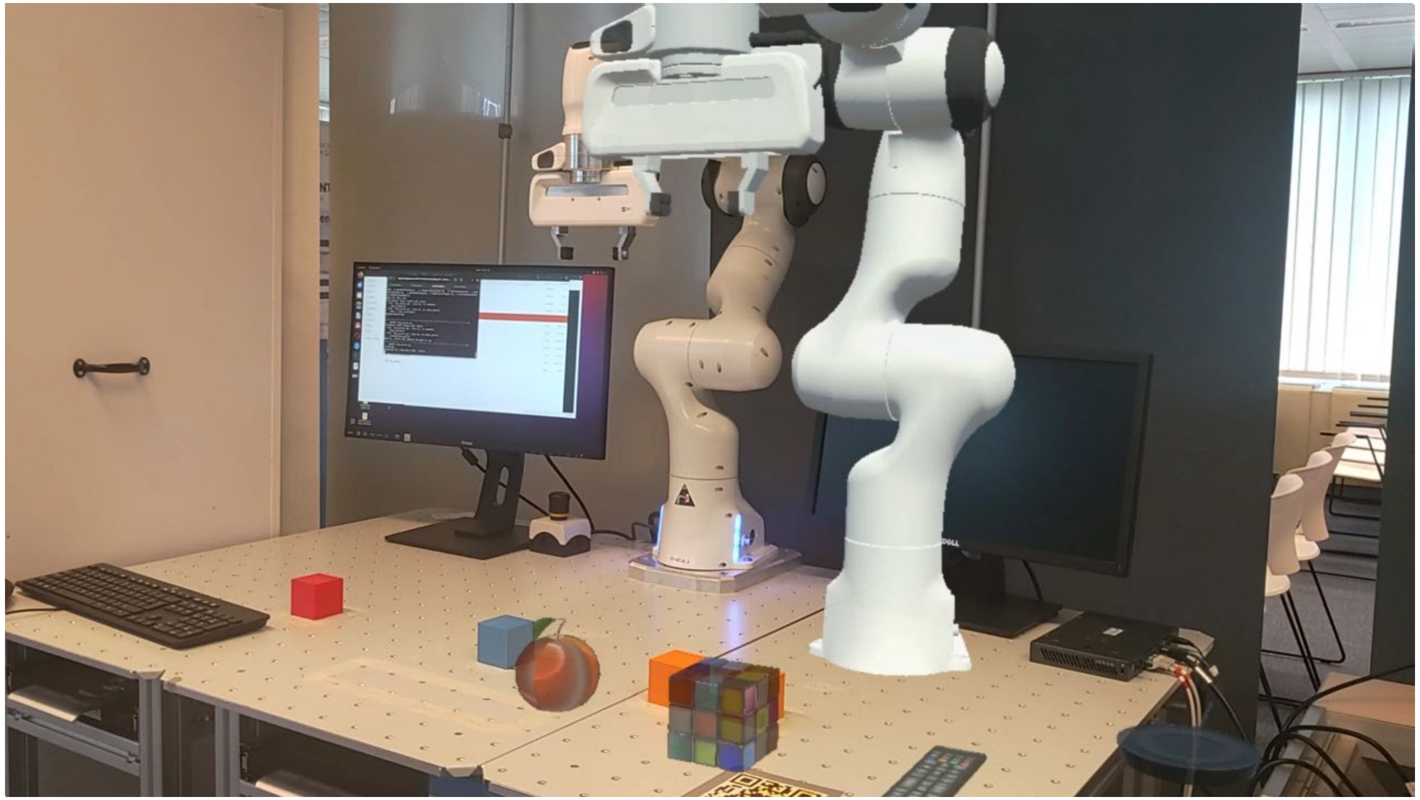
Goal: enable complex interactions while keeping MI decoding simple

Key components:

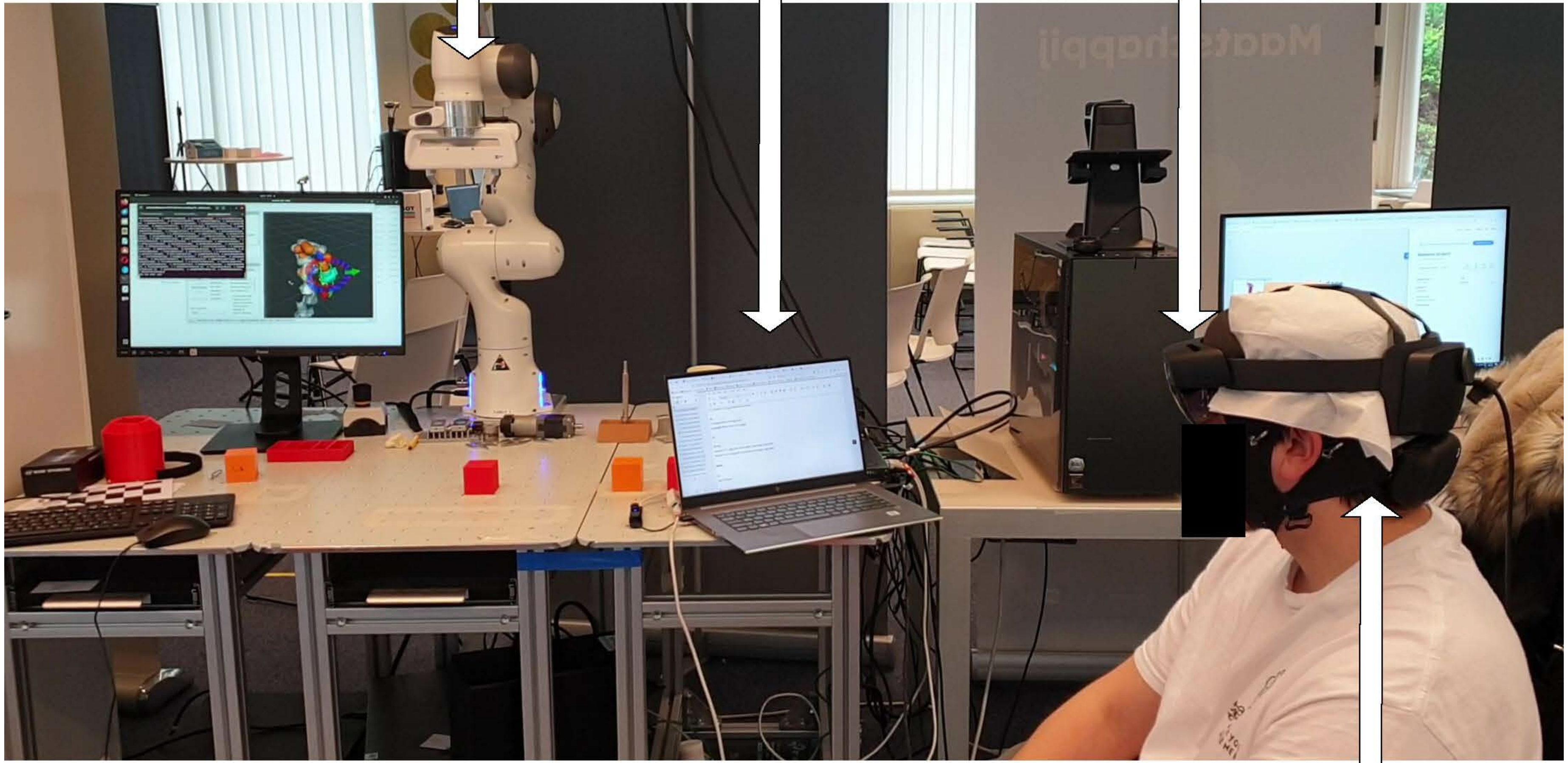
- Augmented reality user interface
- Spatial awareness and object detection
- Object selection with eye tracking
- Action selection with MI BCI (2 classes for this concept)

The shared control strategy





Hardware setup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Franka Research robot

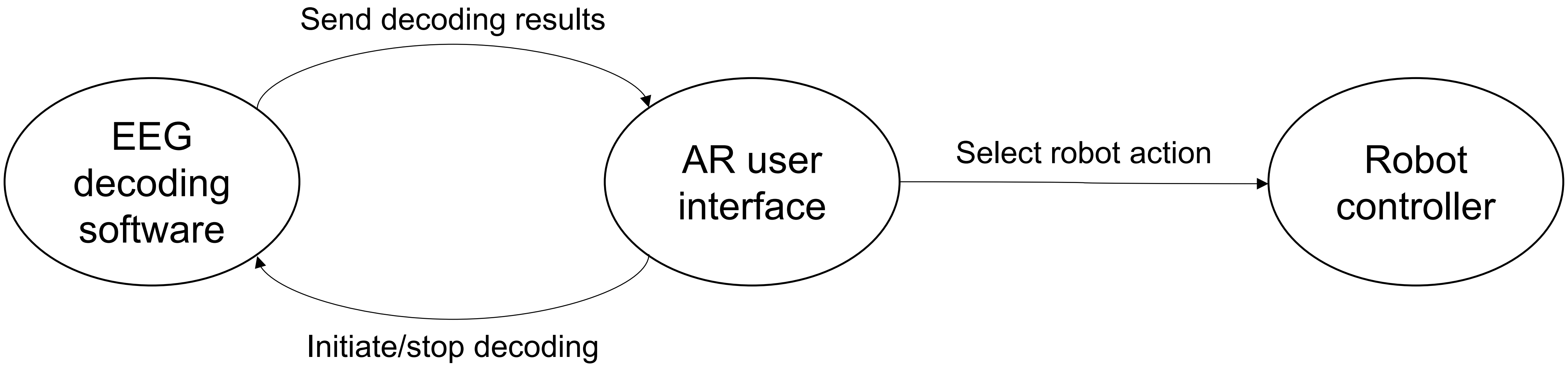
Laptop for EEG decoding

Microsoft HoloLens 2

mbt Smarting ProX

Software overview

3 independent software components:



Send decoding results

EEG decoding software

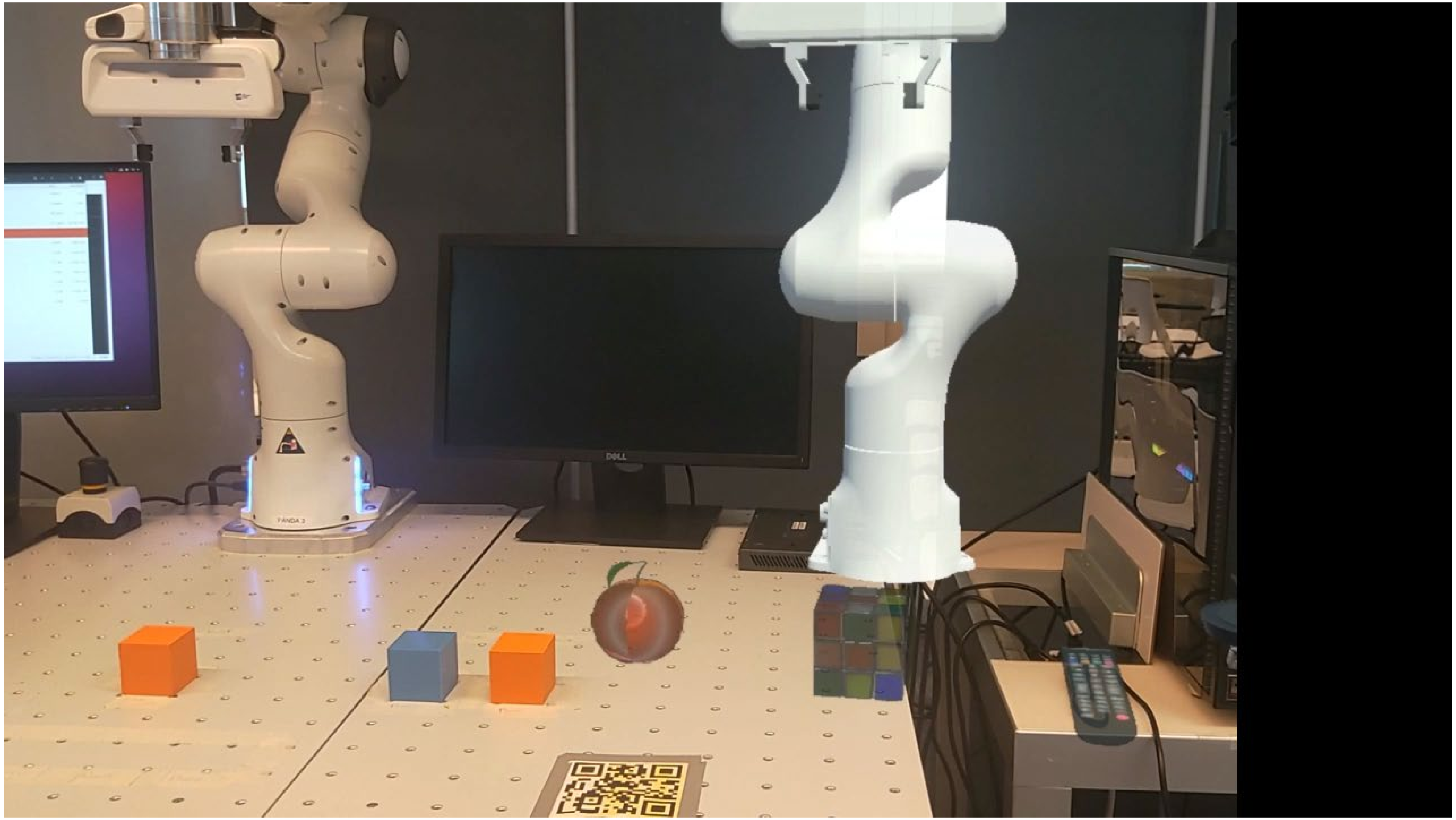
AR user interface

Select robot action

Robot controller

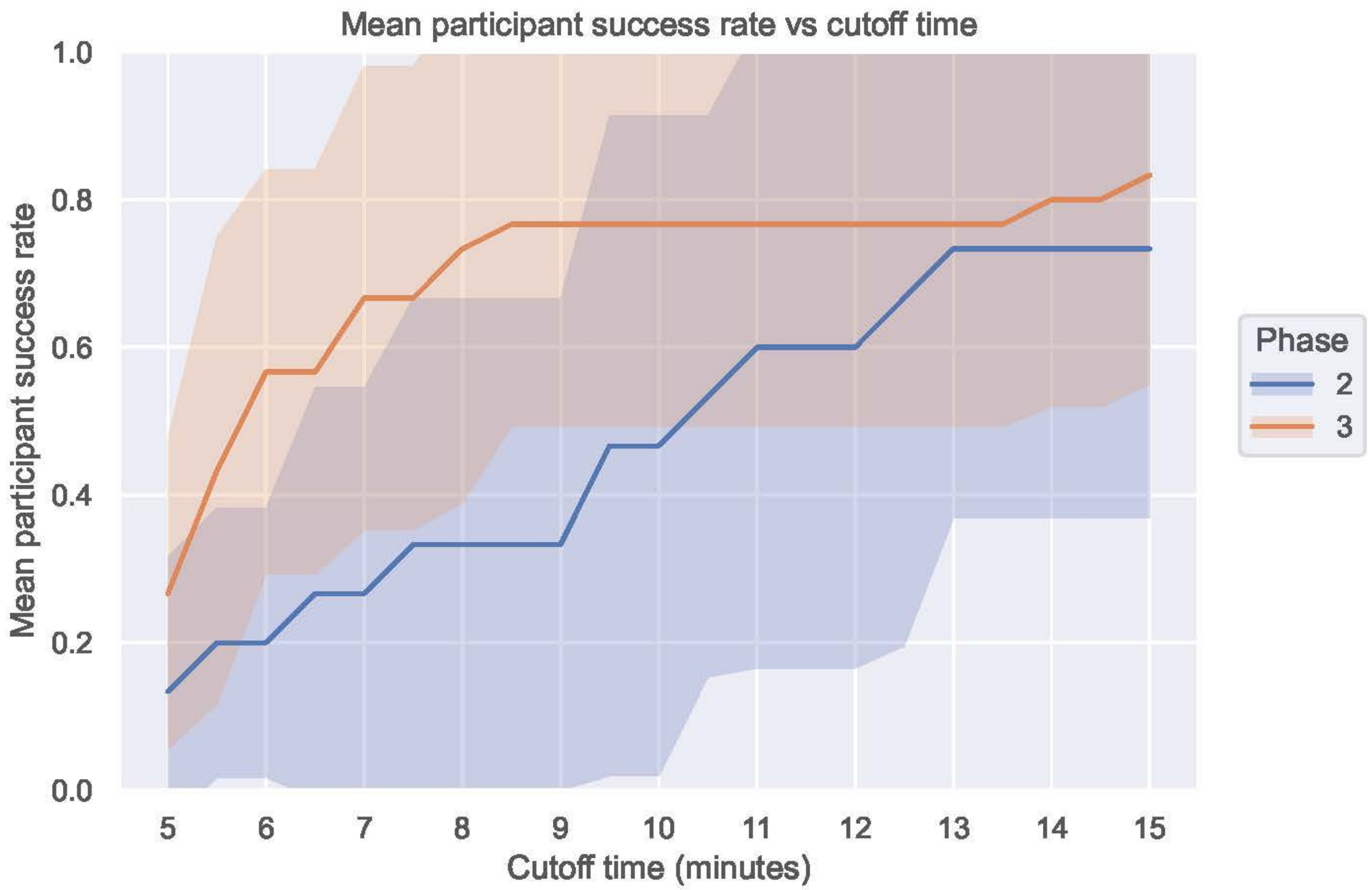
Initiate/stop decoding

Comparison with eye tracking control

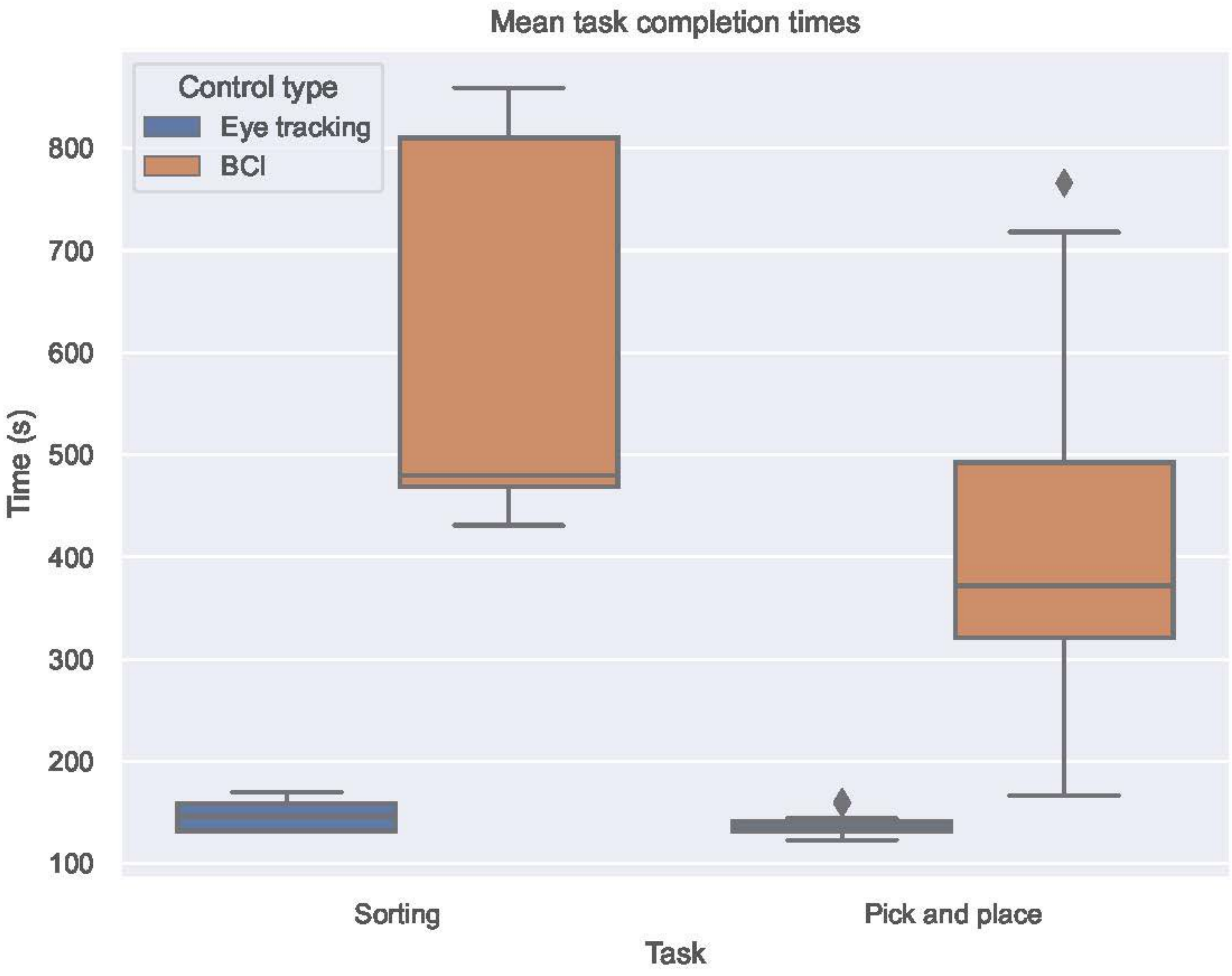


The user evaluation results

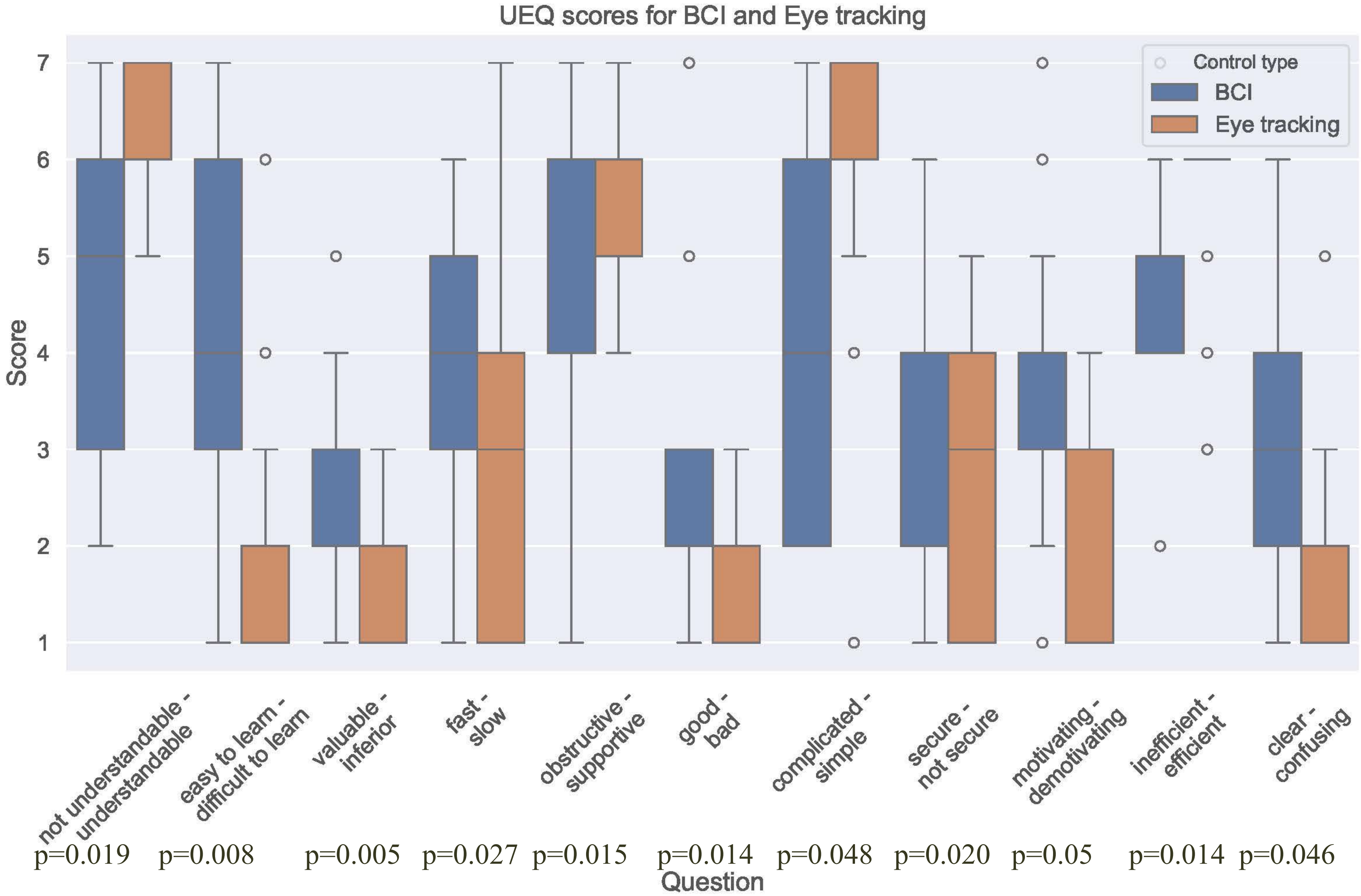
Results: success rate



Results: completion time

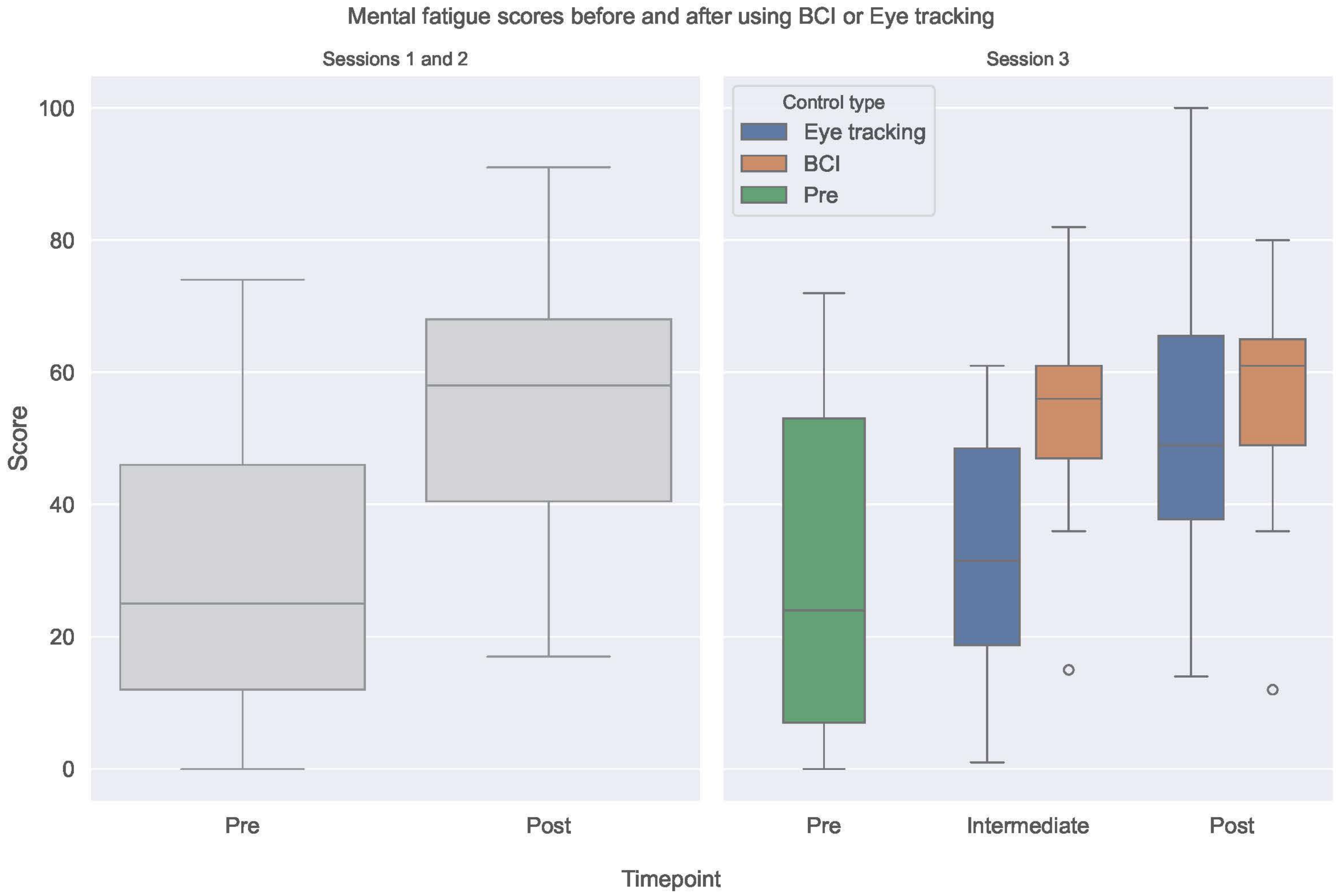


Results: user experience

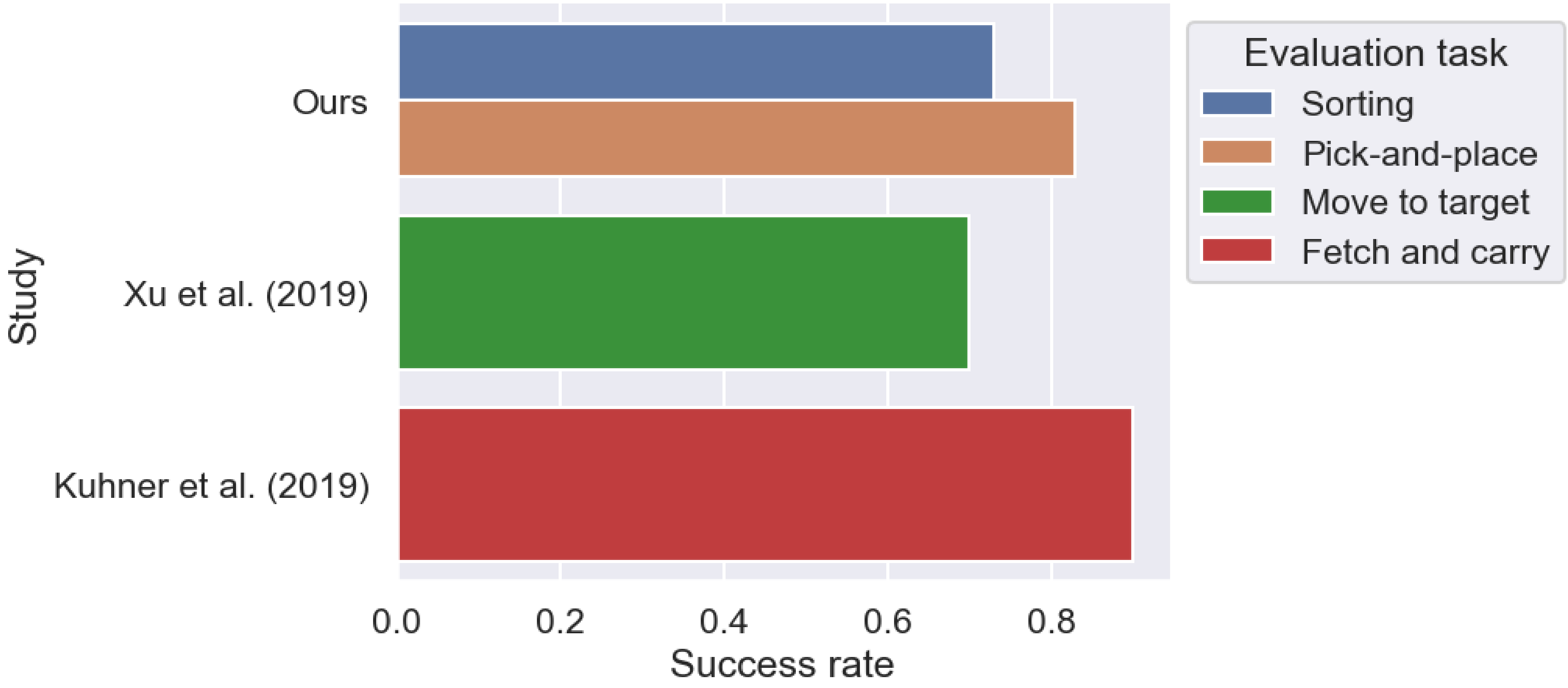


p=0.019 p=0.008 p=0.005 p=0.027 p=0.015 p=0.014 p=0.048 p=0.020 p=0.05 p=0.014 p=0.046

Results: fatigue



Comparison with state-of-the-art



GENERAL DISCUSSION AND CONCLUSIONS

Summary

Research question: How to design a BCI control system that enables users to operate a robot arm without the need to move their limbs or speak?

RO1: Develop a real-time MI decoding pipeline

RO2: Design a robot arm control strategy using MI

RO3: Construct and validate an evaluation framework for BCI prototypes

Key findings

RO 1:

- Best choice of decoding method highly dependent on application requirements
- Eight sensors sufficient to obtain good decoding accuracy
- Customization decoding pipeline to user brings limited improvement

RO 2:

- Shared control simplifies MI decoding
- Multimodal interaction with eye tracking and augmented reality user interface enhances usability

RO 3:

- Our user evaluation framework is a good first step towards real-world deployment
- Eye tracking is currently better, but BCI can be used for certain niche use cases

Strengths

- Portable system
- Off-the-shelf hardware
- Extending and replacing components is trivial
- Realistic evaluation

Weaknesses

- Basic EEG decoding methods
- Unsure if fatigue from calibration or BCI usage
- Low user study sample size
- No evaluation in target population

Future work

Research questions to investigate:

- How can advanced EEG decoding methods benefit usability?
- What benefit will gamification of calibration procedure bring?
- What are the requirements for embedded decoding?
- How will the results translate to in-field user evaluation with target users?

Ultimate goal: all-in-one plug-and-play hardware and software system

Conclusion

Currently, ubiquitous BCI adoption as the standard interaction modality with electronic devices is unlikely.

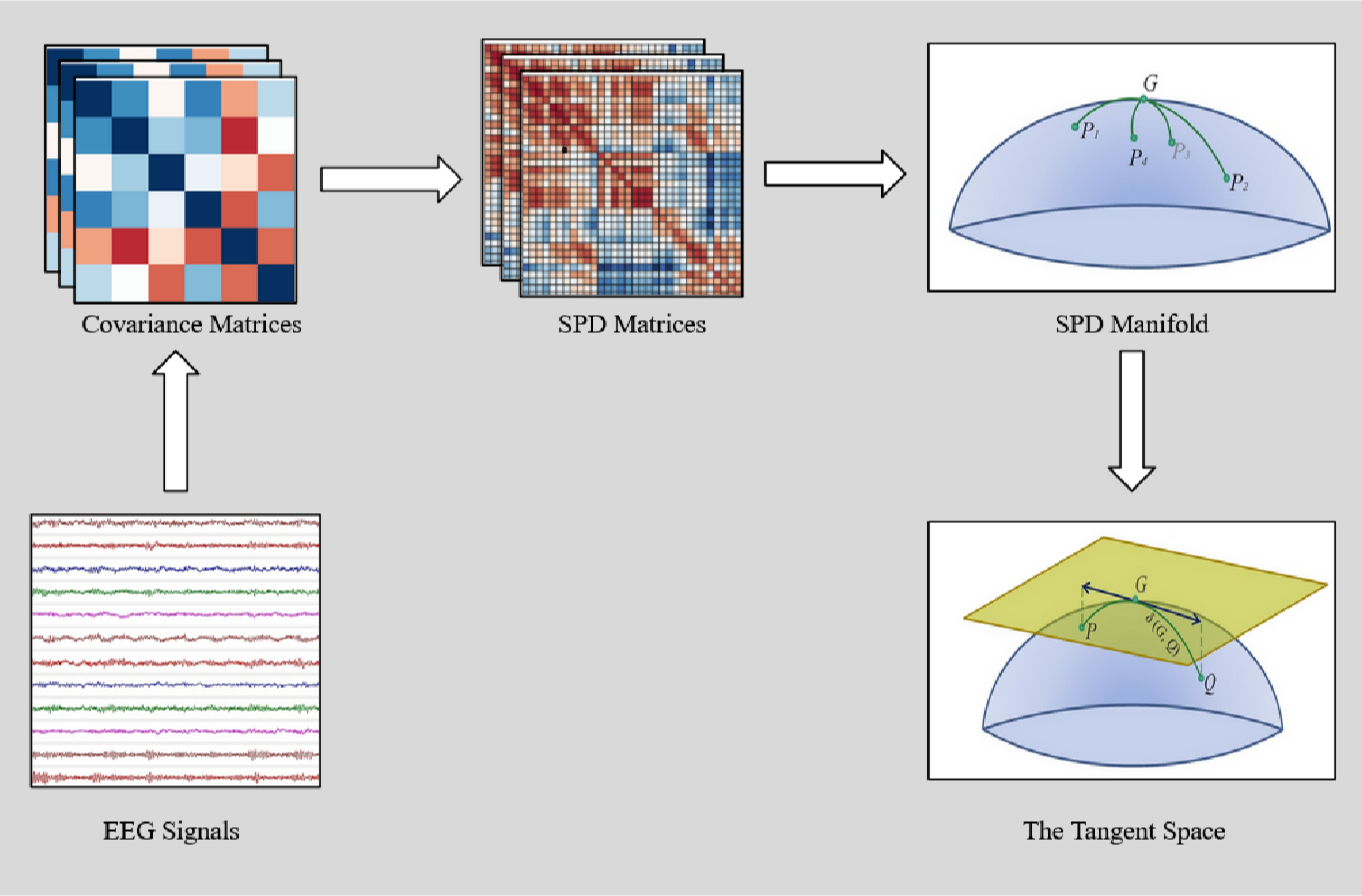
But! targeted and purpose-driven BCI applications hold immense potential.

Current trends in BCI

State-of-the-art decoding methods

Rieman geometry features

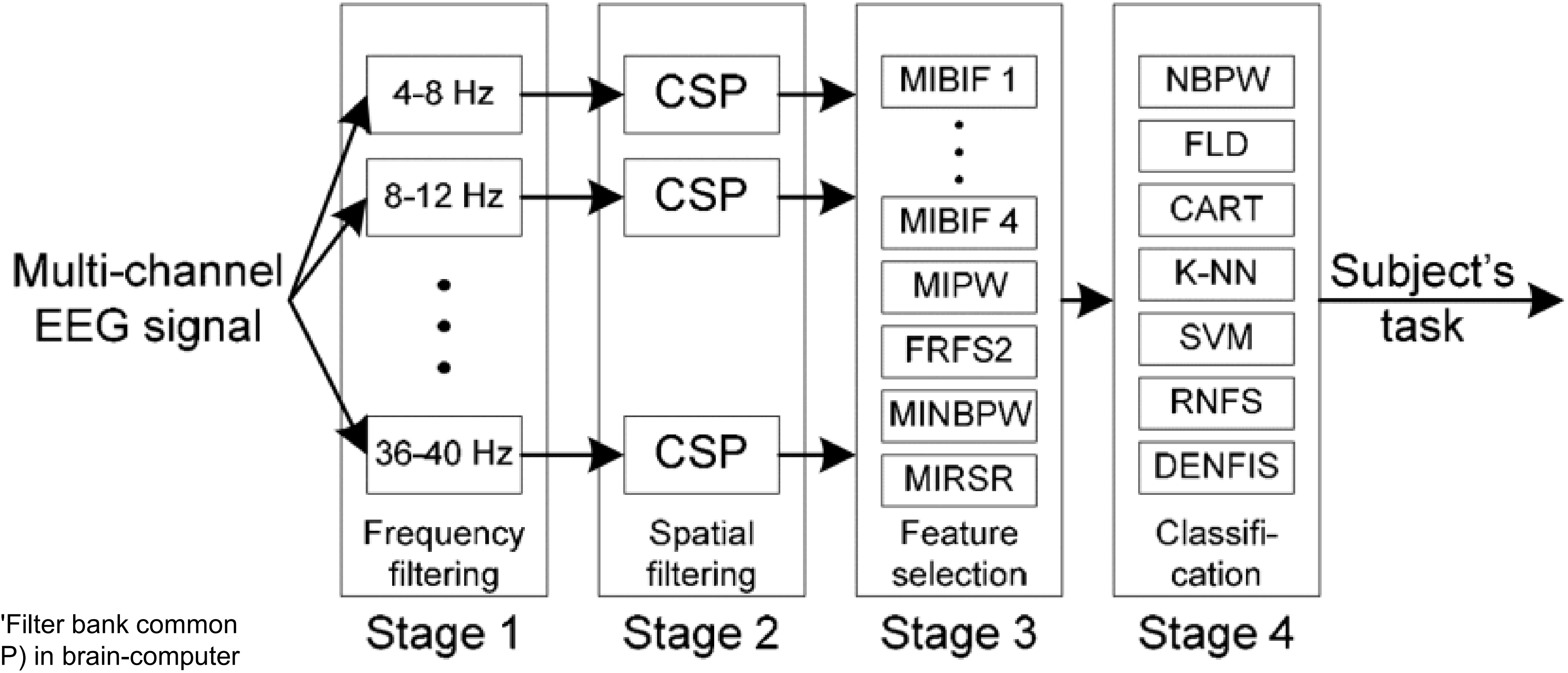
Mapping 2D representation to 3D space (and back)



From:
Tibermacine, Imad Eddine, et al. "Riemannian geometry-based eeg approaches: A literature review." *arXiv preprint arXiv:2407.20250* (2024).

Filter bank common spatial pattern features

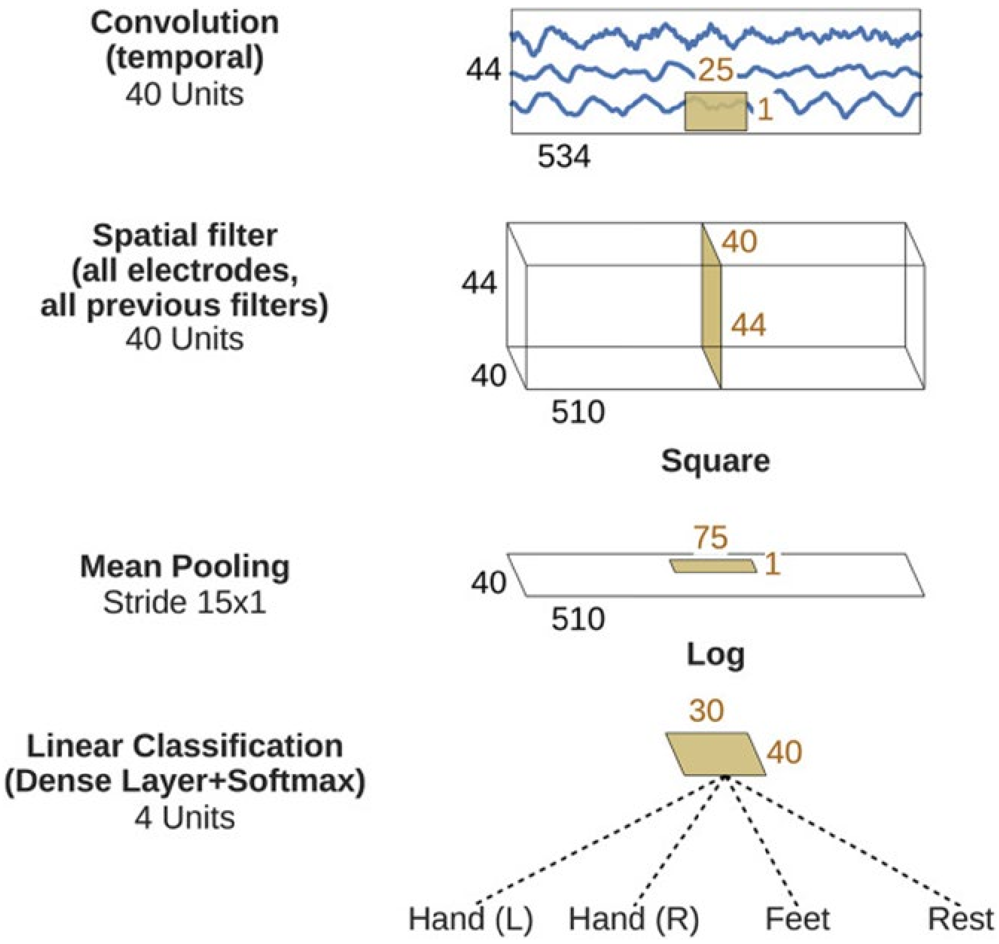
Apply multiple filters and learn which frequencies are most informative for an individual



From:
Ang, Kai Keng, et al. "Filter bank common spatial pattern (FBCSP) in brain-computer interface." *2008 IEEE international joint conference on neural networks (IEEE world congress on computational intelligence)*. IEEE, 2008.

Deep learning

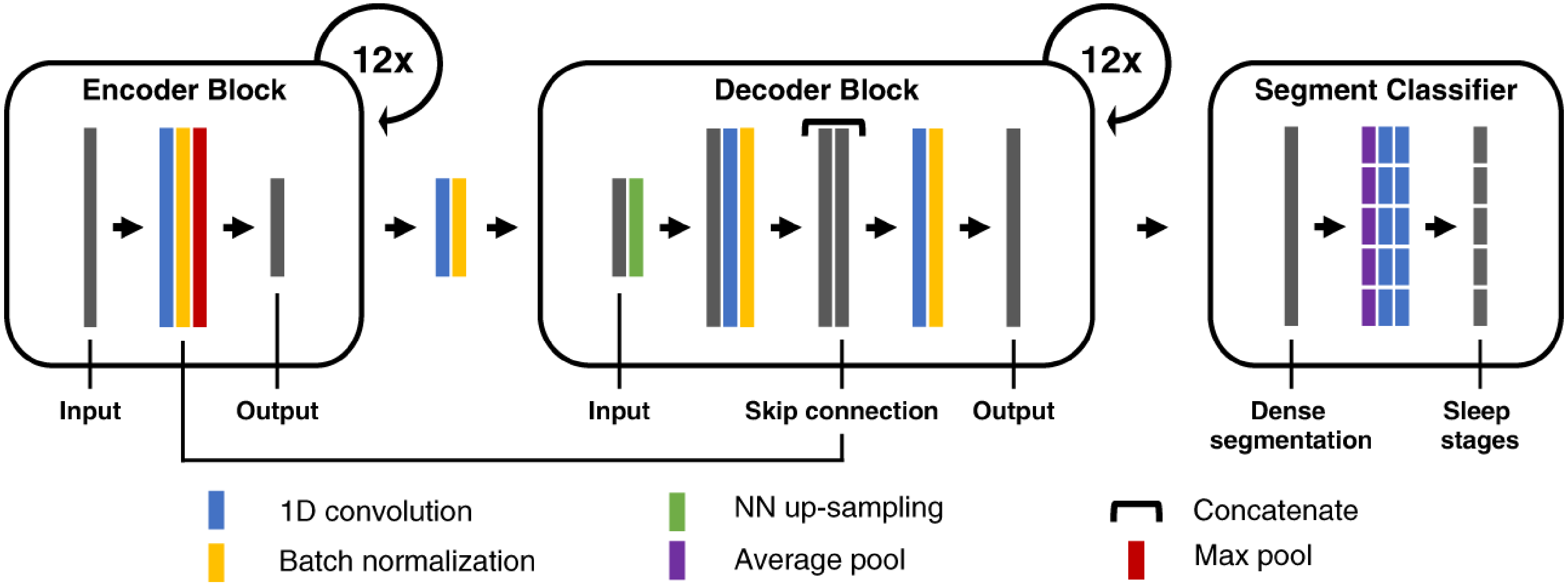
CNNs: encode time and spatial features in the convolutions



From:
Schirrmeister, Robin Tibor, et al. "Deep learning with convolutional neural networks for EEG decoding and visualization." *Human brain mapping* 38.11 (2017): 5391-5420.

Deep learning

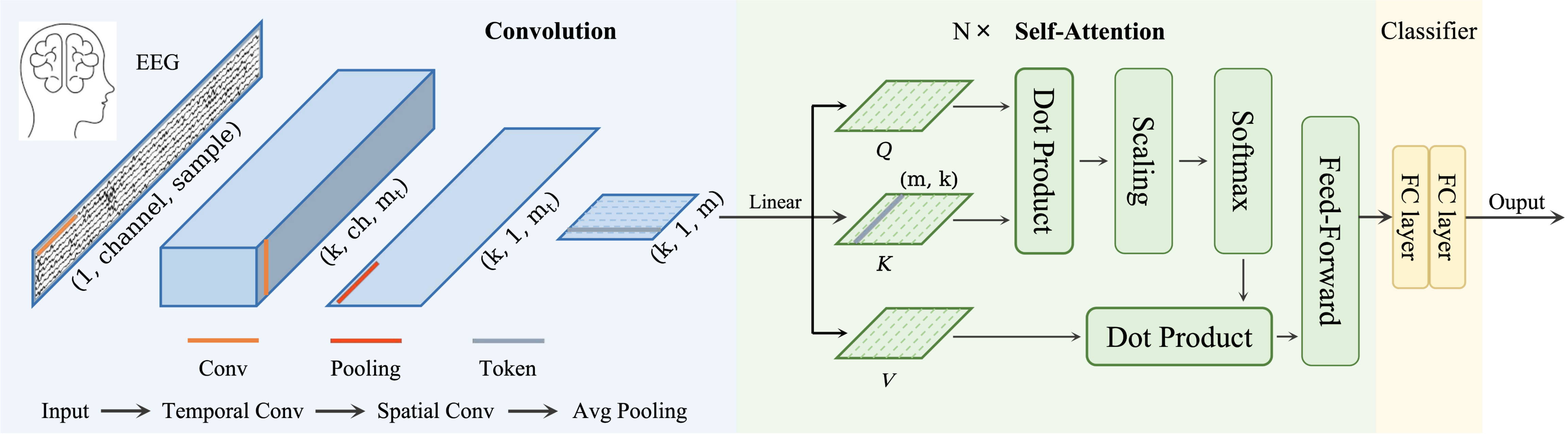
U-net: encoder-decoder architectures



From:
Perslev, Mathias, et al. "U-Sleep: resilient high-frequency sleep staging." *NPJ digital medicine* 4.1 (2021): 72.

Deep learning

Transformer networks: use attention to capture long-range dependencies



From:
Song, Yonghao, et al. "EEG conformer: Convolutional transformer for EEG decoding and visualization." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31 (2022): 710-719.

Deep learning

Want to know more?

Check out braindecode!

https://braindecode.org/stable/index.html

Current trends in BCI

Novel applications

Image generation based on brain signals

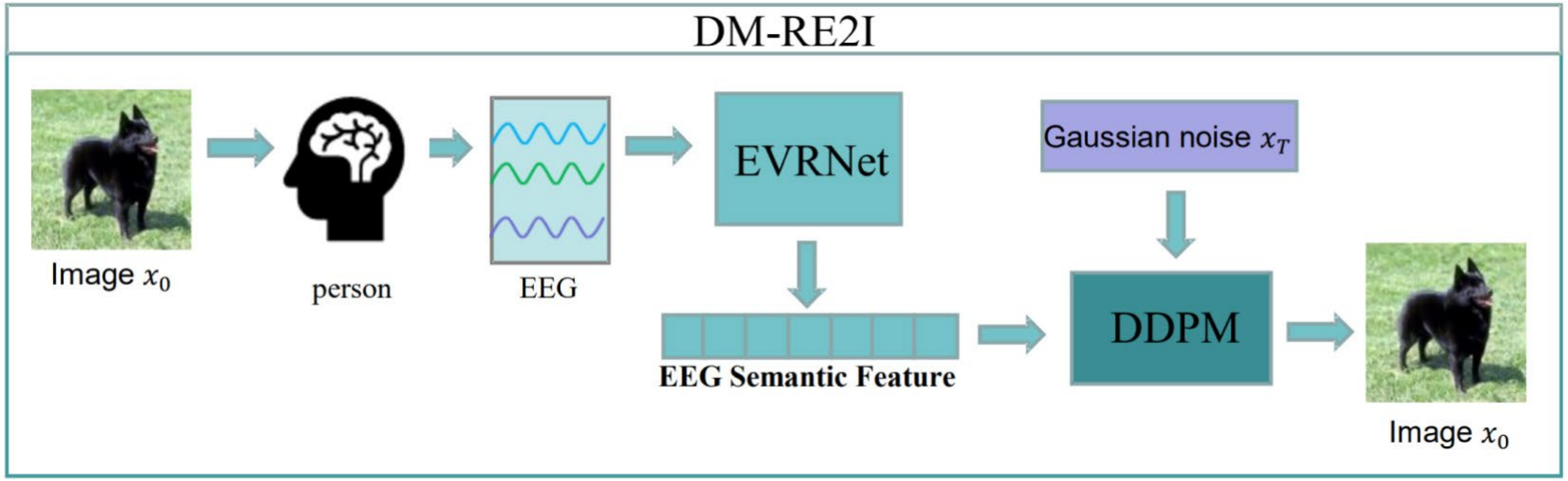
Generate the picture that a person is looking at based on EEG activity

Some recent references:

Singh, P., Pandey, P., Miyapuram, K. and Raman, S., 2023, June. EEG2IMAGE: image reconstruction from EEG brain signals. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 1-5). IEEE.

Khare, S., Choubey, R.N., Amar, L. and Udutalapalli, V., 2022. Neurovision: perceived image regeneration using cprogan. *Neural Computing and Applications*, *34*(8), pp.5979-5991.

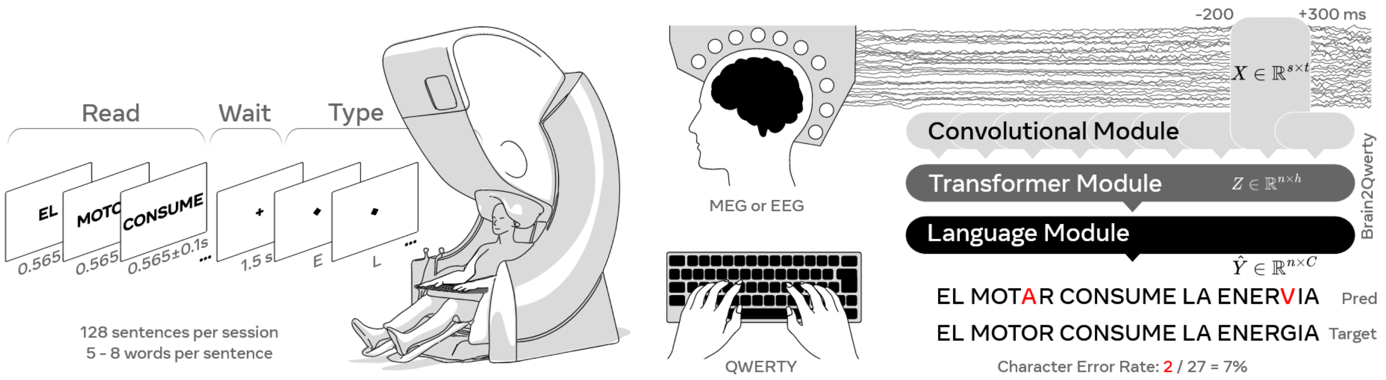
Zeng, H., Xia, N., Qian, D., Hattori, M., Wang, C. and Kong, W., 2023. DM-RE2I: A framework based on diffusion model for the reconstruction from EEG to image. *Biomedical Signal Processing and Control*, *86*, p.105125.



Text generation from brain data

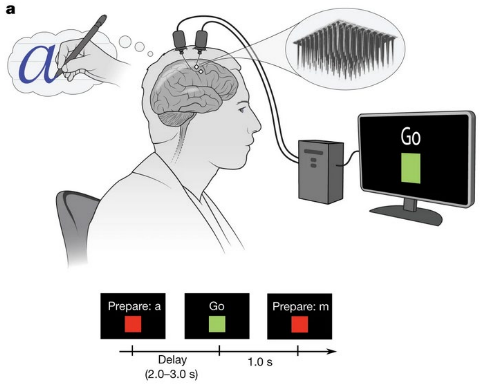
Text from EEG/MEG during typing :

Lévy, J., Zhang, M., Pinet, S., Rapin, J., Banville, H., d'Ascoli, S. and King, J.R., 2025. Brain-to-Text Decoding: A Non-invasive Approach via Typing. *arXiv preprint arXiv:2502.17480*.



From imagined handwriting with ECoG:

Willett, F.R., Avansino, D.T., Hochberg, L.R., Henderson, J.M. and Shenoy, K.V., 2021. High-performance brain-to-text communication via handwriting. *Nature*, *593*(7858), pp.249-254.



Bi-directional BCI

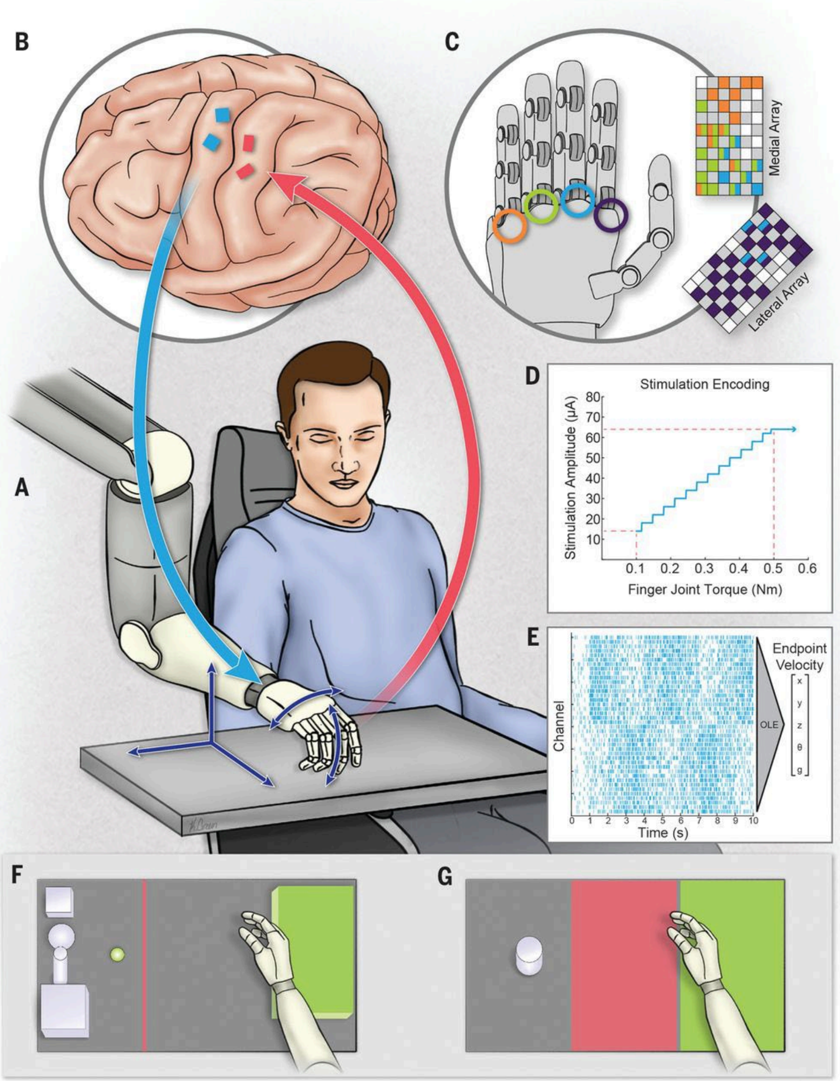
Decoding of movement intention + stimulation to reproduce sensory input

Some references:

Wood, H., 2021. Bidirectional brain–computer interface aids robotic arm control. *Nature Reviews Neurology*, *17*(8), pp.462-462.

Weiss, J.M., Flesher, S.N., Franklin, R., Collinger, J.L. and Gaunt, R.A., 2018. Artifact-free recordings in human bidirectional brain–computer interfaces. *Journal of Neural Engineering*, *16*(1), p.016002.

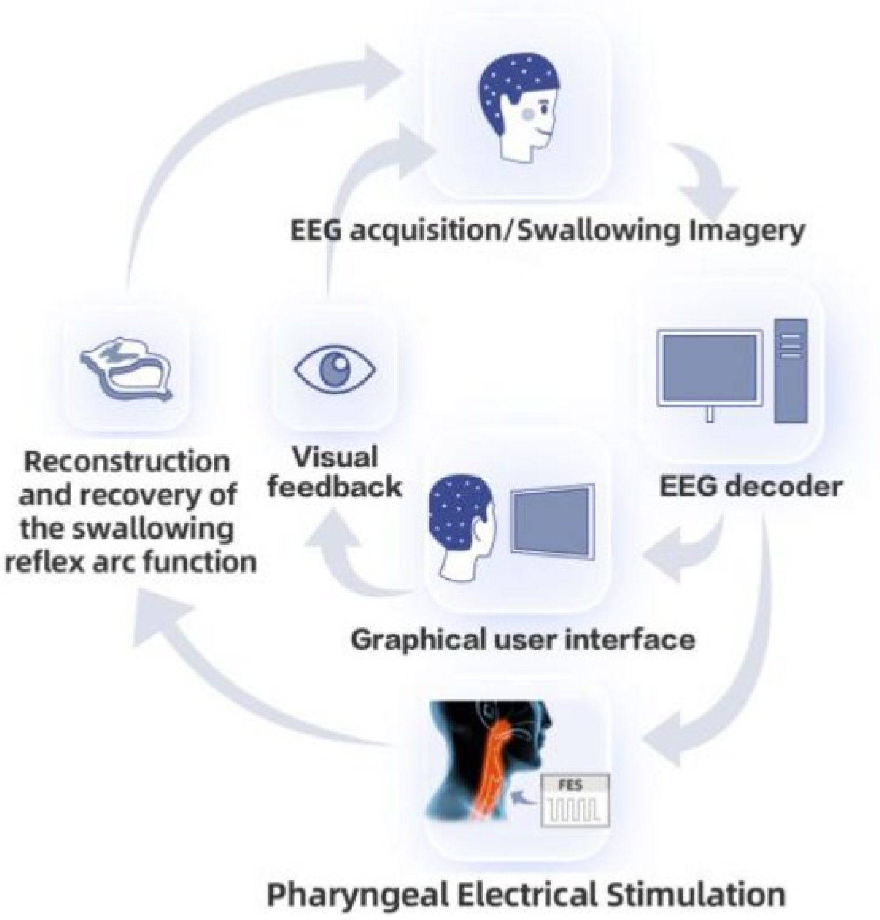
Flesher, S.N., Downey, J.E., Weiss, J.M., Hughes, C.L., Herrera, A.J., Tyler-Kabara, E.C., Boninger, M.L., Collinger, J.L. and Gaunt, R.A., 2021. A brain-computer interface that evokes tactile sensations improves robotic arm control. *Science*, *372*(6544), pp.831-836.



Non-invasive bi-directional BCI

Decode EEG + stimulate with functional electrical stimulation for swallowing

From:
“Development and feasibility of a motor imagery–based closed-loop BCI–FES system for swallowing rehabilitation”, Submitted work to journal of neural engineering (2026)



BCI game control

Playing games with “mind control”

Valve invests in BCI

Next-gen hardware

Dry EEG sensors (e.g. CGX)

Galea: VR + BCI headset

Neuralink: low-risk ECoG implantation

Future perspectives

- Advanced prosthetic control with BCI
- Fatigue detection with biosignal
- Neuroscience research and medical diagnosis of neural diseases
- Cognitive modelling

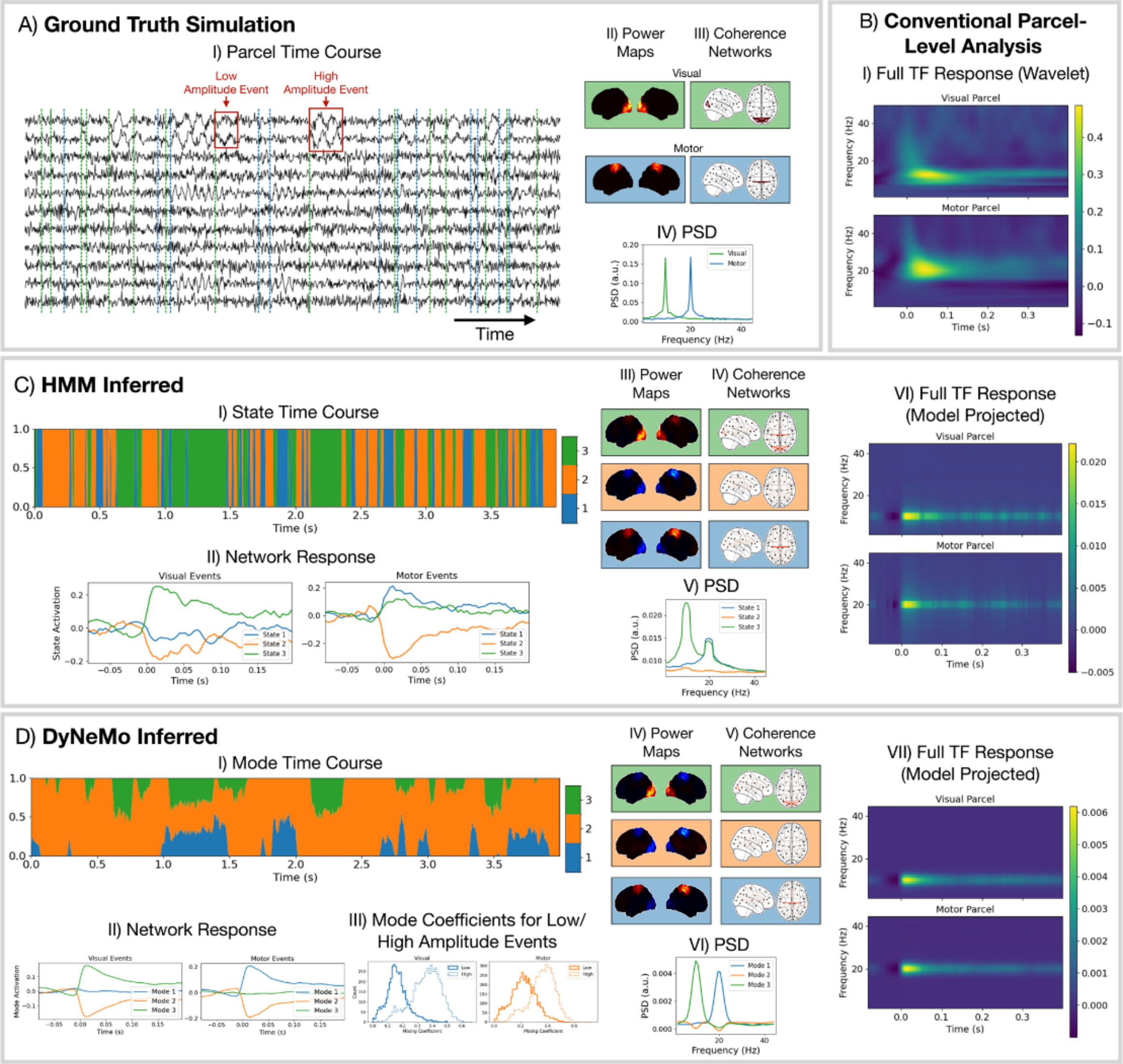
Our latest and future projects

Example: MEMOBRAIN

Goal: extract active brain states from MEG data using AI methods

Improve analysis of what happens where and when in the brain when processing a stimulus

Compare normal brain-state activation patterns with those of patients suffering from multiple sclerosis



Issues

Noisy EEG (artifacts, inter- and intraindividual variability, …)

More MI classes harder to classify

User training necessary

Hard to gather machine learning training data

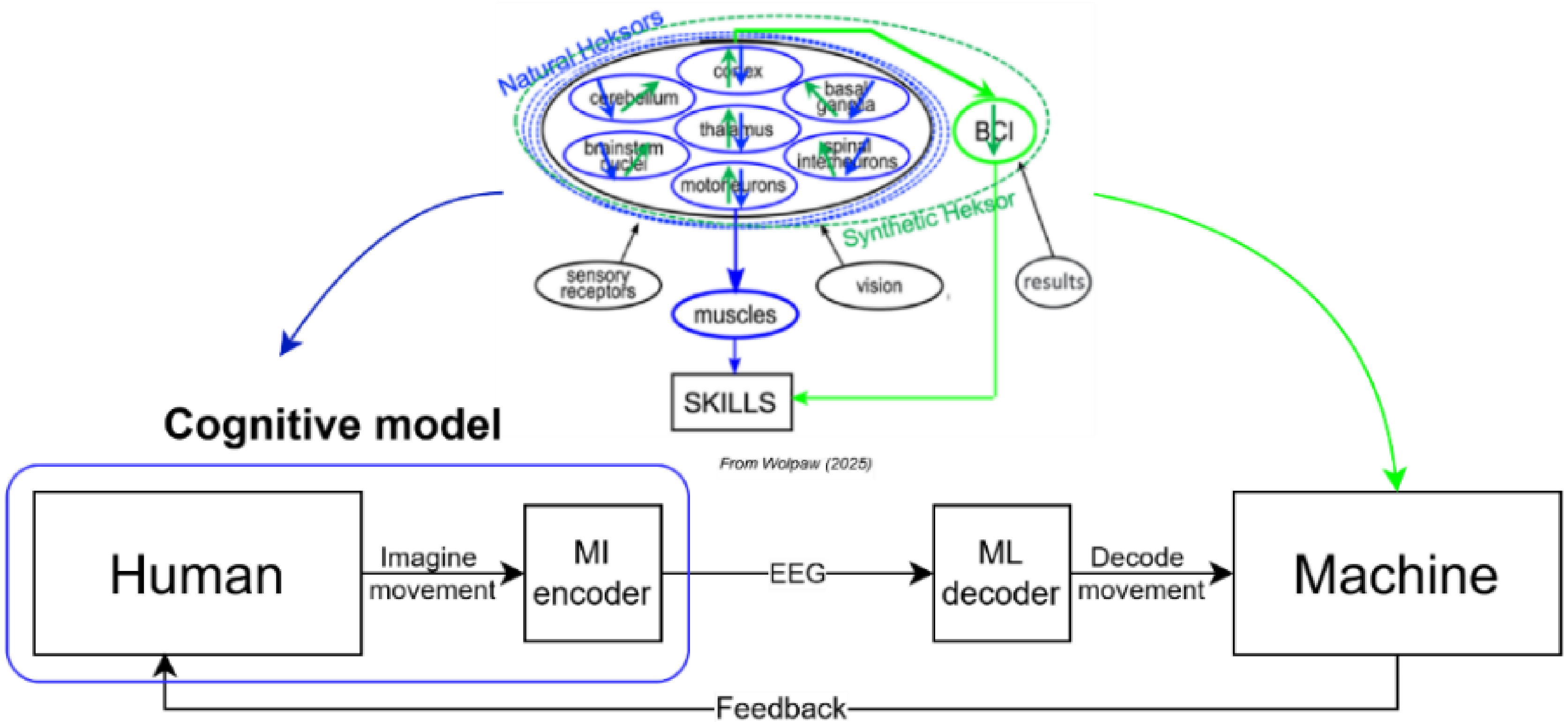
Lack of standardised evaluation for BCI prototypes

Example: cognitive model of BCI skill acquisition

Modelling the adaptation of a human that learns to use a BCI control system

Simulation of a novel neural representation of neural networks related to a skill: heksors

Simulation of interaction between human (encoder) and BCI ML decoder



From Wolpaw (2025)

Thank you

Joint PhD between VUB and CY Cergy Paris University

eUTOPIA
European University

VUB MFYS HUMAN PHYSIOLOGY &
SPORTS PHYSIOTHERAPY
RESEARCH GROUP

VUB BRUBOTICS
HUMAN ROBOTICS
RESEARCH CENTER

+

CY CERGY PARIS
UNIVERSITÉ

ETIS

Extra: Demo video

More info: my publications

- Dillen, A., Lathouwers, E., *et al.* (2022) ‘A data-driven machine learning approach for brain-computer interfaces targeting lower limb neuroprosthetics’, *Frontiers in Human Neuroscience*, 16. Available at: https://doi.org/10.3389/fnhum.2022.949224.
- Dillen, A., Steckelmacher, D., *et al.* (2022) ‘Deep learning for biosignal control: Insights from basic to real-time methods with recommendations’, *Journal of Neural Engineering*, 19(1), p. 011003. Available at: https://doi.org/10.1088/1741-2552/ac4f9a.
- Dillen, A. *et al.* (2023) ‘Optimal Sensor Set for Decoding Motor Imagery from EEG’, *Applied Sciences*, 13(7), p. 4438. Available at: https://doi.org/10.3390/app13074438.
- Dillen, A., Omidi, M., Ghaffari, F., Vanderborght, B., *et al.* (2024) ‘A shared robot control system combining augmented reality and motor imagery brain–computer interfaces with eye tracking’, *Journal of Neural Engineering*, 21(5), p. 056028. Available at: https://doi.org/10.1088/1741-2552/ad7f8d.
- Dillen, A., Omidi, M., Díaz, M.A., *et al.* (2024) ‘Evaluating the real-world usability of BCI control systems with augmented reality: a user study protocol’, *Frontiers in Human Neuroscience*, 18. Available at: https://doi.org/10.3389/fnhum.2024.1448584.
- Dillen, A., Omidi, M., Ghaffari, F., Romain, O., *et al.* (2024) ‘User Evaluation of a Shared Robot Control System Combining BCI and Eye Tracking in a Portable Augmented Reality User Interface’, *Sensors*, 24(16), p. 5253. Available at: https://doi.org/10.3390/s24165253.

Attributions

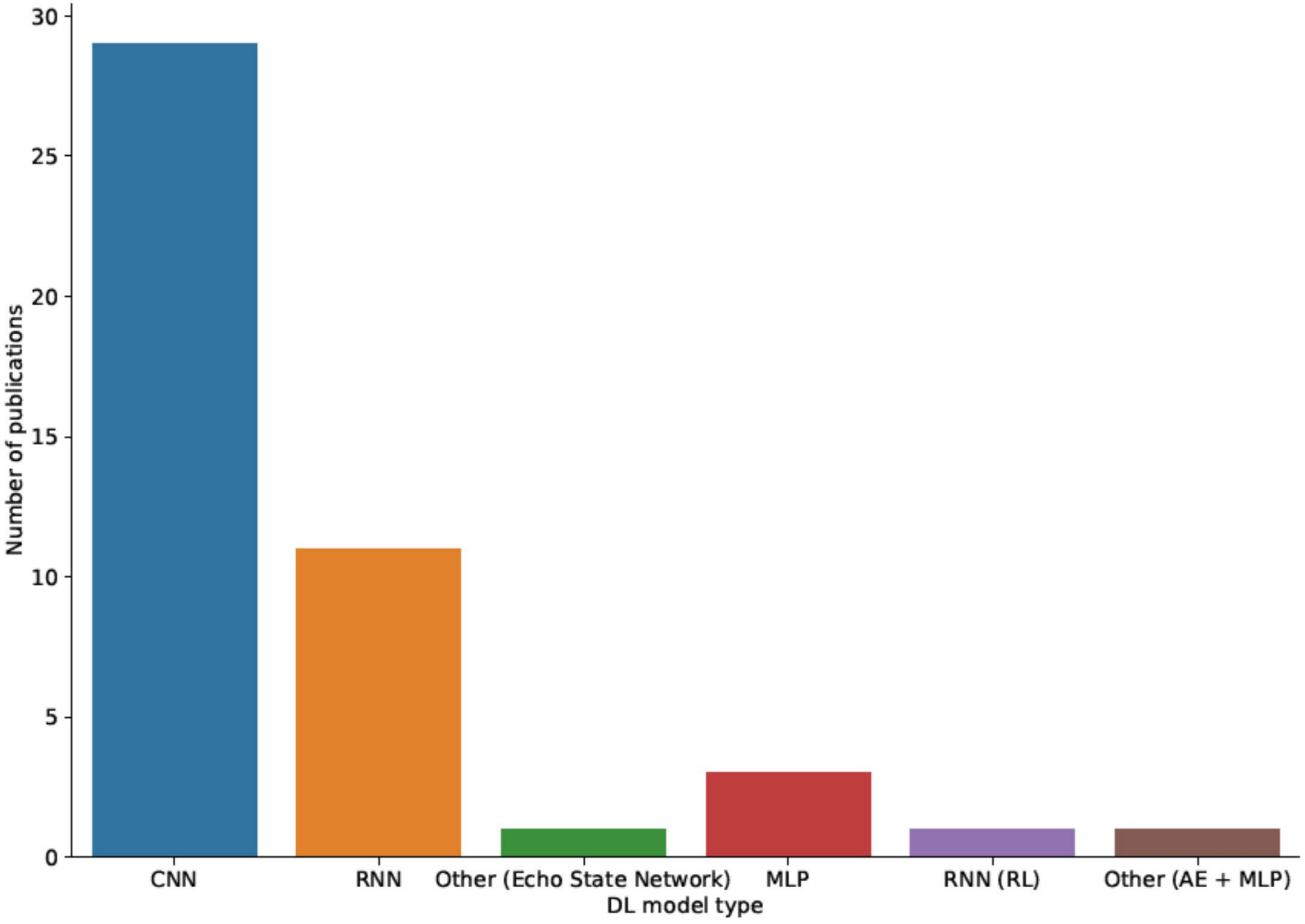
- Neural network icon made by Freepik on Flaticon: https://www.flaticon.com/free-icons/neural-network

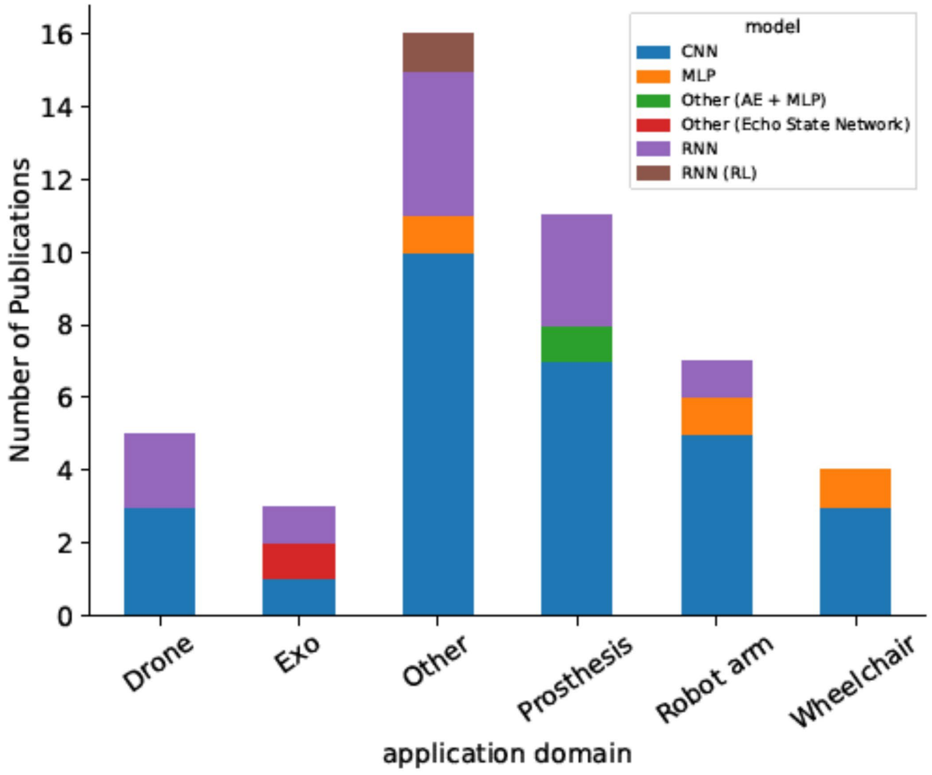
References

Xu, Y., Ding, C., Shu, X., Gui, K., Bezsudnova, Y., Sheng, X., & Zhang, D. (2019). Shared control of a robotic arm using non-invasive brain–computer interface and computer vision guidance. Robotics and Autonomous Systems, 115, 121–129. https://doi.org/10.1016/j.robot.2019.02.014

Kuhner, D., Fiederer, L. D. J., Aldinger, J., Burget, F., Völker, M., Schirrmeister, R. T., Do, C., Boedecker, J., Nebel, B., Ball, T., & Burgard, W. (2019). A service assistant combining autonomous robotics, flexible goal formulation, and deep-learning-based brain–computer interfacing. Robotics and Autonomous Systems, 116, 98–113. https://doi.org/10/gjs8gp

Number of publications





Systematic literature Search

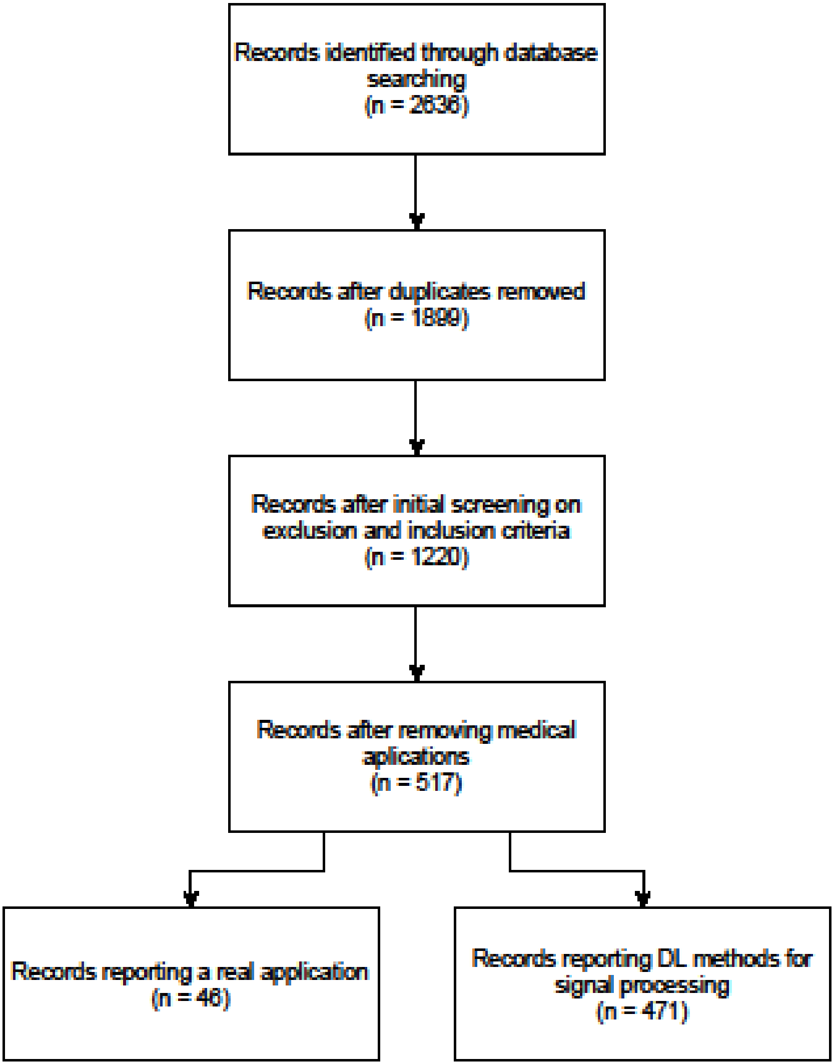
Databases: PubMed, Scopus, IEEE Explore, and

Search string:

(Brain Computer Interface OR Electroencephalog OR EEG OR Brain Machine Interface OR Biolog Signal∗ OR Magnetoencephalogra∗ OR MEG OR Electromyogra∗ OR EMG OR Human Computer Interaction∗ OR HCI)

AND (Deep Learning OR Convolutional Neural Network∗ OR Recurrent Neural Network OR Generative Adversarial Network∗ OR GAN OR Encoder OR Transformer Network)

AND (Motor Image∗ OR Control∗ OR Applied)



Records identified through database searching
(n = 2636)

Records after duplicates removed
(n = 1899)

Records after initial screening on exclusion and inclusion criteria
(n = 1220)

Records after removing medical aplications
(n = 517)

Records reporting a real application
(n = 46)

Records reporting DL methods for signal processing
(n = 471)

Benchmarking pipelines

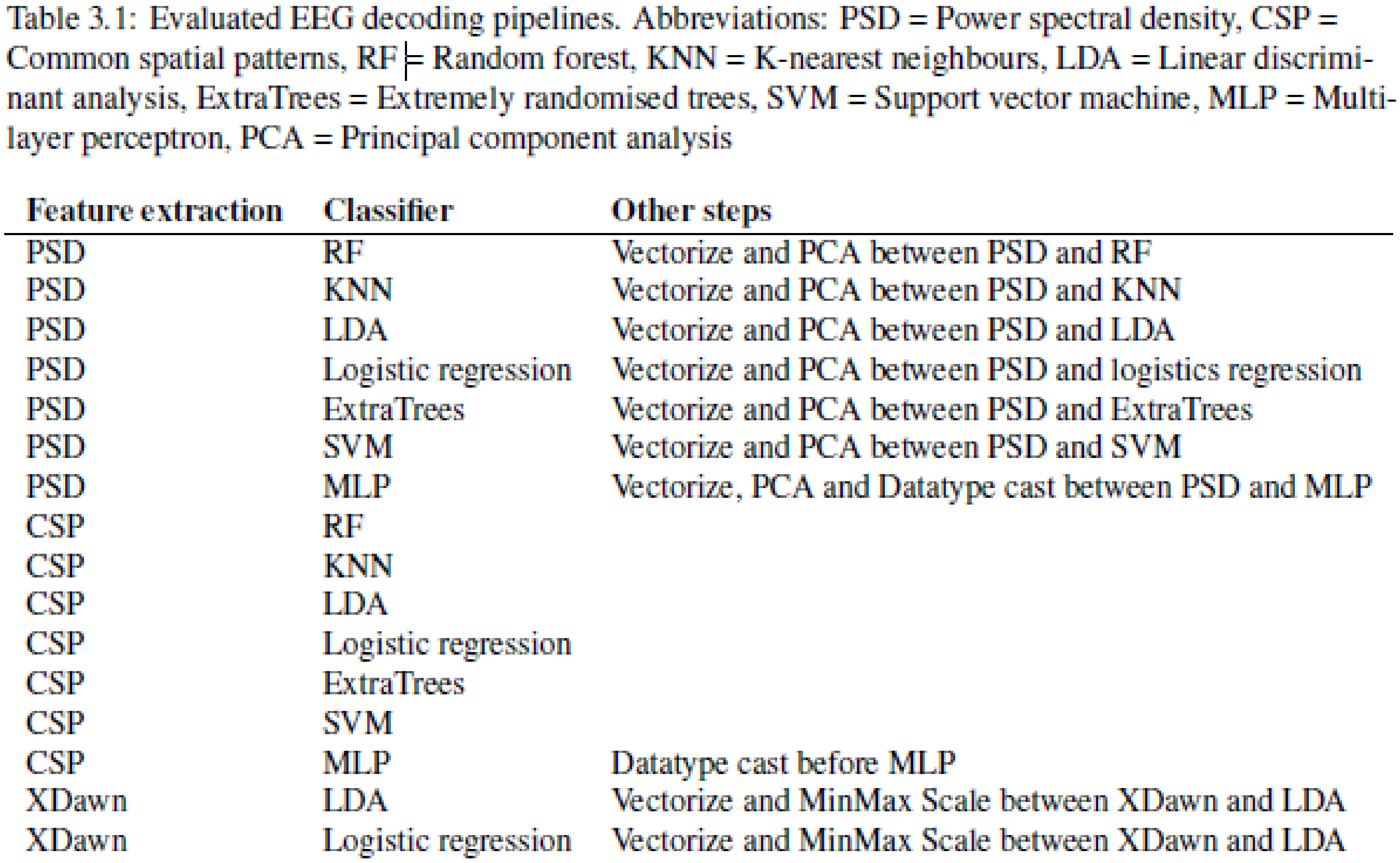


Table 3.1: Evaluated EEG decoding pipelines. Abbreviations: PSD = Power spectral density, CSP = Common spatial patterns, RF = Random forest, KNN = K-nearest neighbours, LDA = Linear discriminant analysis, ExtraTrees = Extremely randomised trees, SVM = Support vector machine, MLP = Multilayer perceptron, PCA = Principal component analysis

Feature extraction	Classifier	Other steps
PSD	RF	Vectorize and PCA between PSD and RF
PSD	KNN	Vectorize and PCA between PSD and KNN
PSD	LDA	Vectorize and PCA between PSD and LDA
PSD	Logistic regression	Vectorize and PCA between PSD and logistics regression
PSD	ExtraTrees	Vectorize and PCA between PSD and ExtraTrees
PSD	SVM	Vectorize and PCA between PSD and SVM
PSD	MLP	Vectorize, PCA and Datatype cast between PSD and MLP
CSP	RF	
CSP	KNN	
CSP	LDA	
CSP	Logistic regression	
CSP	ExtraTrees	
CSP	SVM	
CSP	MLP	Datatype cast before MLP
XDawn	LDA	Vectorize and MinMax Scale between XDawn and LDA
XDawn	Logistic regression	Vectorize and MinMax Scale between XDawn and LDA

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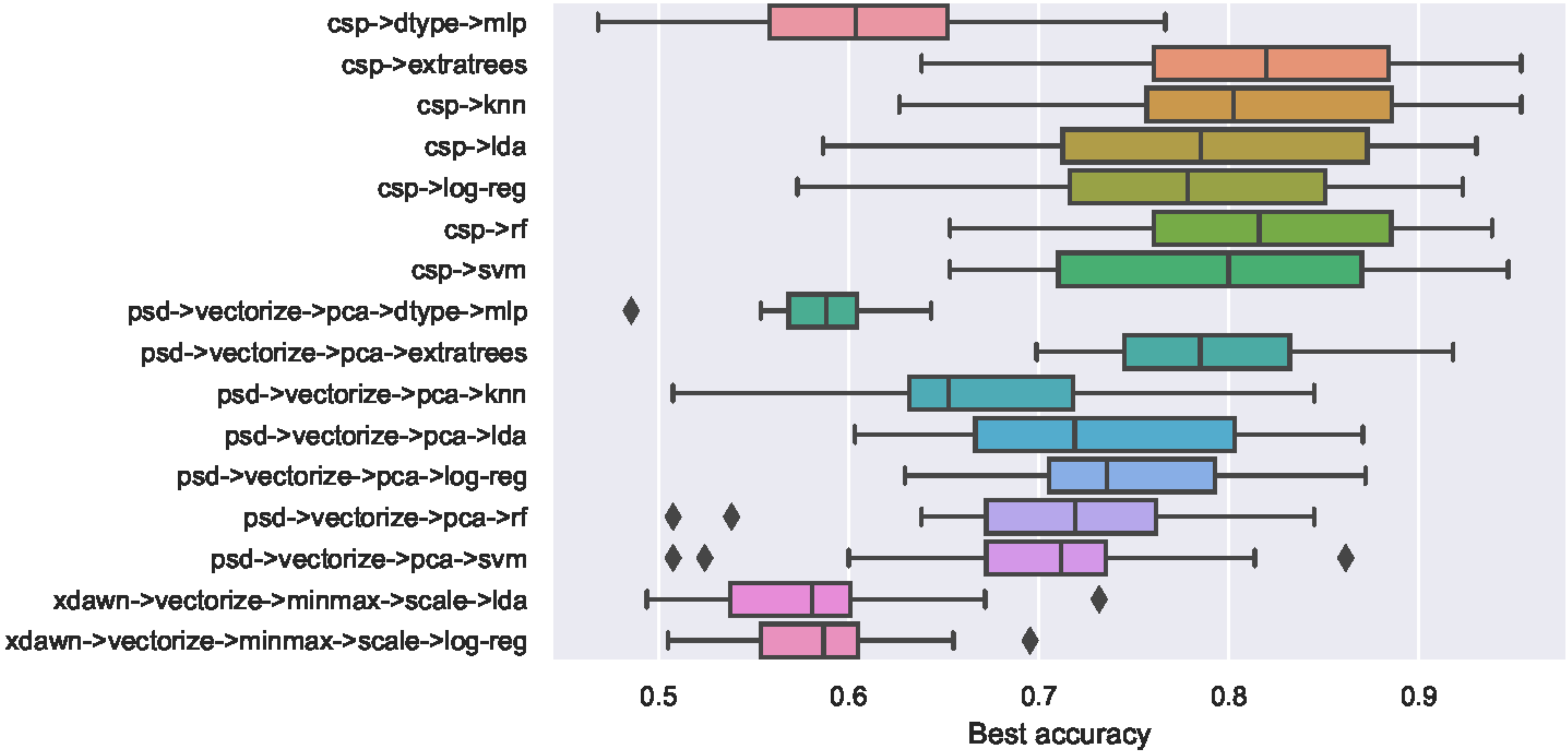
Best accuracy for each optimized pipeline



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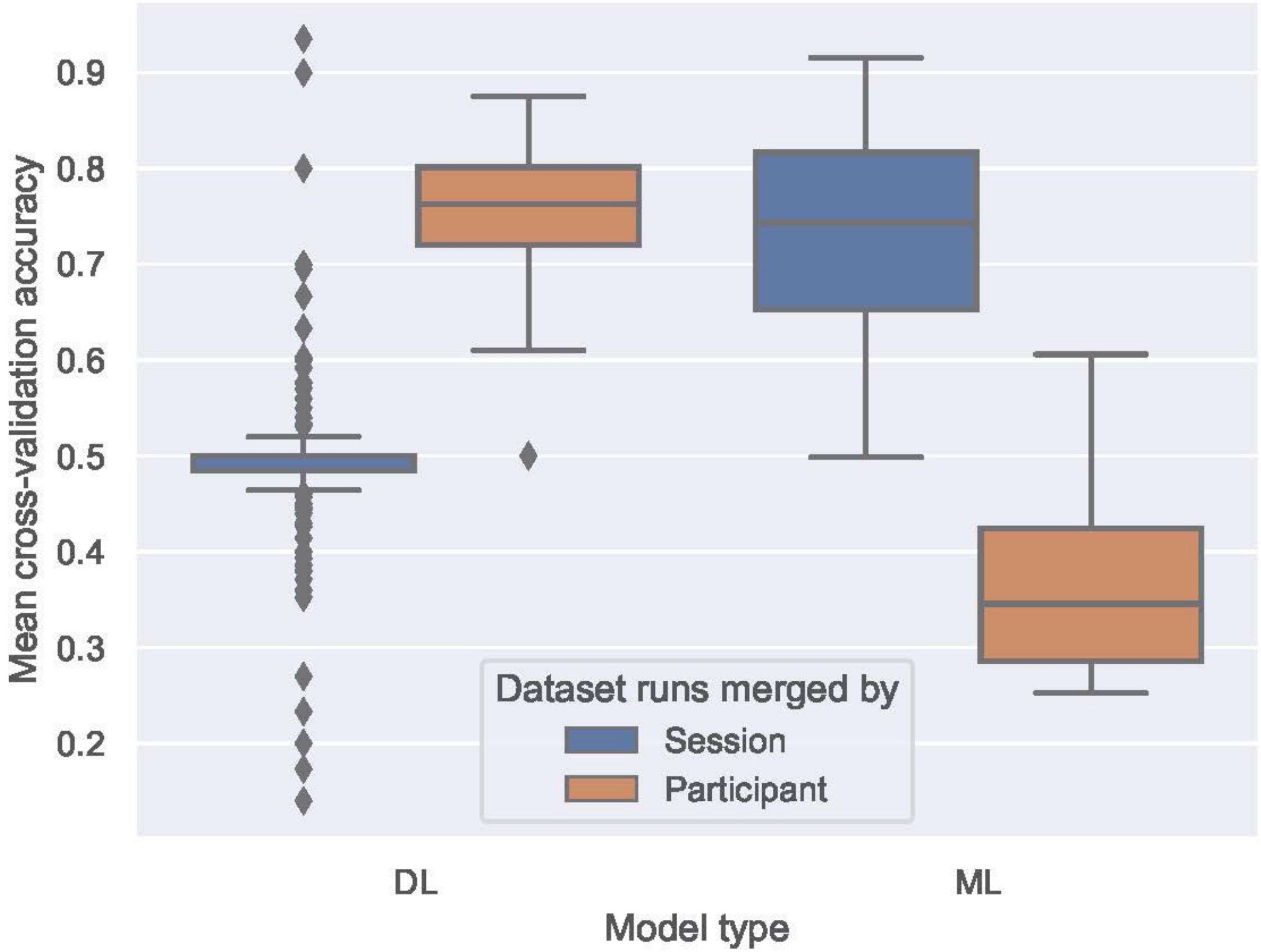
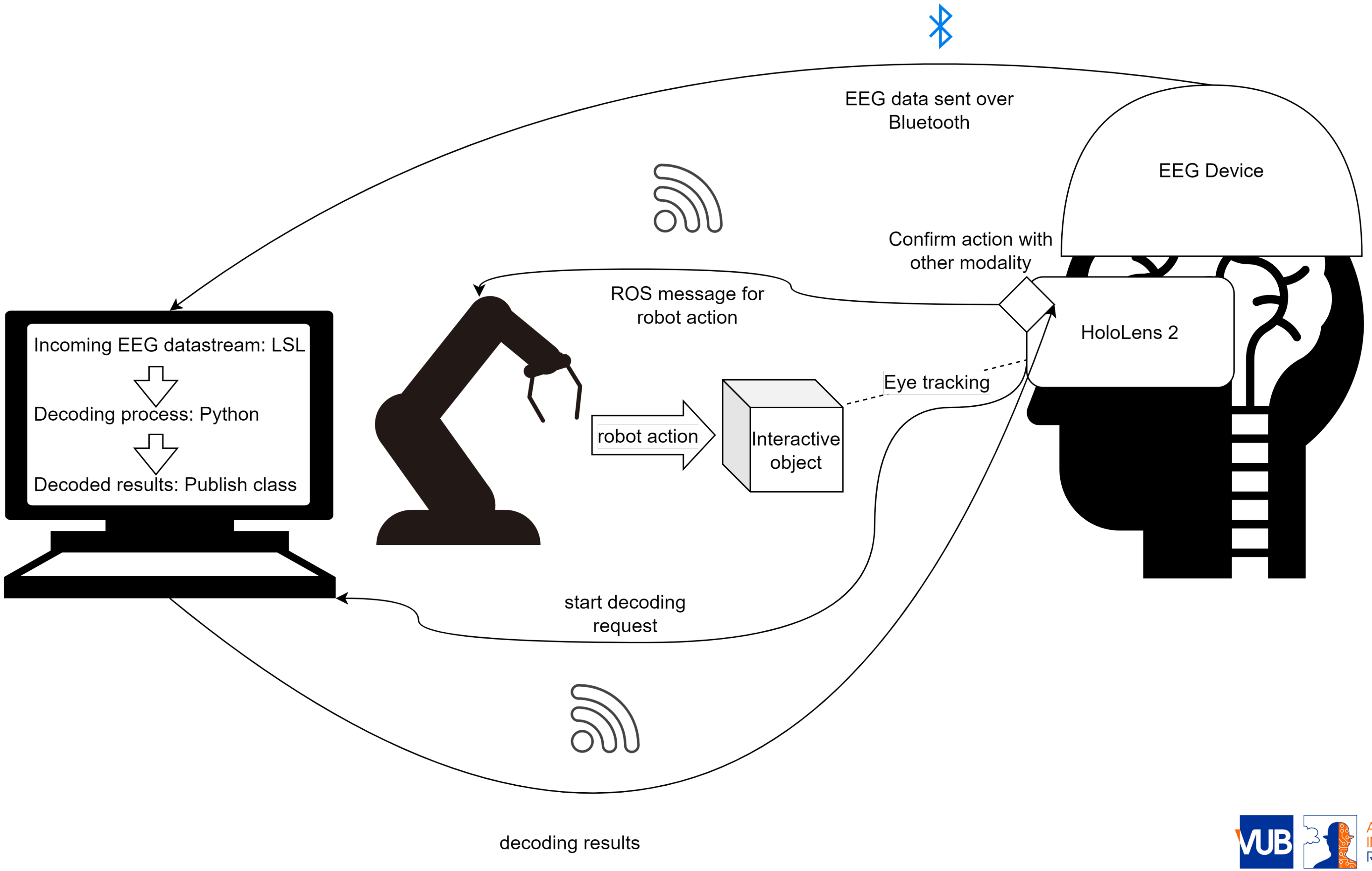
INTELLIGENCE
RESEARCH GROUP

DL vs Ml on MI data

Poster at BCI meeting: Arnau Dillen. Calibration methods during EEG signal acquisition and their impact on motor imagery. (2023) doi:10.3217/978-3-85125-962-9-124.



Hardware setup details



EEG data sent over Bluetooth

EEG Device

Confirm action with other modality

HoloLens 2

ROS message for robot action

Eye tracking

Incoming EEG datastream: LSL

Decoding process: Python

Decoded results: Publish class

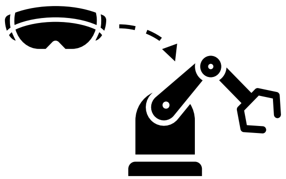
robot action

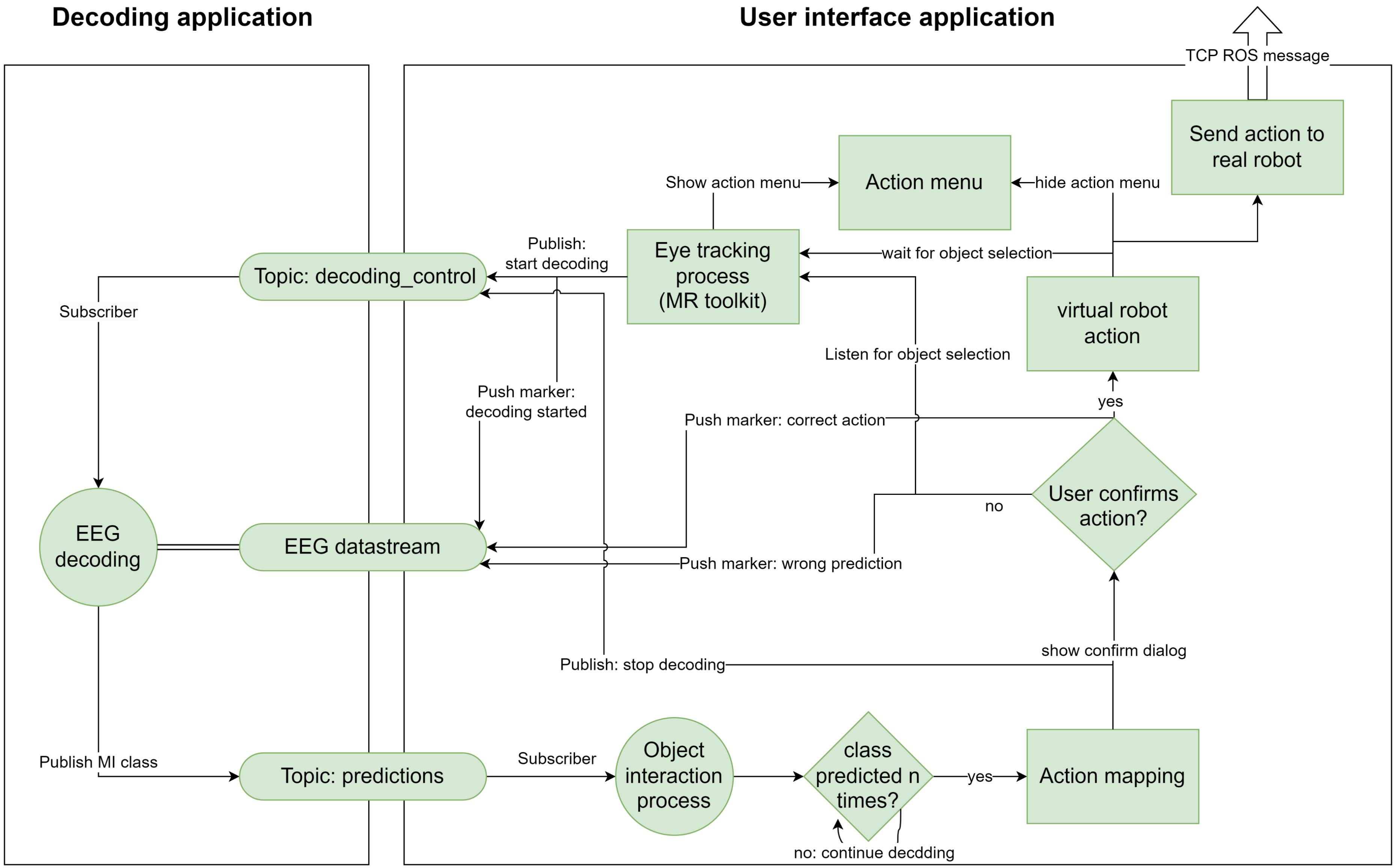
Interactive object

start decoding request

decoding results

BCI software details





Decoding application

User interface application

TCP ROS message

Send action to real robot

Action menu

Show action menu

hide action menu

Eye tracking process (MR toolkit)

wait for object selection

Publish: start decoding

Topic: decoding_control

Subscriber

virtual robot action

Listen for object selection

yes

Push marker: decoding started

Push marker: correct action

User confirms action?

no

EEG decoding

EEG datastream

Push marker: wrong prediction

show confirm dialog

Publish: stop decoding

Publish MI class

Topic: predictions

Subscriber

Object interaction process

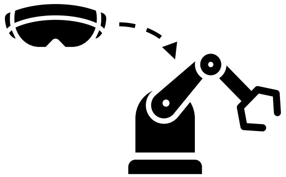
class predicted n times?

yes

Action mapping

no: continue decdding

Software implementation details



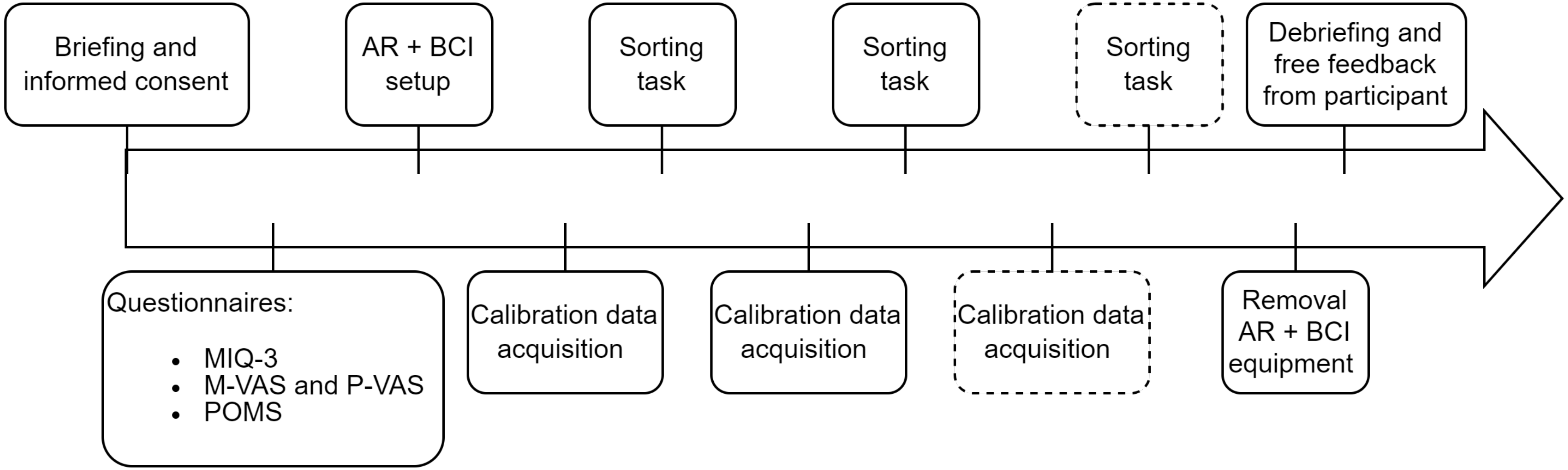
- EEG decoding: Custom Python software
- AR user interface: Unity 3D + mixed reality toolkit
- EEG acquisition: lab streaming layer
- Communication between software components: ZeroMQ

Sample size calculations

Study Power

- Phase 1: Not relevant. Validation in more than one individual
- Phase 2: Pilot study with no statistical validation.
  5 was chosen to balance time efficiency and assessment thoroughness
- Phase 3: Power for 20 participants (original goal)
  - 90 % confidence interval
  - 20 % margin of error
  - medium risk and fair precision
  - Formula: $N = K^2 \frac{s^2}{m^2}$, where K =1.645 (constant for 90% CI), s = standard deviation as a proportion of the mean (estimated as 0.52) and m = 0.20 (desired margin of error)

User study Phase 1 procedure: Session 1



Briefing and informed consent

AR + BCI setup

Sorting task

Sorting task

Sorting task

Debriefing and free feedback from participant

Questionnaires:

- MIQ-3
- M-VAS and P-VAS
- POMS

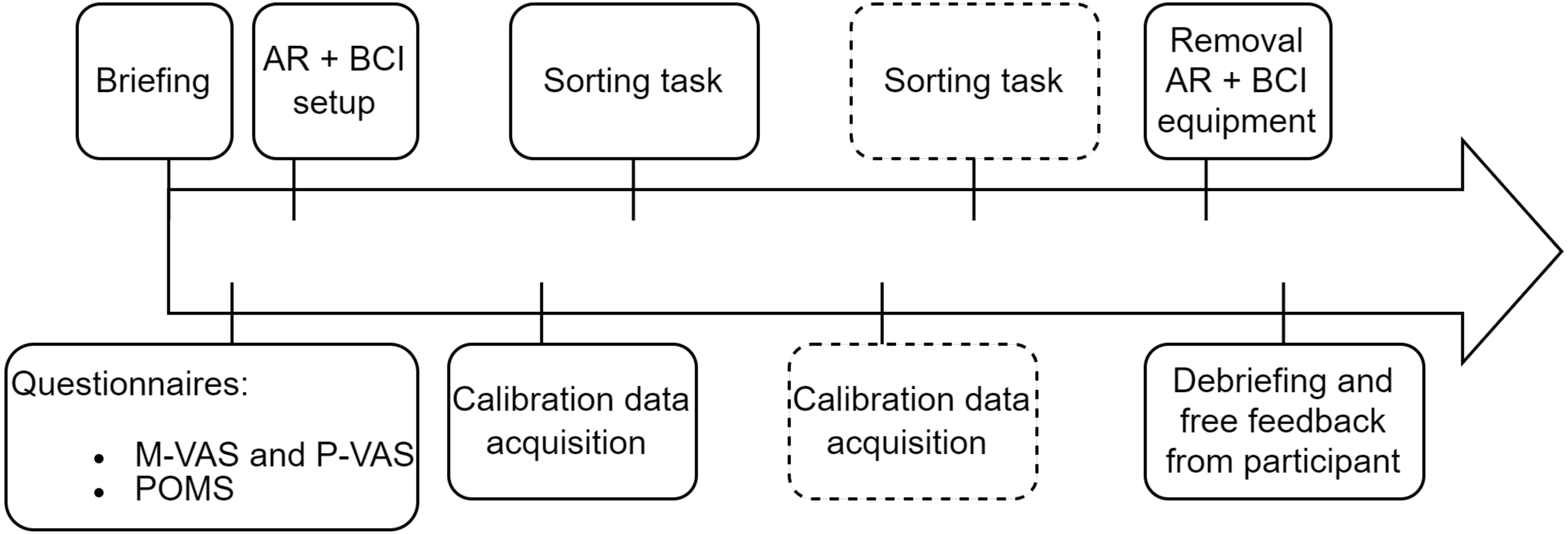
Calibration data acquisition

Calibration data acquisition

Calibration data acquisition

Removal AR + BCI equipment

User study Phase 1 procedure: Session 2



Briefing

AR + BCI setup

Sorting task

Sorting task

Removal AR + BCI equipment

Questionnaires:

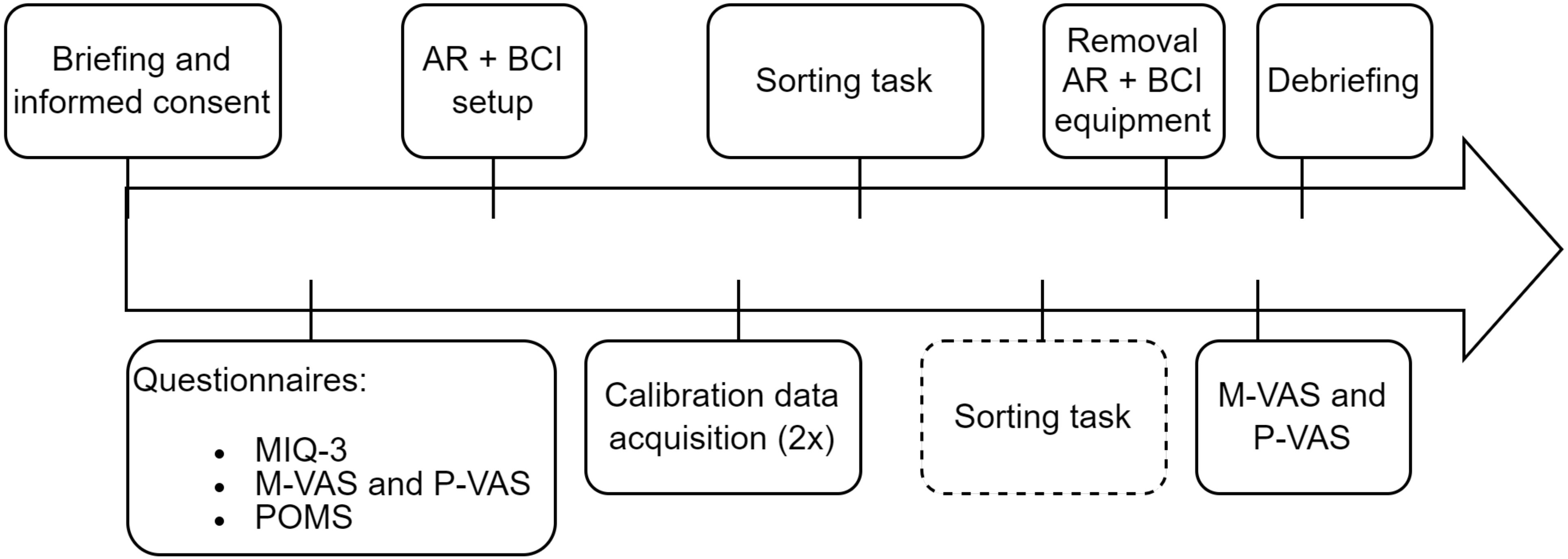
- M-VAS and P-VAS
- POMS

Calibration data acquisition

Calibration data acquisition

Debriefing and free feedback from participant

User study Phase 2 and 3 procedure: Session 1



Briefing and informed consent

Questionnaires:

- MIQ-3
- M-VAS and P-VAS
- POMS

AR + BCI setup

Calibration data acquisition (2x)

Sorting task

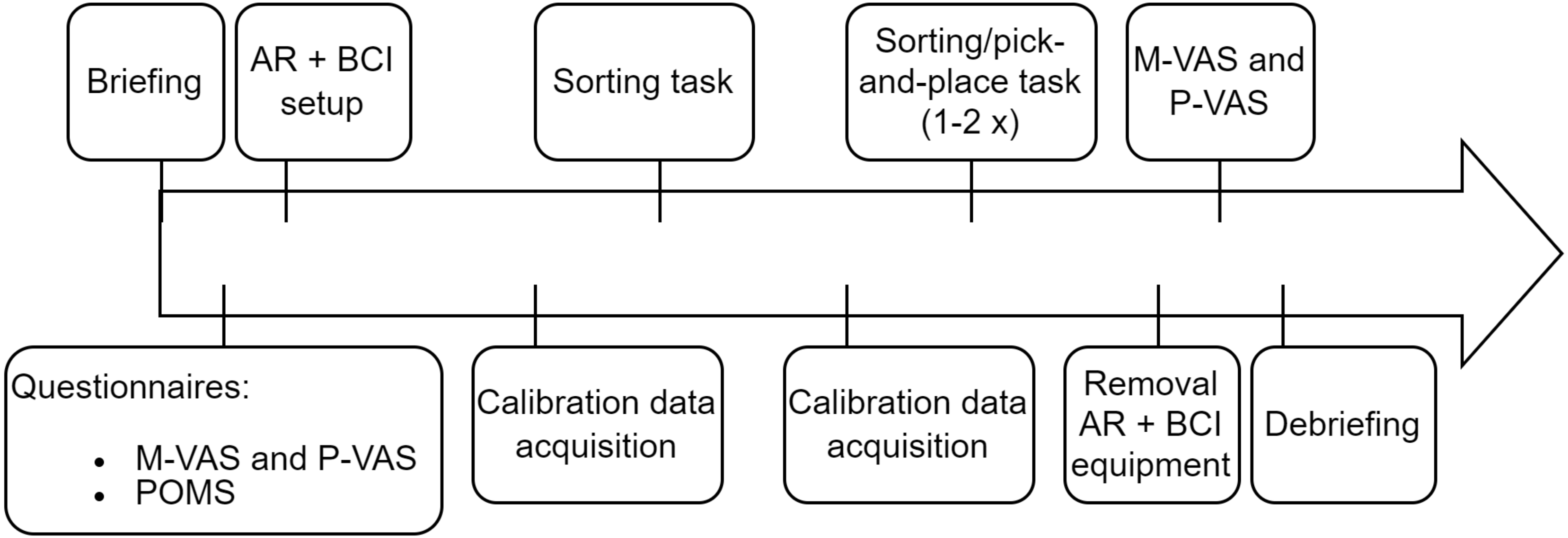
Sorting task

Removal AR + BCI equipment

M-VAS and P-VAS

Debriefing

User study Phase 2 and 3 procedure: Session 2



Briefing

AR + BCI setup

Sorting task

Sorting/pick-and-place task (1-2 x)

M-VAS and P-VAS

Questionnaires:

- M-VAS and P-VAS
- POMS

Calibration data acquisition

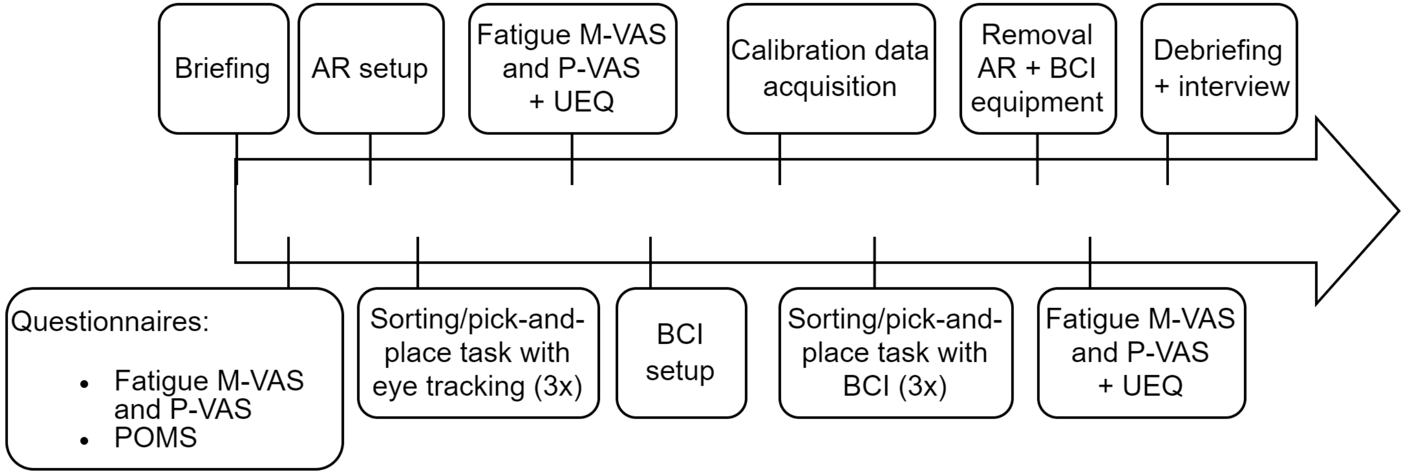
Calibration data acquisition

Removal AR + BCI equipment

Debriefing

User study Phase 2 and 3 procedure: Session 3

A



Briefing

AR setup

Fatigue M-VAS and P-VAS + UEQ

Calibration data acquisition

Removal AR + BCI equipment

Debriefing + interview

Questionnaires:

- Fatigue M-VAS and P-VAS
- POMS

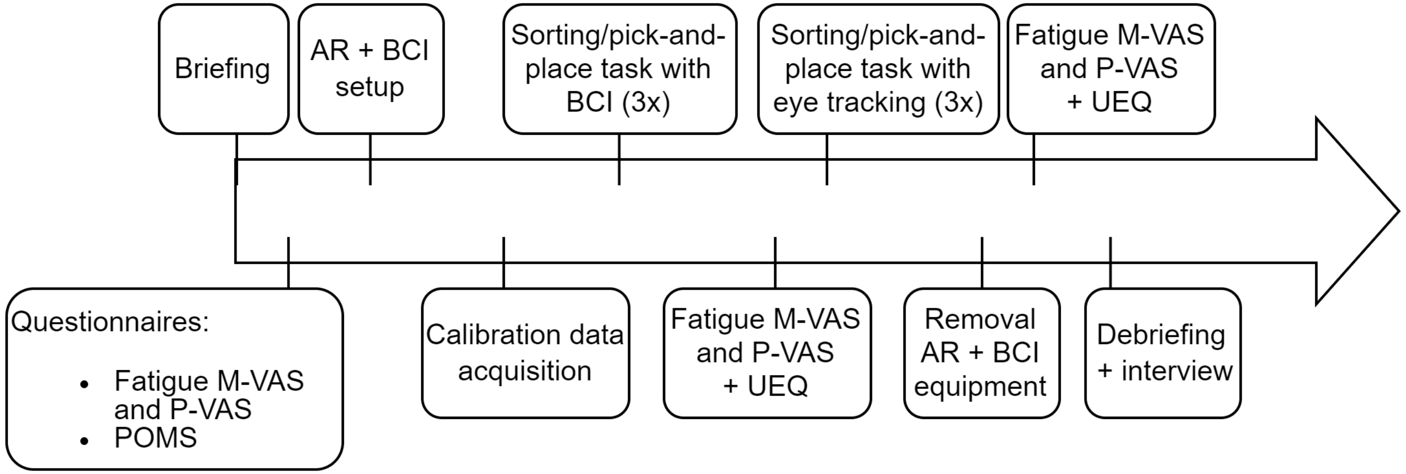
Sorting/pick-and-place task with eye tracking (3x)

BCI setup

Sorting/pick-and-place task with BCI (3x)

Fatigue M-VAS and P-VAS + UEQ

B



Briefing

AR + BCI setup

Sorting/pick-and-place task with BCI (3x)

Sorting/pick-and-place task with eye tracking (3x)

Fatigue M-VAS and P-VAS + UEQ

Questionnaires:

- Fatigue M-VAS and P-VAS
- POMS

Calibration data acquisition

Fatigue M-VAS and P-VAS + UEQ

Removal AR + BCI equipment

Debriefing + interview

User experience details

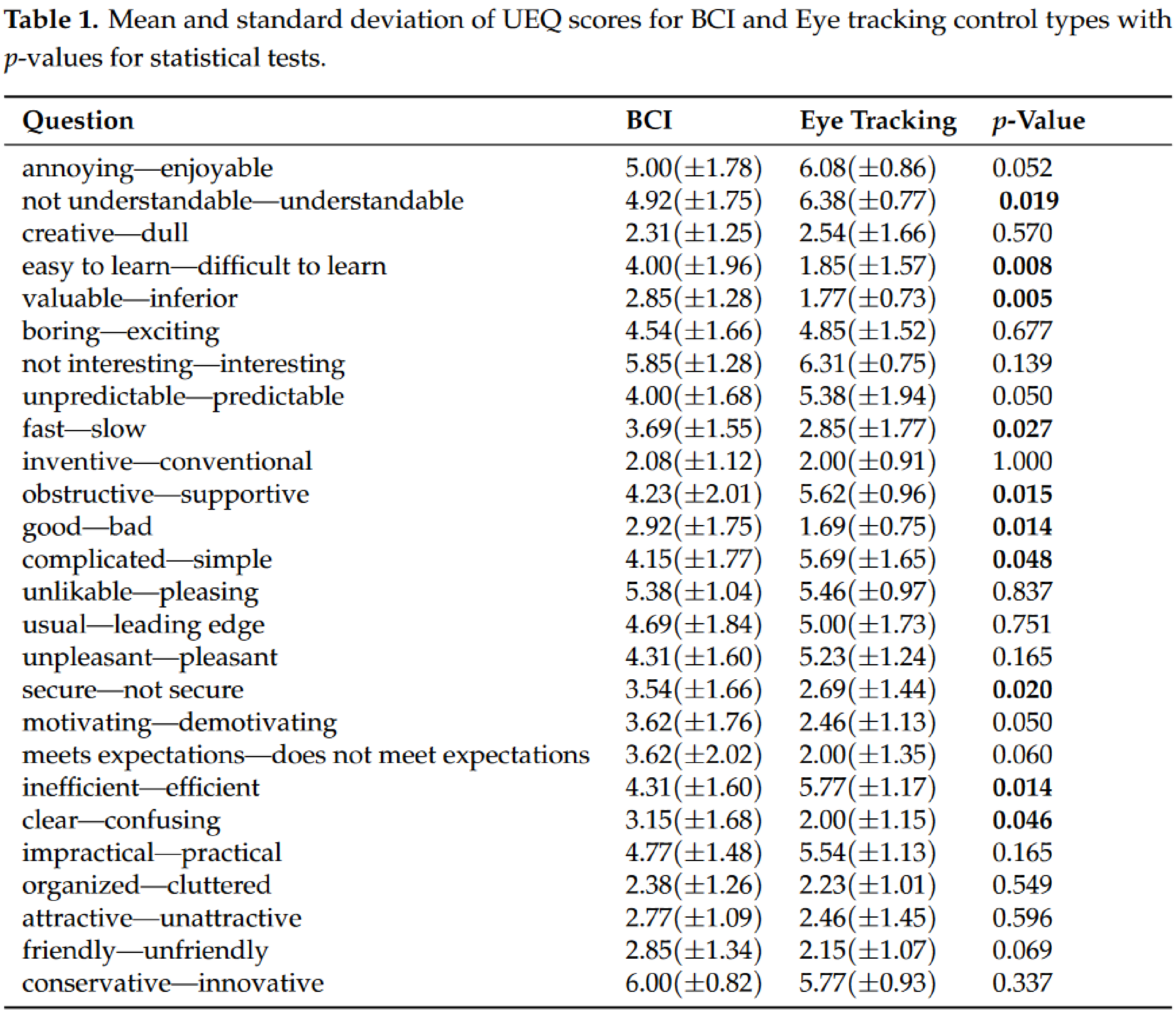


Table 1. Mean and standard deviation of UEQ scores for BCI and Eye tracking control types with p-values for statistical tests.

Question	BCI	Eye Tracking	p-Value
annoying—enjoyable	5.00(±1.78)	6.08(±0.86)	0.052
not understandable—understandable	4.92(±1.75)	6.38(±0.77)	**0.019**
creative—dull	2.31(±1.25)	2.54(±1.66)	0.570
easy to learn—difficult to learn	4.00(±1.96)	1.85(±1.57)	**0.008**
valuable—inferior	2.85(±1.28)	1.77(±0.73)	**0.005**
boring—exciting	4.54(±1.66)	4.85(±1.52)	0.677
not interesting—interesting	5.85(±1.28)	6.31(±0.75)	0.139
unpredictable—predictable	4.00(±1.68)	5.38(±1.94)	0.050
fast—slow	3.69(±1.55)	2.85(±1.77)	**0.027**
inventive—conventional	2.08(±1.12)	2.00(±0.91)	1.000
obstructive—supportive	4.23(±2.01)	5.62(±0.96)	**0.015**
good—bad	2.92(±1.75)	1.69(±0.75)	**0.014**
complicated—simple	4.15(±1.77)	5.69(±1.65)	**0.048**
unlikable—pleasing	5.38(±1.04)	5.46(±0.97)	0.837
usual—leading edge	4.69(±1.84)	5.00(±1.73)	0.751
unpleasant—pleasant	4.31(±1.60)	5.23(±1.24)	0.165
secure—not secure	3.54(±1.66)	2.69(±1.44)	**0.020**
motivating—demotivating	3.62(±1.76)	2.46(±1.13)	0.050
meets expectations—does not meet expectations	3.62(±2.02)	2.00(±1.35)	0.060
inefficient—efficient	4.31(±1.60)	5.77(±1.17)	**0.014**
clear—confusing	3.15(±1.68)	2.00(±1.15)	**0.046**
impractical—practical	4.77(±1.48)	5.54(±1.13)	0.165
organized—cluttered	2.38(±1.26)	2.23(±1.01)	0.549
attractive—unattractive	2.77(±1.09)	2.46(±1.45)	0.596
friendly—unfriendly	2.85(±1.34)	2.15(±1.07)	0.069
conservative—innovative	6.00(±0.82)	5.77(±0.93)	0.337

Comparison with state-of-the-art

Study	Evaluation tasks	Results
Ours	Sorting and pick-and-place	Success rate: 0.73 and 0.83 Avg. completion time: 490 s and 380 s
Xu et al. (2019)	Move to target area	Success rate: 0.7 Avg. completion time: 16.99 s – 25.83s
Kuhner et al. (2019)	Fetch and carry task	Success rate 0.9 Avg. completion time: 258.7 s