Beyond Workload: Paving the Road for the Next Generation of Implicit Prefrontal Cortex Based Brain-Computer Interfaces

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April 18 2025

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Motivation

- Expanding bandwidth of communication between human and machine
- Brain!
- Implicit Interfaces
- Implicit Brain-Computer Interfaces (BCIs)
  - Functional Near-Infrared Spectroscopy (fNIRS)
  - Electroencephalography (EEG)
- Prefrontal cortex (PFC)
- How can we expand the current state-of-the-art in implicit BCI using fNIRS/EEG measuring the PFC?

Contributions

- Multiple user studies focusing on lesser-explored aspects of PFC function towards real-time interfaces based on classification of more nuanced user states
- Contributions in this direction with both fNIRS and low-cost EEG
- Targeted opportunities for future work
- Analytical framework for straightforward analysis of the fNIRS signal
- Applied BCI within the context of Human-Sensor-Computer interaction

Outline

- Background (15m)
- Projects (20m)
  - Project I: two proof-of-concept fNIRS studies
    - Episodic memory for realtime fNIRS-based BCI
    - Complex decision-making during LLM use
  - Project II: Applied user study: brain-network based implicit BCI
  - Project III: Two proof-of-concept low-cost EEG studies
    - Neural correlates of chess move quality
    - Cross-task classification
- Conclusion (5m)
- Human-Sensor-Computer Interaction (HSCI) (5m)

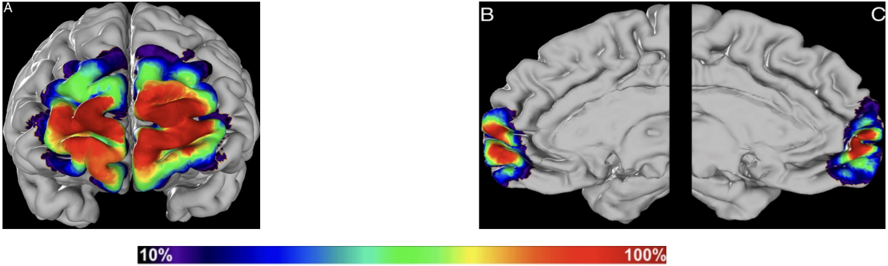
Background
Brain-In-Action

- The work in this dissertation explores the nuances of neural state differentiation in conditions stepping towards real-world applications
- Important to consider the complexities of "real-world" neurocognitive tasks
  - Differences in characteristics of the measurement devices used
    - fNIRS vs. EEG vs. fMRI, etc.
    - Differences between individual devices within a given domain (e.g. fNIRS)
  - Extracerebral noise introduced in applied tasks
    - Participant movements
    - Environmental factors
- Subtlety of neural responses during real-world tasks

Background

Prefrontal Cortex

- **“The anterior prefrontal cortex (aPFC), or Brodmann area 10, is one of the least well understood regions of the human brain.”** (Ramnani and Owen, 2004)



Cytoarchitectonic probability maps of the lateral (left image) and medial (right images) aspects of the PFC Bludau et al. (2014). Reprinted with permission from Elsevier.

Background
Lateral PFC

Lateral aspect of the PFC has been shown to activate based on a wide variety of cognitive tasks

- **Problem-solving**, **planning**, **reasoning**, **working memory**, and **cognitive flexibility** for creative processing and thinking (Bunce et al., 2011; Koechlin et al., 1999; Ramnani and Owen, 2004; Barbey et al., 2013; Bludau et al., 2014; Dietrich, 2004; Shah et al., 2013)
- **Episodic memory** tasks (Bludau et al., 2014; Gilbert et al., 2006)
  - Episodic memory: recollection of personal past experiences; characterized by a distinct sense of reliving events from one's own history (Tulving, 1989)
- In terms of networks of brain activity, lPFC activation has been known to be part of the **Task-Positive Network (TPN)**, which increases in relation to cognitive demand (Basten et al., 2013)

Background
Medial PFC

The medial aspect has been shown to activate most commonly during emotion and social cognition (Eickhoff et al., 2016)

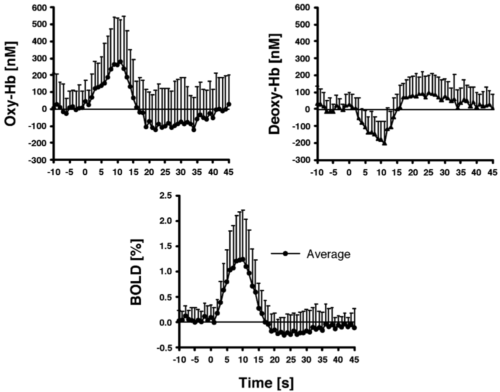
- **Social processing** (Amodio and Frith, 2006; Mitchell, 2009), **processing of uncertainty** (Bzdok et al., 2013), **social cognitive processes** related to theory of mind (Spreng and Grady, 2010; Spreng et al., 2009), **moral reasoning** (Bzdok et al., 2012), **"nonsocial" semantic processing** (Binder et al., 2009), and **autobiographical memory retrieval** (Spreng et al., 2009; Chen et al., 2017)
- In terms of networks of brain activity, mPFC activation has been known to be part of the **Default-Mode Network (DMN)** which activates during to social cognition, mind wandering, and self-referential processes such as thinking about the past or future (Akbar et al., 2022), and which deactivates during cognitive demand (Basten et al., 2013)

Background
fNIRS

- fNIRS uses diffuse optical imaging of near-infrared light to non-invasively measure changes in oxygenated Δ[HbO] and deoxygenated Δ[HbR] hemoglobin concentrations in the human brain (Fantini and Sassaroli, 2020)
- Light pulses of different wavelengths are sent through the forehead; detectors capture the amount of light which returns, and the Modified Beer-Lambert Law is used to calculate hemoglobin concentrations (Sassaroli et al., 2012)
- Although the depth of fNIRS is limited to the outer regions of the cortex, relatively shallow in comparison with fMRI, the precision of the localization of the measurement is approximately 2-3cm (Pinti et al., 2020), much higher than that of EEG (Nicolas-Alonso and Gomez-Gil, 2012)

Background

fNIRS: from blood to brain (Δ[HbD])



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- The optimal method of inferring neural activation from the metrics of Δ[HbO] and Δ[HbR] is still an open question (Kreplin and Fairclough, 2013)
- General principle is Hemodynamic response, where an increase in Δ[HbO] and decrease in Δ[HbR] is observed following neural activity
- In fMRI, the Blood-Oxygen-Level-Dependent (BOLD) signal measures magnetic perturbations in the vasculature in response to oxygen consumption associated with neural activity
- Δ[HbD]=Δ[HbO]-Δ[HbR]

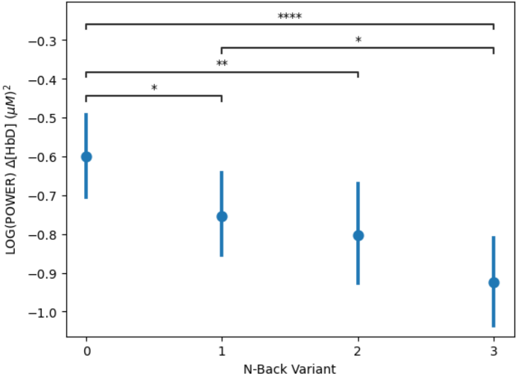
Background

fNIRS: VLF Oscillations

- Very Low Frequency (VLF) band: 0.07 Hz - 0.02 Hz [14.3 - 50 seconds]
- Previous findings:
  - Decrease in VLF band relates to task-based cortical activation
  - Observed in visual cortex (Obrig et al., 2000)
  - Observed in prefrontal cortex (Vermeij et al., 2014)
- Comprehensive understanding of the physiological mechanisms underlying this VLF correspondence to neural activity remains incomplete (Sassaroli et al., 2012)
- Prevailing theoretical basis for the physiological underpinning of these oscillations relates to cerebral autoregulation (CA), which is the body's ability to maintain consistent blood supply to the brain (Andersen et al., 2018)

Background

VLF Oscillations in Practice



- Tufts Mental Workload Dataset (Huang et al., 2021)
- 68 Participants doing N-Back
- As N-Back workload increases, corresponding decrease in VLF band-power of the left lateral PFC
- No significant differences in closest levels of N-Back outside of 0-back (1-2, 2-3)

Background
fNIRS in BCI

- Many PFC-based fNIRS studies approximate mental workload, in both **real-time tasks** (Girouard et al., 2013; Afergan et al., 2014b, 2015, 2014a; Hirshfield et al., 2011, 2009b,a) and during **offline brain state classification** (Power et al., 2010; Strait, 2014; Ayaz et al., 2012)
- Most studies train models on N-Back tasks, then apply them to modulate difficulty in separate tasks (Afergan et al., 2014b; Shibata et al., 2019; Strait, 2014; Yuksel et al., 2016; Afergan et al., 2015, 2014a)

Background

fNIRS in BCI: Applications

- Workload-based interfaces have been applied to
  - Game difficulty identification (Girouard et al., 2009)
  - Interface optimization for user state (Afergan et al., 2014b; Strait, 2014)
  - Intelligent interruption timing (Afergan et al., 2015; Shibata et al., 2019)
  - Adaptive learning environments (Yuksel et al., 2016)
  - Multitasking identification for target selection (Afergan et al., 2014a)
  - Usability testing (Hirshfield et al., 2011)
  - Operator fatigue and cognitive overload monitoring in aviation (Ayaz et al., 2012)
- Additional PFC-based fNIRS applications include
  - Consumer product preference evaluation (Luu and Chau, 2008)
  - Emotional valence during music listening (Moghimi et al., 2012)

Background

fNIRS in BCI: this work

- Notably, no fNIRS-based BCIs leveraging episodic memory
- Also, although Hincks (2019) introduced the notion of DMN/TPN-based interfaces, this is likewise underexplored in the current literature

Background
EEG

- EEG directly measures electrical activity of neuronal activation, with excellent temporal resolution (milliseconds) compared to fNIRS's hemodynamic response-based measurements (Zhang et al., 2023; Gable et al., 2022; Luck, 2014)
- EEG suffers from limited spatial resolution (Brienza and Mecarelli, 2019)
- EEG signals are commonly analyzed through rhythmic activity across multiple frequency bands (δ: 1-4 Hz, θ: 4-8 Hz, α: 8-12 Hz, β: 13-30 Hz, and γ: 30-150 Hz), which roughly correspond to distinct biological processes at the cellular level (Buzsaki, 2006; Cohen, 2014)

Background

(Low-cost) Prefrontal EEG in BCI

- Frequency-domain features of prefrontal EEG have been widely used in BCI applications to distinguish between various cognitive and emotional states, including **cognitive load** (Chikhi et al., 2022; Roy et al., 2016), **concentration vs. rest** (Kang et al., 2015), **emotional states** (Balconi et al., 2015), and **drowsiness** (Jang et al., 2013)
- Consumer-grade, low-cost EEG devices from companies like InteraXon, OpenBCI, NeuroSky, and Emotiv have emerged as viable alternatives to expensive traditional systems, offering accessibility for real-world applications despite limitations in spatial resolution and signal fidelity (Vos et al., 2025; Lee et al., 2024)
- Applications have been demonstrated in **stress detection**, **drowsiness monitoring**, **emotion classification**, and **mental workload** (Vashisht and Sharma, 2024; LaRocco et al., 2020; Girardi et al., 2017; So et al., 2017)

- Typically, EEG-based BCIs focus on leveraging a “vertical” vector of state-classification based on a single state: e.g. levels of cognitive load, negative vs. positive emotions, etc.
- The EEG work done in this dissertation attempts to abstract more subtle state-information with a low-cost EEG system
- Core hypothesis is that complex combinations of spectral features can express nuanced neurophysiological states

Background

Linear Mixed Effects Regression

Let us consider the simplest implementation of a Linear Mixed Effects Model (LMM) (Gomes, 2022)

$$Y_{ij} = \beta_0 + \sum_{k=1}^{n} \beta_k X_{ki} + \alpha_j + \epsilon_{ij} \tag{1}$$

- The LMM equation extends the original Linear Model by adding a new term α_j
- This represents a unique intercept for each level of the grouping category j
- For example, provided individual participant identification as a grouping factor, this extension explicitly models separate intercepts per participant
- Also possible to model nested random intercepts, and random slopes

Background

Machine Learning Techniques

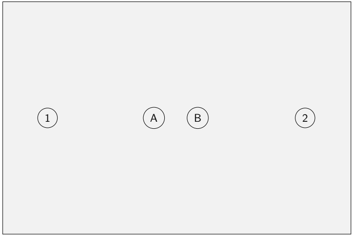
- Leave-One-Out Cross-Validation
- KNN, LDA, QDA, ANN, SVM, RF, SVM, SVM with RBF kernel
  - Default hyperparameters
- fNIRS
  - Transform 20-second windows of data
  - Mean, standard deviation, slope of linear regression, skew
  - Apply transformations individually across probe positions [e.g. L, R], wavelengths [HbO, HbR], and measurements [I, ϕ]
- EEG
  - Transform frequency domain features from 1-second windows
- Different models performed well for different people; report best scores per-person
- Metric: Macro-F1 (harmonic mean of precision and recall)

Project I
Overview

- Project I: two proof-of-concept fNIRS studies
  - Episodic memory for real-time fNIRS-based BCI
  - Complex decision-making with and without LLM use

Project I
fNIRS Device

- Two optical probes, 1 each over the L and R PFC
- Dual-slope method to remove extracerebral artifacts (Blaney et al., 2020)
- Resulting measures are [DSI, DSϕ] $\times$ [HbO, HbR] $\times$ [L, R]



(a) fNIRS probe configuration. 1/2 are the source locations, and A/B are the detectors.

Project I

Study I: Copilot for Microsoft Word

Microsoft

- Effects of using Large Language Models (LLMs) on human users
- Multiple metrics: fNIRS, Empatica E4, NASA-TLX, enjoyment, correctness
- Analyzed participant activity with and without LLM-help across multiple tasks
- Tasks were organized across a *gradient of subjectivity*
  - Highly structured and objective tasks were intended to be "easy" for the LLM
    - SAT reading comprehension
    - Event planning
  - Open-ended and subjective tasks were intended to be "difficult" for the LLM
    - Poetry writing
    - Personal reflection on favorite album/movie
- Endpoints of the gradient had basis in neural function: the subjective tasks were intended to activate default mode network and episodic memory
- Are neural states differentiable across tasks, and/or based on Copilot use?

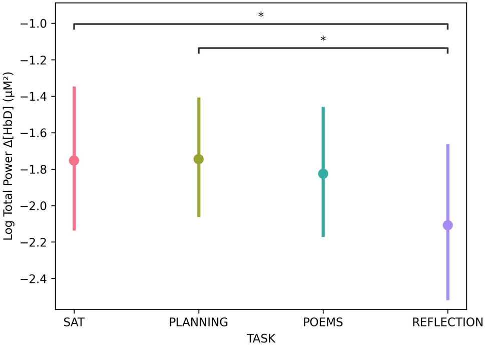
Project I

Study I: Task Paradigm

- 15 participants (20 run)
- Each participant did the four task types in randomized order
- For each task, one sub-task was done with Copilot, and the other without Copilot
- Each sub-task was 6 minutes
- Sub-tasks within each task type were equally difficult
- Following each task type, participants filled out NASA-TLX and questionnaires asking about their experience

Project I

Study I: Results



- Increase in R PFC activity in the episodic memory (REFLECTION) task as compared to the two objective tasks (SAT, PLANNING)
  - Confirms work in neuroscience literature Nolde et al. (1998); Tulving et al. (1994), but in a more applied context
- No statistical differences found in PFC activation as a consequence of Copilot use
- Machine Learning
  - REFLECTION vs. SAT (61%)
  - NO-AI REFLECTION vs. NO-AI SAT (71%)
  - AI SAT vs. NO-AI SAT (69%)

Study I: Takeaways

- Episodic memory in comparison to reading comprehension is a viable vector for real-time implicit BCI work with fNIRS using the PFC
- LLM-use effects the fNIRS signal during reading comprehension tasks such that ML methods can be used to develop real-time interfaces with the data
  - The subtlety of this effect likely requires more participants to quantify with VLF analysis

Project I

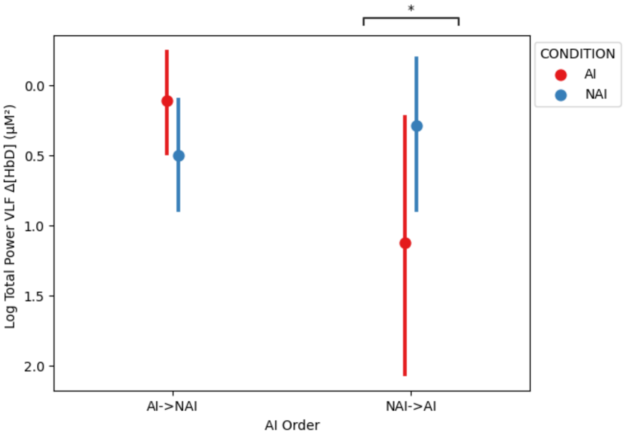
Study II: Copilot for MS365

- Similar to Study II, but with two complex decision-making tasks
- Copilot for MS365
- Metrics: fNIRS, NASA-TLX, valence-arousal, correctness
- Longer (25m) task design
- Given longer tasks, Copilot order was added as a between-subjects factor

- 30 participants (ran 37)
- Each participant performed the tasks as
  - 1-minute rest
  - 25 minute task
  - NASA-TLX and valence-arousal forms

Project I

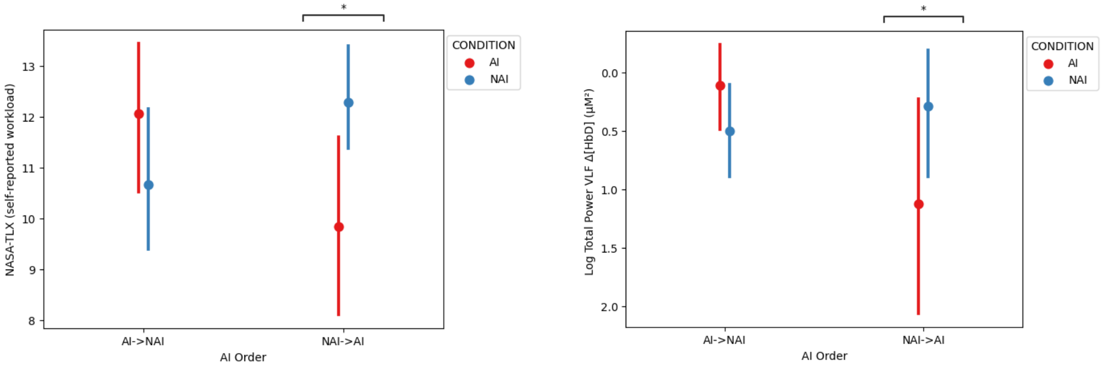
Study II Results: Neural Activity



- R PFC DSI (y-axis inverted)
- Significant interaction effect of ORDER × CONDITION
- Decrease in R PFC during Copilot task when experienced second
- Decrease in L PFC for both levels of ORDER during the second task

Project I

Study II Results: NASA-TLX and fNIRS



- Best overall model: Random Forest (50.5% F1-score)
- Best per-participant average Macro F1: 56%
- Not currently viable for realtime BCI applications, although more complex ML paradigms might help classification

Project I

Study II Results: Summary

- Decrease in L PFC during second task signifies decrease in cognitive load due to understanding task
- Decrease in R PFC when using AI tool after experiencing the task
  - Goel (2019) has posited R PFC function to interrelate with indeterminacy tolerance, specifically in the context of an information representation system
  - This may therefore relate to a relaxation of the processes which underlie hesitance to settle on inferences from knowledge representations
- Distinction in types of workload changes as reflected in the neural data highlights a key gap in the approximation capable by NASA-TLX
- Despite statistical results, applied machine learning results indicate lack of applicability towards real-time implicit BCIs

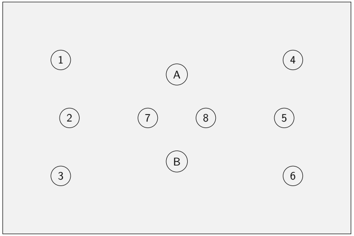
Project II

Network-Based Implicit BCI

- This study tests a prototype fNIRS-based BCI leveraging TPN/DMN brain networks
- The idea follows what is proposed by (Hincks, 2019), and does so within the limitation of measurement only from the PFC
- This study is a realtime implicit BCI which represents a first prototype implementation of the memory prosthesis introduced by (Rhodes, 1997) and (Lieberman, 1995), wherein the interface presents information moment-to-moment that is appropriate to the user.

Project II
fNIRS Device

- One optical probe over the L PFC
- Recursive Least Squares (RLS) adaptive filter used to remove extracerebral artifacts (Klein and Kranczioch, 2019)
- Resulting measures are [I] × [HbO, HbR] × [probe-detector pair]



(a) fNIRS probe configuration. A/B are the detectors; 7/8 are the short sources.

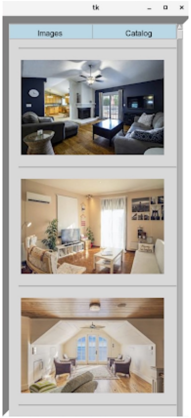
Project II
Task Design

- After prototyping with 6 participants, we recruited 8 participants for the study
- Participants were tasked with designing rooms in their home
- For each of 3 rooms, we split the task up into two phases
  - Inspiration & Visualization Phase [DMN]
  - Furniture Selection Phase [TPN]

Project II

Task Design: Inspiration & Visualization [DMN]

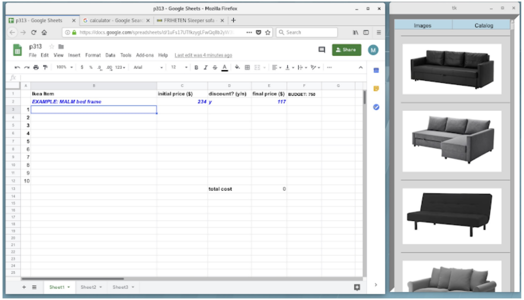
- Participants were shown a sidebar of images
- Clicking on an image would magnify it
- Participants were instructed to consider ideas based on their preferences
- Intended to activate DMN in comparison to Furniture Selection task



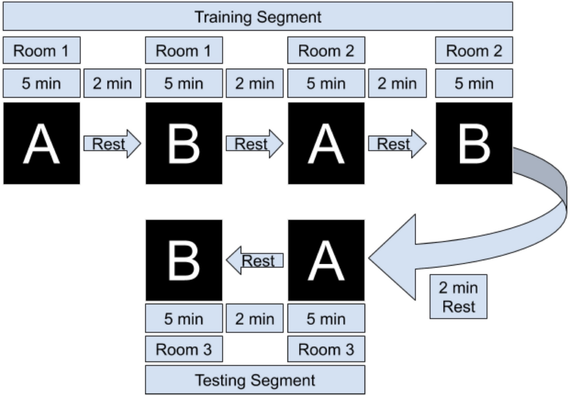
Project II

Task Design: Furniture Selection Phase [TPN]

- Participants were given a spreadsheet and a sidebar with furniture items from the IKEA store
- Clicking any item opens a link in the browser to the IKEA website with prices and more information
- They were to keep track of costs
- Goal: keep total item selection under a given budget
- Intended to activate TPN in comparison to Inspiration task



Project II
Task Design: Task Structure

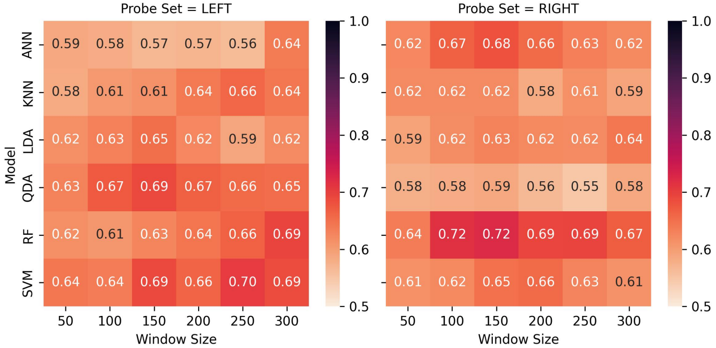


Project II
Analysis

We tried a few things different from the previous work

- The analytical framework was adapted to also explore classification within the contexts of only the lateral or medial probes of the fNIRS
- We tried multiple window lengths for classification
- Performed inner hyperparameter tuning loop during LOO-CV

Project II
Results I



Increases in performance are seen for RF at lower window sizes for the right probes, whereas SVM performed best using the left probes' data at higher window sizes

Project II
Results II

- Different locations respond better to different classifiers & window sizes
- Best result per participant, probe set, window size, and model averages to 84%
- Despite the promising ML results, no significant trends visible in the VLF analysis
- More work should be done in developing meta-classification approaches, and/or in running similar studies with DMN/TPN-based classification using larger numbers of participants

Project III

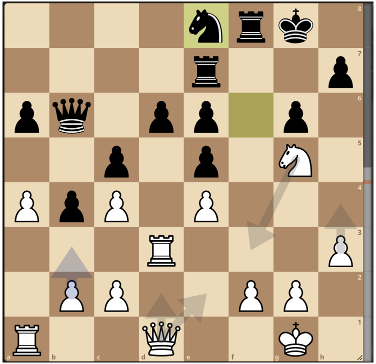
Project III: Two proof-of-concept low-cost EEG studies

- Neural correlates of chess move quality
- Cross-task classification

Project III

Study I: Neural correlates of chess move quality

- Can we distinguish between subtle aspect of human state in applied contexts?
- Can we do this with a low-cost and low-sensor count EEG system?



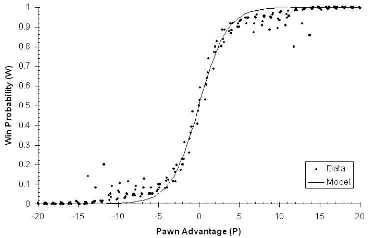
Project III

Study I: Background

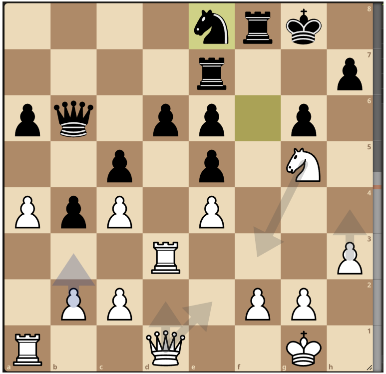
What makes a "good" move?

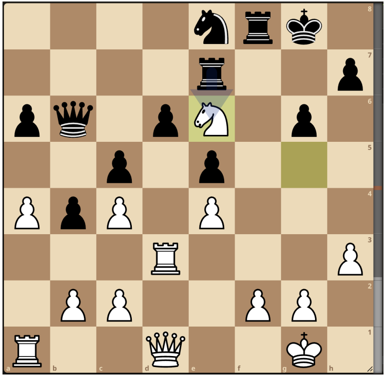
$$W = \frac{1}{1 + 10^{\frac{-p}{4}}} \qquad (2)$$

Logistic function defining probability of winning the game W as a function of pawn advantage p (Biswas and Regan, 2015)



Graph demonstrating the relation between p and W with emperical datapoints added (Chess Programming Wiki, 2025)





A poor move made by White. Pawn advantage p moves from .2 to -2. Thus, $W_{\text{initial}} = 0.53$, and $W_{\text{after}} = 0.24$. Move score is thus $.24 - .53 = -0.29$.

- 13 participants (17 run)
- Participants played 5, 5 minute games against a computer opponent
- They selected the difficulty rating (1-8), and could adjust it by 1 after each game
- We used the Mind Monitor application to extract frequency domain data

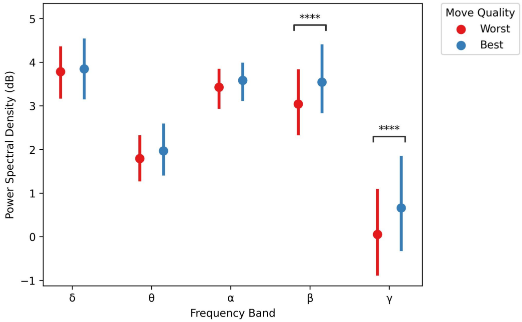
Project III

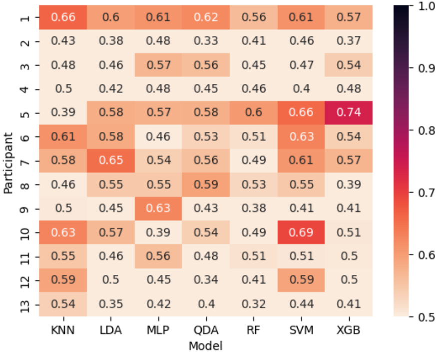
Data Preprocessing

- For each participant
  - Split their data into three tertiles, based on move quality
  - Keep BEST and WORST, drop MIDDLE
- Results in 694 total moves, 347 per class
- Average L and R data to increase signal-to-noise ratio

Project III

Study I: Results





Average of best-scores is 60%.

Project III
Study II

- Can we distinguish between subtle aspects of human state in applied contexts?
- This study explores this idea within the context of multiple standard cognitive psychology tasks, as well as an ecological chess puzzles task

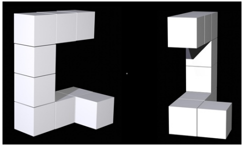
Project III

Study II: Tasks and Study Design

frontiers in Human Neuroscience

- 9 participants for this sub-study (30 total)
- Participants did multiple blocks of each task type

Stroop task - participant would press ‘b’



Rotation task - participant would press ‘n’

- N-Back (working memory)
- Stroop (cognitive inhibition)
- Mental Rotation (spatial reasoning)
- Chess puzzles (complex combination)

Project III

Study II: Preprocessing

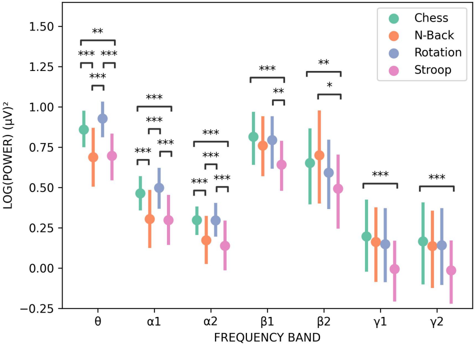
- Raw data were collected with Muse-JS
- For each participant
  - 60Hz notch filter to remove electrical noise
  - Bandpass filter [.1, 45]Hz
  - AutoReject algorithm (Jas et al., 2017) used on rest data
  - Artifact Subspace Reconstruction (Chang et al., 2018) trained on resting data and applied to task data
- Data epoched to 1s samples
- Epochs containing values outside the range [-100 μV, 100 μV] were excluded
- Frequency domain transformation
- Integrate over standard EEG bands to extract total power
- Log transform

Project III

Study II: ML

- Because of differing sample sizes across tasks and participants, performed grouped and sub-sampled Monte Carlo ML procedure
- Each Monte Carlo iteration had evenly balanced training and testing samples both within and across participants
- Grouping based on task block meant that all participants were represented in training and testing data, but temporally autocorrelated samples were not present in both
- Performed 1k MC iterations; width of the 95% confidence interval converged to less than 1%

frontiers in Human Neuroscience



Task	Precision	Recall	F1	Support
Chess	0.552	0.460	0.499	195
N-Back	0.485	0.425	0.452	195
Rotation	0.493	0.580	0.531	195
Stroop	0.474	0.519	0.494	195
Macro Average	0.501	0.496	0.494	780

With 25% baseline classification accuracy, average is 50%. These results indicate very promising ability to distinguish across classes in real time scenarios.

Conclusion

- This dissertation has been a breadth-first exploration of classification of more subtle neural states based on electrical and hemodynamic activity measured in the PFC
- fNIRS-based results indicate that episodic memory and DMN/TPN-based interfaces are viable areas for future real-time implicit BCI
- Low-cost EEG results indicate that subtle state classification both within the context of chess move quality and across tasks targeting different aspects of human state are possible
- Side quest reinforcing VLF oscillations as a correlate of neural activation

Human-Sensor-Computer Interaction

- Neural data is *noisy*, especially in applied contexts
- Primary sources of "noise" are from physiological artifacts
- What if some of this "noise" is useful towards human-state classification?
- We should work harder to
  - Quantify the utility of sources of extracerebral activity (e.g. eye blinks in EEG, extracerebral hemodynamics in fNIRS)
  - Embrace the use of such extracerebral activity for HCI
- Philosophical shifts
  - Take each sensor "at face value": EEG measures electrical activity, fNIRS measures light, etc.
  - Consider self-report and other information as valid "sensors"
- All of these ideas in combination point to a broader umbrella of study: Human-Sensor-Computer Interaction

Thank you!

Bibliography I

Afergan, D., Hincks, S. W., Shibata, T. and Jacob, R. J. (2015), Phylter: A system for modulating notifications in wearables using physiological sensing, *in* 'International Conference on Augmented Cognition', Springer, Springer International Publishing, pp. 167–177.

Afergan, D., Peck, E. M., Solovey, E. T., Jenkins, A., Hincks, S. W., Brown, E. T., Chang, R. and Jacob, R. J. (2014b), Dynamic difficulty using the brain metrics of workload, *in* 'Proceedings of the SIGCHI Conference on Human Factors in Computing Systems', CHI '14, ACM, New York, NY, USA, pp. 3797–3806.

Afergan, D., Shibata, T., Hincks, S. W., Peck, E. M., Yuksel, B. F., Chang, R. and Jacob, R. J. (2014a), Brain-based target expansion, *in* 'Proceedings of the 27th annual ACM symposium on User interface software and technology', UIST '14, ACM, ACM, pp. 583–593.

Akbar, S. A., Mattfeld, A. T., Laird, A. R. and McMakin, D. L. (2022), 'Sleep to internalizing pathway in young adolescents (sipya): A proposed neurodevelopmental model', *Neuroscience & Biobehavioral Reviews* **140**, 104780.

Amodio, D. M. and Frith, C. D. (2006), 'Meeting of minds: The medial frontal cortex and social cognition', *Nature Reviews Neuroscience* **7**(4), 268.

Andersen, A. V., Simonsen, S. A., Schytz, H. W. and Iversen, H. K. (2018), 'Assessing low-frequency oscillations in cerebrovascular diseases and related conditions with near-infrared spectroscopy: A plausible method for evaluating cerebral autoregulation?', *Neurophotonics* **5**(03), 1.

Bibliography II

Ayaz, H., Shewokis, P. A., Bunce, S., Izzetoglu, K., Willems, B. and Onaral, B. (2012), 'Optical brain monitoring for operator training and mental workload assessment', *NeuroImage* **59**(1), 36–47.
URL: *http://www.ncbi.nlm.nih.gov/pubmed/21722738*

Balconi, M., Grippa, E. and Vanutelli, M. E. (2015), 'What hemodynamic (fNIRS), electrophysiological (EEG) and autonomic integrated measures can tell us about emotional processing', *Brain and Cognition* **95**, 67–76.

Barbey, A. K., Koenigs, M. and Grafman, J. (2013), 'Dorsolateral prefrontal contributions to human working memory', *Cortex* **49**(5), 1195–1205.

Basten, U., Stelzel, C. and Fiebach, C. J. (2013), 'Intelligence is differentially related to neural effort in the task-positive and the task-negative brain network', *Intelligence* **41**(5), 517–528.

Binder, J. R., Desai, R. H., Graves, W. W. and Conant, L. L. (2009), 'Where is the semantic system? a critical review and meta-analysis of 120 functional neuroimaging studies', *Cerebral Cortex* **19**(12), 2767–2796.

Biswas, T. and Regan, K. (2015), Measuring level-k reasoning, satisficing, and human error in game-play data, *in* '2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)', IEEE, IEEE, pp. 941–947.

Bibliography III

Blaney, G., Sassaroli, A., Pham, T., Fernandez, C. and Fantini, S. (2020), 'Phase dual-slopes in frequency-domain near-infrared spectroscopy for enhanced sensitivity to brain tissue: First applications to human subjects', *Journal of biophotonics* **13**(1), e201960018.

Bludau, S., Eickhoff, S. B., Mohlberg, H., Caspers, S., Laird, A. R., Fox, P. T., Schleicher, A., Zilles, K. and Amunts, K. (2014), 'Cytoarchitecture, probability maps and functions of the human frontal pole', *NeuroImage* **93**, 16.

Brienza, M. and Mecarelli, O. (2019), 'Neurophysiological basis of eeg', *Clinical electroencephalography* pp. 9–21.

Bunce, S. C., Izzetoglu, K., Ayaz, H., Shewokis, P., Izzetoglu, M., Pourrezaei, K. and Onaral, B. (2011), Implementation of fNIRS for Monitoring Levels of Expertise and Mental Workload, *in* D. D. Schmorrow and C. M. Fidopiastis, eds, 'Foundations of Augmented Cognition. Directing the Future of Adaptive Systems', Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 13–22.

Buzsaki, G. (2006), *Rhythms of the Brain*, Oxford university press.

Bzdok, D., Langner, R., Schilbach, L., Engemann, D. A., Laird, A. R., Fox, P. T. and Eickhoff, S. B. (2013), 'Segregation of the human medial prefrontal cortex in social cognition', *Frontiers in Human Neuroscience* **7**, 232.

Bibliography IV

Bzdok, D., Schilbach, L., Vogeley, K., Schneider, K., Laird, A. R., Langner, R. and Eickhoff, S. B. (2012), 'Parsing the neural correlates of moral cognition: Ale meta-analysis on morality, theory of mind, and empathy', *Brain Structure and Function* **217**(4), 783–796.

Chang, C.-Y., Hsu, S.-H., Pion-Tonachini, L. and Jung, T.-P. (2018), Evaluation of artifact subspace reconstruction for automatic EEG artifact removal, *in* 'Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)', IEEE, pp. 1242–1245.

Chen, H.-Y., Gilmore, A. W., Nelson, S. M. and McDermott, K. B. (2017), 'Are there multiple kinds of episodic memory? an fmri investigation comparing autobiographical and recognition memory tasks', *Journal of Neuroscience* **37**(10), 2764–2775.

Chess Programming Wiki (2025), 'Wp2pa.png', `https://www.chessprogramming.org/File:Wp2pa.PNG`. Licensed under CC BY 3.0.

Chikhi, S., Matton, N. and Blanchet, S. (2022), 'Eeg power spectral measures of cognitive workload: A meta-analysis', *Psychophysiology* **59**(6), e14009.

Cohen, M. (2014), *Analyzing Neural Time Series Data: Theory and Practice*, The MIT Press.

Dietrich, A. (2004), 'The cognitive neuroscience of creativity', *Psychonomic Bulletin & Review* **11**(6), 1011–1026.

Bibliography V

Eickhoff, S. B., Laird, A. R., Fox, P. T., Bzdok, D. and Hensel, L. (2016), 'Functional segregation of the human dorsomedial prefrontal cortex', *Cerebral Cortex* **26**(1), 304–321.

Fantini, S. and Sassaroli, A. (2020), 'Frequency-domain techniques for cerebral and functional near-infrared spectroscopy', *Frontiers in neuroscience* **14**, 519087.

Gable, P. A., Miller, M. W. and Bernat, E. M. (2022), Introduction: Methods for collecting EEG data for frequency analyses in humans, *in* 'The Oxford Handbook of EEG Frequency', Oxford University Press, pp. 3–14.

Gilbert, S. J., Spengler, S., Simons, J. S., Steele, J. D., Lawrie, S. M., Frith, C. D. and Burgess, P. W. (2006), 'Functional specialization within rostral prefrontal cortex (area 10): A meta-analysis', *Journal of Cognitive Neuroscience* **18**(6), 932–948.

Girardi, D., Lanubile, F. and Novielli, N. (2017), Emotion detection using noninvasive low cost sensors, *in* '2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)', IEEE, IEEE, pp. 125–130.

Girouard, A., Solovey, E. T., Hirshfield, L. M., Chauncey, K., Sassaroli, A., Fantini, S. and Jacob, R. J. K. (2009), *Distinguishing Difficulty Levels with Non-invasive Brain Activity Measurements*, Springer Berlin Heidelberg, pp. 440–452.

Bibliography VI

Girouard, A., Solovey, E. T. and Jacob, R. J. (2013), 'Designing a passive brain computer interface using real time classification of functional near-infrared spectroscopy', *International Journal of Autonomous and Adaptive Communications Systems* **6**(1), 26.

Goel, V. (2019), *Hemispheric asymmetry in the prefrontal cortex for complex cognition*, Elsevier, pp. 179–196.

Gomes, D. G. (2022), 'Should i use fixed effects or random effects when i have fewer than five levels of a grouping factor in a mixed-effects model?', *PeerJ* **10**, e12794.

Hincks, S. W. (2019), A Physical Paradigm for Bidirectional Brain-Computer Interfaces, PhD thesis, Tufts University.
URL: *https://tufts.primo.exlibrisgroup.com/permalink/01TUN_INST/1kc9gia/alma991018876990203851*

Hirshfield, L., Chauncey, K., Gulotta, R., Girouard, A., Solovey, E., Jacob, R., Sassaroli, A. and Fantini, S. (2009a), Combining electroencephalograph and near infrared spectroscopy to explore users' instantaneous and continuous mental workload states, *in* 'HCI International', Vol. 2009, Springer Berlin Heidelberg, pp. 239–247.

Hirshfield, L. M., Gulotta, R., Hirshfield, S., Hincks, S., Russell, M., Ward, R., Williams, T. and Jacob, R. (2011), This is your brain on interfaces: Enhancing usability testing with functional near-infrared spectroscopy, *in* 'Proceedings of the SIGCHI Conference on Human Factors in Computing Systems', CHI '11, ACM, ACM, pp. 373–382.

Bibliography VII

Hirshfield, L. M., Solovey, E. T., Girouard, A., Kebinger, J., Jacob, R. J., Sassaroli, A. and Fantini, S. (2009b), Brain measurement for usability testing and adaptive interfaces: An example of uncovering syntactic workload with functional near infrared spectroscopy, *in* 'Proceedings of the SIGCHI Conference on Human Factors in Computing Systems', CHI '09, ACM, ACM, pp. 2185–2194.

Huang, Z., Wang, L., Blaney, G., Slaughter, C., McKeon, D., Zhou, Z., Jacob, R. and Hughes, M. C. (2021), The tufts fNIRS mental workload dataset & benchmark for brain-computer interfaces that generalize, *in* 'Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track'.
URL: *https://openreview.net/pdf?id=QzNHE7QHhut*

Jang, Y.-S., Lee, S.-L. and Ryu, S.-A. (2013), 'Characteristics of frequency band on EEG signal causing human drowsiness', *The Journal of the Korea institute of electronic communication sciences* **8**(6), 949–954.

Jas, M., Engemann, D. A., Bekhti, Y., Raimondo, F. and Gramfort, A. (2017), 'Autoreject: Automated artifact rejection for MEG and EEG data', *NeuroImage* **159**, 417–429.
URL: *https://www.sciencedirect.com/science/article/pii/S1053811917305013*

Kang, J.-S., Ojha, A. and Lee, M. (2015), Concentration monitoring with high accuracy but low cost EEG device, *in* 'Neural Information Processing: 22nd International Conference, ICONIP 2015, November 9-12, 2015, Proceedings, Part IV 22', Springer, Springer International Publishing, pp. 54–60.

Bibliography VIII

Klein, F. and Kranczioch, C. (2019), 'Signal processing in fnirs: A case for the removal of systemic activity for single trial data', *Frontiers in Human Neuroscience* **13**, 331.

Koechlin, E., Basso, G., Pietrini, P., Panzer, S. and Grafman, J. (1999), 'The role of the anterior prefrontal cortex in human cognition', *Nature* **399**(6732), 148–151.

Kreplin, U. and Fairclough, S. H. (2013), 'Activation of the rostromedial prefrontal cortex during the experience of positive emotion in the context of esthetic experience. an fNIRS study', *Frontiers in Human Neuroscience* **7**, 879.

LaRocco, J., Le, M. D. and Paeng, D.-G. (2020), 'A systemic review of available low-cost eeg headsets used for drowsiness detection', *Frontiers in Neuroinformatics* **14**.

Lee, S., Kim, M. and Ahn, M. (2024), 'Evaluation of consumer-grade wireless EEG systems for brain-computer interface applications', *Biomedical Engineering Letters* **14**(6), 1433–1443.

Lieberman, H. (1995), Letizia: An agent that assists web browsing, *in* C. S. Mellish, ed., 'Proceedings of the 14th International Joint Conference on Artificial Intelligence - Volume 1', IJCAI'95, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp. 924–929.

Luck, S. J. (2014), *An Introduction to the Event-Related Potential Technique*, A Bradford Book Ser., 2nd ed. edn, MIT Press, Cambridge, Mass. [u.a.].

Bibliography IX

Luu, S. and Chau, T. (2008), 'Decoding subjective preference from single-trial near-infrared spectroscopy signals', *Journal of Neural Engineering* **6**(1), 016003.

Mitchell, J. P. (2009), 'Social psychology as a natural kind', *Trends in Cognitive Sciences* **13**(6), 246–251.

Moghimi, S., Kushki, A., Power, S., Guerguerian, A. M. and Chau, T. (2012), 'Automatic detection of a prefrontal cortical response to emotionally rated music using multi-channel near-infrared spectroscopy', *Journal of Neural Engineering* **9**(2), 026022.

Nicolas-Alonso, L. F. and Gomez-Gil, J. (2012), 'Brain computer interfaces, a review', *Sensors* **12**(2), 1211–1279.

Nolde, S. F., Johnson, M. K. and Raye, C. L. (1998), 'The role of prefrontal cortex during tests of episodic memory', *Trends in Cognitive Sciences* **2**(10), 399–406.

Obrig, H., Neufang, M., Wenzel, R., Kohl, M., Steinbrink, J., Einhäupl, K. and Villringer, A. (2000), 'Spontaneous low frequency oscillations of cerebral hemodynamics and metabolism in human adults', *NeuroImage* **12**(6), 623–639.

Pinti, P., Tachtsidis, I., Hamilton, A., Hirsch, J., Aichelburg, C., Gilbert, S. and Burgess, P. W. (2020), 'The present and future use of functional near-infrared spectroscopy (fNIRS) for cognitive neuroscience', *Annals of the New York Academy of Sciences* **1464**(1), 5–29.

Bibliography X

Power, S. D., Falk, T. H. and Chau, T. (2010), 'Classification of prefrontal activity due to mental arithmetic and music imagery using hidden markov models and frequency domain near-infrared spectroscopy', *Journal of Neural Engineering* **7**(2), 026002.

Ramnani, N. and Owen, A. M. (2004), 'Anterior prefrontal cortex: Insights into function from anatomy and neuroimaging', *Nature Reviews Neuroscience* **5**(3), 184–194.

Rhodes, B. J. (1997), 'The wearable remembrance agent: A system for augmented memory', *Personal Technologies* **1**(4), 218–224.

Roy, R. N., Charbonnier, S., Campagne, A. and Bonnet, S. (2016), 'Efficient mental workload estimation using task-independent EEG features', *Journal of Neural Engineering* **13**(2), 026019.

Sassaroli, A., Pierro, M., Bergethon, P. R. and Fantini, S. (2012), 'Low-frequency spontaneous oscillations of cerebral hemodynamics investigated with near-infrared spectroscopy: A review', *IEEE Journal of Selected Topics in Quantum Electronics* **18**(4), 1478–1492.

Schroeter, M. L., Kupka, T., Mildner, T., Uludağ, K. and von Cramon, D. Y. (2006), 'Investigating the post-stimulus undershoot of the bold signal—a simultaneous fMRI and fNIRS study', *NeuroImage* **30**(2), 349–358.

Bibliography XI

Shah, C., Erhard, K., Ortheil, H.-J., Kaza, E., Kessler, C. and Lotze, M. (2013), 'Neural correlates of creative writing: An fmri study', *Human Brain Mapping* **34**(5), 1088–1101.

Shibata, T., Borisenko, A., Hakone, A., August, T., Deligiannidis, L., Yu, C., Russell, M., Olwal, A. and Jacob, R. J. (2019), An implicit dialogue injection system for interruption management, *in* 'Proceedings of the 10th Augmented Human International Conference 2019', AH2019, ACM, New York, NY, USA, pp. 1–9.

So, W. K. Y., Wong, S. W. H., Mak, J. N. and Chan, R. H. M. (2017), 'An evaluation of mental workload with frontal EEG', *PLoS One* **12**(4), e0174949.

Spreng, R. N. and Grady, C. L. (2010), 'Patterns of brain activity supporting autobiographical memory, prospection, and theory of mind, and their relationship to the default mode network', *Journal of Cognitive Neuroscience* **22**(6), 1112–1123.

Spreng, R. N., Mar, R. A. and Kim, A. S. N. (2009), 'The common neural basis of autobiographical memory, prospection, navigation, theory of mind, and the default mode: A quantitative meta-analysis', *Journal of Cognitive Neuroscience* **21**(3), 489–510.

Strait, M, M. S. (2014), 'What we can and cannot (yet) do with functional near-infrared spectroscopy', *Frontiers in Neuroscience* **8**.

Bibliography XII

Tulving, E. (1989), 'Memory: Performance, knowledge, and experience', *European Journal of Cognitive Psychology* **1**(1), 3–26.

Tulving, E., Kapur, S., Craik, F., Moscovitch, M. and Houle, S. (1994), 'Hemispheric encoding/retrieval asymmetry in episodic memory: Positron emission tomography findings.', *Proceedings of the National Academy of Sciences* **91**(6), 2016–2020.

Vashisht, S. and Sharma, B. (2024), A comparative analysis of neurosky and emotiv EEG systems for brain-computer interface applications, *in* '2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI)', IEEE, IEEE, pp. 1113–1118.

Vermeij, A., Meel-van den Abeelen, A. S., Kessels, R. P., van Beek, A. H. and Claassen, J. A. (2014), 'Very-low-frequency oscillations of cerebral hemodynamics and blood pressure are affected by aging and cognitive load', *NeuroImage* **85**, 608–615.

Vos, G., Ebrahimpour, M., van Eijk, L., Sarnyai, Z. and Rahimi Azghadi, M. (2025), 'Stress monitoring using low-cost electroencephalogram devices: A systematic literature review', *International Journal of Medical Informatics* **198**, 105859.

Bibliography XIII

Yuksel, B., Oleson, K. B., Harrison, L., Peck, E. M., Afergan, D., Chang, R. and Jacob, R. J. (2016), Learn piano with bach: An adaptive learning interface that adjusts task difficulty based on brain state, *in* 'Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems', CHI '16, ACM, New York, NY, USA, pp. 5372–5384.

Zhang, H., Zhou, Q.-Q., Chen, H., Hu, X.-Q., Li, W.-G., Bai, Y., Han, J.-X., Wang, Y., Liang, Z.-H., Chen, D. et al. (2023), 'The applied principles of eeg analysis methods in neuroscience and clinical neurology', *Military Medical Research* **10**(1), 67.