

Neural correlates from the middle temporal gyrus via machine learning decode decision making variables during gambling in humans

Daniel Wang¹, Sridevi V. Sarma¹, Aaron L. Sampson², Veit Stuphorn², Ernst Niebur², Pierre Sacré³, Jorge González-Martínez⁴, and Daniel B. Dorman⁵

Abstract—The ability to make good decisions is contingent upon extracting the most relevant information from one's contextual surroundings. The middle temporal gyrus lies at the nexus of visual processing streams and is hypothesized to play a crucial role in the semantic processing of visual information. In this study, stereoelectroencephalography measurements from the middle temporal gyrus were used to train random forest classifiers to decode betting behavior in a financial-decision making task for 10 subjects. Spectral features from the middle temporal gyrus were computed. The performance of these subject-specific classifiers ranged between 75% and 98% accuracy when predicting human betting behavior and provide evidence that the middle temporal gyrus encodes information related to decision-making. This study is the first to use stereoelectroencephalography to explore the functionality of the middle temporal gyrus in decision-making.

Index Terms—machine learning, neural data, decision-making, middle temporal gyrus

I. INTRODUCTION

Every decision starts with information [1]. In a gambling game, we bet more money if we perceive high odds of winning, and less money if we perceive low odds of winning. Understanding how higher order cognition transforms sensory input to motor output remains a challenging problem in neuroscience. Identifying the neural correlates associated with cognition may unveil details on where such processes may occur in the brain.

The middle temporal gyrus (MTG) has been implicated in semantic processing and is surrounded by the ventral visual pathway, which is primarily responsible for high-level visual processing [1] [2] [3] [4] [5]. Previous work has studied the role of the MTG processing semantic information for goal-oriented cognition [6] [7] [8] [9], and identified a positive correlation in MTG activity with gambling urges among men with pathological gambling and individuals with internet gaming disorder [10] [11]. Researchers using both fMRI and scalp EEG have localized the MTG as a principal location for chosen value signals that emerged after subjects make their decisions [8]. However, fMRI is known to have poor

temporal resolution, which is disadvantageous to studying decision-making, a process that happens on a tens to hundreds of millisecond scale [12]. EEG has good temporal resolution, but poor spatial resolution, as it becomes difficult to localize the sources of neural activity with high precision from scalp measurements [13].

However, no study has used stereoelectroencephalography (sEEG) to investigate the MTG's role in decision making. sEEG allows capturing signals related to local field potentials at the source (MTG) at high temporal resolution (2KHz), offering both high temporal and spatial resolution [14]. Our study uses sEEG data to identify neural correlates of the MTG in a financial decision-making task performed by 10 subjects [15] [16] [17] [18]. The particular task at hand is a game of "high card," in which the subject wins virtual money if their card is greater than the opponent's card, loses virtual money if it is less than, and neither wins nor loses money if their card is of equal value [19]. For each of the 10 subjects, we train machine learning classifiers on spectral features from sEEG data [20] in the left and right MTG to predict decision variables (e.g. predict whether the subject bet high or low amount of money in a particular trial) and task variables (e.g. predict the card value the player had in a particular trial). The classification accuracy ranged from fractions of 0.75 to 0.98 correct predictions across subjects. Classifiers showed better performance when predicting the bet rather than the card value for some subjects. This offers evidence for the role of the MTG in decision making in addition to high-level visual processing.

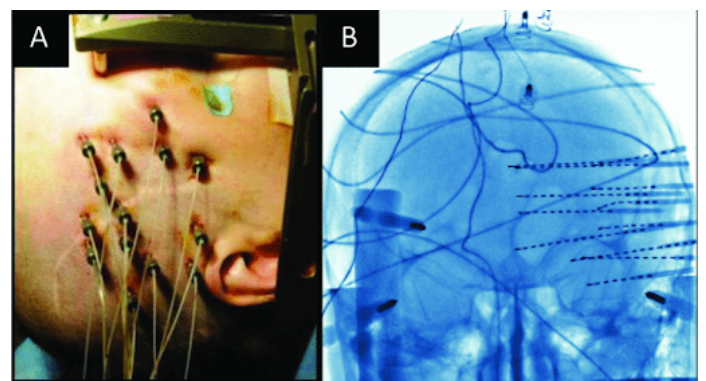


Fig. 1. **A:** Photograph showing 14 sEEG electrodes at the skin surface **B:** Fluoroscopy image of a sEEG-implanted subject (coronal view with eyes facing forward). Electrodes are placed parallel, with tips terminating at the midline or dural surface.

¹D. Wang (correspondence: dwang118@jhu.edu) and S. V. Sarma are with the Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD 21218 USA.

²A. L. Sampson, V. Stuphorn, and E. Niebur are with the Department of Neuroscience and the Zanvyl Krieger Mind/Brain Institute, Johns Hopkins University, Baltimore, MD 21218 USA.

³P. Sacré is with the Department of Electrical Engineering and Computer Science, University of Liège, Quartier Polytech 1, Allée de la découverte 10, 4000 Liège, Belgium.

⁴J. González-Martínez is with the Department of Neurological Surgery, University of Pittsburgh, Pittsburgh, PA 14213 USA.

⁵D. B. Dorman (correspondence: dorman@hope.edu) is with the Department of Neuroscience, Hope College, Holland, MI 49422 USA.

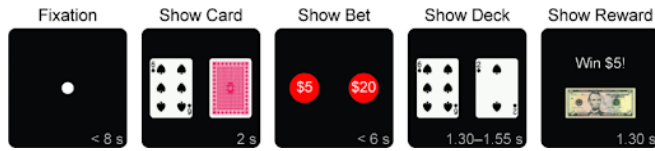


Fig. 2. Timeline of the gambling task. Subjects are shown their card for 2 seconds after the fixation period. Afterwards, subjects have 6 seconds to decide how much money to bet, following a delay the computer's card is then revealed. If the player's card is higher than their opponents, they win the amount they bet, if lower then they lose that amount, and if they tie nothing happens.

II. METHODS

A. Subjects

Ten human participants (seven females and three males) with medically refractory epilepsy, who underwent a surgical procedure at the Cleveland Clinic in which 10 to 14 depth electrodes were implanted for seizure monitoring, performed our gambling task (Fig. 1). The implantation of sEEG electrodes was performed via robotic-assisted surgery in conjunction with co-registered fMRI and angiograms for safety (Fig. 1) [15]. The number and location of implanted electrodes are preoperatively planned based on prior hypotheses of the epileptogenic zone location. Subjects enrolled voluntarily and gave informed consent, and none had their epileptogenic zone located in the MTG. For clinical purposes, patients were kept off anti-seizure medication for their entire duration at the Cleveland Clinic. Thus minimizing concerns that such medication would affect the neurophysiology of the brain, and therefore the neural data collected. All experiments and methods were performed in accordance with the guidelines and regulations of the Cleveland Clinic Institutional Review Board. Participant criteria required individuals over the age of 18 with the ability to provide informed consent and perform the behavioral task as previously described in [15] [16] [17] [18] [19]. Apart from the behavioral experiment, no other alterations were made to the patients clinical care, including placement of electrodes.

B. Neural recordings - Stereoelectroencephalography

sEEG electrodes allow for analysis of large-scale brain networks by recording neural activity from both cortical and subcortical brain areas with high temporal resolution.

Electrophysiology data from sEEG electrodes was acquired using a Nihon Kohden 1200 EEG diagnostic and monitoring system (Nihon Kohden America, USA) at a sampling rate of 2 kHz. Behavioral data was acquired simultaneously via the MonkeyLogic Matlab toolbox [21]. A total of six subjects who volunteered to perform the task had sEEG electrodes in the left MTG and five subjects had sEEG electrodes in the right MTG.

C. Gambling Task

Subjects performed the behavioral experiment in their Epilepsy Monitoring Unit room [17]. The task was administered via a computer screen and subjects interacted with the task via an InMotion2 robotic manipulandum (Interactive Motion

Technologies, USA). The manipulandum is controlled by the subject's hand and moves in a two-dimensional planar motion, which is translated to movement of the computer cursor.

The gambling task (Fig. 2) is based on a simple version of the game of high card (see below for details) where subjects win virtual money if their card is higher than the computer's card, lose money if their card is of lower value, and neither win nor lose money if there is a tie. At the beginning of each trial, the subject uses the manipulandum to move the cursor to a central fixation target. Once centered and after a random delay (mean = 1.58 sec, std = 0.77 sec), the subject is shown their card (2, 4, 6, 8, or 10) which is randomly chosen from a uniform distribution (subjects were informed of the card distribution beforehand). The computer's card remains hidden during this phase. The screen then presents an option to bet a high (\$20) or low (\$5) amount of virtual money that their own card is higher than the computer's card. The subject is given 6 seconds to move the cursor via the manipulandum to make the decision; the beginning of this movement will be referred to as the movement onset. Afterwards the computer's card (which is also chosen randomly from the same distribution) is revealed. If the player has a card of higher value, they win the virtual money bet. If they have a lower value card, they lose the virtual money. Otherwise, if the player and computer tie, neither won nor lost. The final screen shows the amount won/lost for that trial. After a variable inter-trial-interval of 1 sec, the subject is instructed to move the cursor to the central fixation location for the beginning of the next trial (Fig. 2).

D. Decoding Pipeline

All electrophysiological and behavioral data was analyzed offline using custom Python scripts. A snapshot of sEEG data was taken starting 3 seconds before movement onset (defined as the time when the subject begins to move the manipulandum to indicate their bet selection) until the beginning of movement onset for all trials. The neural data underwent Laplacian referencing, wavelet transformation (spectral power computed for 63 frequencies between 2 to 150 Hz), z-scoring, and grouping into frequency bands (delta 1–3 Hz, theta 4–7 Hz, alpha 8–12 Hz, beta 13–30 Hz, and gamma 30–100 Hz) [22].

A random forest classifier [23] was trained to predict a behavioral or task variable using frequency band power from a specific MTG channel averaged across an optimal time window (defined in the next paragraph) within the snapshot.

The optimal time window was computed by analyzing prediction accuracy of a random forest classifier trained on the frequency power averaged across a particular time window within the analysis window. This was done for every possible time window within the analysis window, and the time window that led to the highest overall accuracy for predicting behavioral or task variables for all trials was designated as the optimal time window for that particular channel.

The pipeline (Fig. 3) was used to predict the bet and card value separately: the amount of money the subject bet (\$20 = high, \$5 = low) and the value of the subject's card (8 and 10 = high, 2, 4, and 6 = low). Each possible time window in

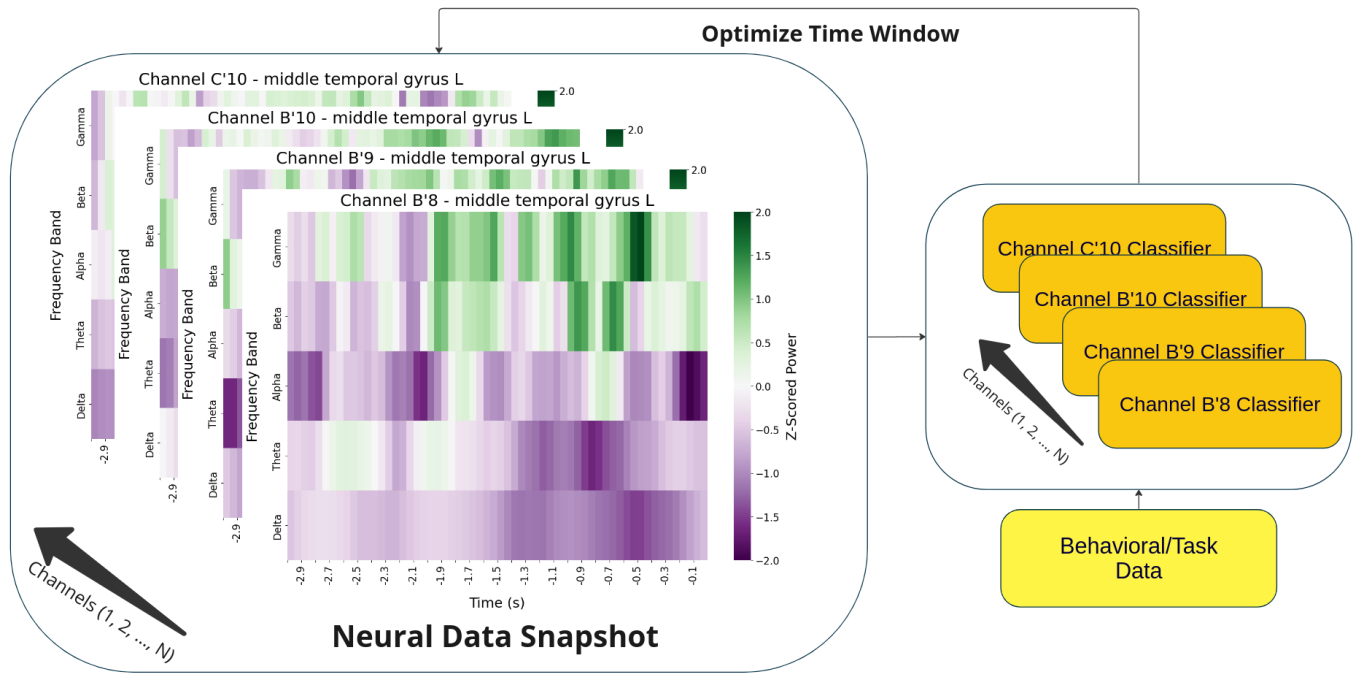


Fig. 3. sEEG data from a particular channel in the MTG undergoes Laplacian referencing, wavelet transform (spectral power computed for 63 frequencies between 2 to 150 Hz), z-scored (based on the mean and standard deviation of the spectral power for the 63 frequencies for all trials in each subject), and finally binned into frequency bands (delta 1–3 Hz, theta 4–7 Hz, alpha 8–12 Hz, beta 13–30 Hz, and gamma 30–100 Hz). Data in frequency band is averaged across a particular time window in the analysis window and used to train a classifier to predict a behavioral or task variable (amount of money bet or the value of the card drawn). The time window leading to the highest prediction accuracy for a particular classifier is identified by computing all possible time windows and selecting the one that leads to the highest prediction accuracy. This is repeated for every channel in the left or right MTG per patient. The top 10 (or fewer if the subject has less channels in the left or right MTG) performing classifiers for a given patient are identified, and the subset of those 10 classifiers that leads to the greatest majority vote accuracy is identified and its majority vote accuracy is recorded.

the analysis window was iterated through to see which would yield the highest accuracy when predicting the behavioral or task variable from the time window's averaged frequency band power. This was repeated for all channels in the left/right MTG for a given subject. In the end, each channel in the left/right MTG would have its own respective classifier and optimal time window. A majority rule vote (i.e. identifying the most common prediction among all the classifiers for a trial) was then performed to identify which combination of channels in each of the brain hemispheres separately led to highest accuracy for a particular subject. The accuracy of the majority rule prediction was recorded for each subject (Table I).

III. RESULTS

We applied our methods to 10 patients with recordings from the left or right MTG (5 patients only had recordings in the left MTG, 4 patients only had recordings in the right MTG, and 1 patient had electrodes in both the right and left MTG). The accuracy of each classifier trained on neural data from a particular channel and its associated time window leading to the most accurate predictions were recorded for the left and right MTG (Fig. 4).

Decoding Bet

We first predicted the amount bet by all subjects in the experiment, with accuracies ranging from 0.75 to 0.98 (Table

TABLE I
CLASSIFIER ACCURACY

Subject	Correlation: Card and Bet Value	Accuracy: Predict Bet Value	Accuracy: Predict Card Value
6 (L)	0.957	0.77	0.75
7 (R)	0.883	0.83	0.77
10 (R)	0.882	0.76	0.80
12 (R)	0.787	0.90	0.80
13 (L)	0.930	0.81	0.76
15 (R)	0.892	0.75	0.76
16 (L)	0.727	0.84	0.76
16 (R)	0.727	0.98	0.78
17 (L)	0.988	0.81	0.82
18 (L)	0.955	0.81	0.80
21 (L)	0.956	0.79	0.77

I). Classifiers were trained to predict a subject's bet behavior for all trials based on neural data from a single channel averaged across the most optimal time window. For each channel the accuracy of its respective classifier and associated optimal time window was visualized for channels in the left and right MTG (Fig. 4).

Decoding Player Card

Since bet and card value are often very correlated, it becomes difficult to delineate whether the MTG is encoding the card



Fig. 4. Classifiers predicting amount bet by a subject were trained on neural data from single channel in the left or right MTG. Labels on the y-axis indicate the particular subject (P06 indicates subject 06) and channel (Ch1 indicates channel 1 for that subject) the classifier was trained on. The width of the colored rectangles represents the time window that led to the most optimal prediction accuracy when classifiers were trained on neural data averaged across that time window. The color of each rectangle represents the prediction accuracy for the classifier trained on data from that particular channel. Time 0 on the x-axis indicates moment of movement onset. The discrepancy in the number of channels in the right and left MTG is due to predetermined placement of sEEG electrodes by physicians prior to surgery.

value or decision making. The same methods were applied to train a classifier to predict the card value drawn by the subject for all trials, classifier accuracies ranged from 0.75 to 0.8 (Table I). The correlation between the card and bet value for each subject was also calculated.

The three subjects, P12 and P16, with the lowest correlation (< 0.8) had a 10-20% improvement in classification accuracy when using neural data from the right MTG to predict bet rather than card value (Table I). The rest of the subjects had accuracies that varied less than 10% when classifying bet vs card value. The improvement in performance for the two subjects indicates that the neural activity from the MTG is more correlated with the bet rather than the card value. This suggests that the

MTG may be implicated in the decision-making process. This is consistent with the current understanding of the temporal lobe's role in high level visual processing [4] [5]. High level visual processing is concerned with extracting behaviorally meaningful features of the environment [1]. Our results provide evidence that there may be neural mechanisms in the MTG that take neural information encoding visual semantic information of the card value to guide behavior such as financial decision making.

IV. DISCUSSION

Our analysis shows that there is a correlation between neural activity and bet decision before the overt decision. This supports

the idea that this region contributes causally to the decision by generating signals on which the decision is based on.

There is a functional chain of processes that must be undertaken by the subject to optimally perform this experimental task. First, the player must visually perceive their card when it is shown. Second, they must extract functionally relevant information, i.e. the numerical value of the card, from the perceived visual data. Third, the player must have a representation of the game rules to estimate the probability that their card has a higher numerical value than the computer's. Fourth, the estimation of this probability directly impacts the choice of betting high or low. Fifth, the commitment to one of these choices leads to a decision. And sixth, motor planning/execution transforms the decision into a specific motor response.

The existing literature contains evidence that the MTG serves a vital role in deriving semantic meaning from the card image and facilitating executive control processes to estimate the probability of the card having a higher numerical value.

The MTG has been hypothesized to be a critical interface for semantic information due to it being at the junction of auditory and visual processing streams [4] [5] [24]. Additionally, neighboring brain regions, such as the anterior temporal gyrus (ATG), have been found underpinning an amodal semantic system [2]. The information received from the visual processing streams, such as visual information of a playing card, must be interpreted for functionally relevant semantic meaning, such as card value. Using distortion-corrected fMRI, researchers have found activation of the MTG in a word and picture semantic processing task, supporting the notion of its function as a semantic processor [3]. Retrieving this processed semantic information for goal-oriented behavior involves the automatic spread of activation between related concepts and the executive control to tailor such activations to suit a particular context or goal, such as evaluating the probability of a card being of higher numerical value. Structural and functional connectivity analysis demonstrated that the posterior MTG was positioned at the nexus of networks recruited in automatic semantic processing and executively demanding tasks [8]. Studies found that stimulating the posterior MTG with transcranial magnetic stimulation inhibited the ability for subjects to executively tailor semantic information to be in line with a particular task [7] [25]. This offers evidence that the MTG plays an important role in integrating semantic information with executive processes for goal-orientated behavior.

We have described how previous studies support the hypothesis that the MTG carries neural information directly related to the numerical value of the card and the estimated probability of winning the round. This gives rationale as to why neural information from the MTG can be used to decode card value and bet decision.

The goal of this study was to use sEEG data to investigate the functionality of the MTG in a financial decision-making task. This study trained subject-specific classifiers on neural data from an individual channel to predict behavioral or task variables. We found that the classifiers were able to achieve

higher accuracy when predicting bet rather than card value for subjects with the lowest correlation between the two. This suggests that MTG encodes neural information related to decision-making, and future work may unveil more details of the MTG's role in decision making and how it may even be modulated to treat neurological disorders.

ACKNOWLEDGMENT

This work was supported by NIH IRACDA K12GM154720 awarded to D.D., NSF 1835202 awarded to S.V.S., A.S., V.S., E.N. and J.G.M.

REFERENCES

- [1] E. R. Kandel, J. D. Koester, S. H. Mack, and S. A. Siegelbaum, "High-level visual processing: From vision to cognition," in *Principles of Neural Science*, 6th ed. McGraw Hill, 2021. [Online]. Available: neurology.mhmedical.com/content.aspx?aid=1180642113
- [2] M. Visser, E. Jefferies, and M. A. Lambon Ralph, "Semantic processing in the anterior temporal lobes: A meta-analysis of the functional neuroimaging literature," *Journal of Cognitive Neuroscience*, vol. 22, no. 6, pp. 1083–1094, 2010. [Online]. Available: <https://doi.org/10.1162/jocn.2009.21309>
- [3] M. Visser, E. Jefferies, K. V. Embleton, and M. A. Lambon Ralph, "Both the middle temporal gyrus and the ventral anterior temporal area are crucial for multimodal semantic processing: Distortion-corrected fMRI evidence for a double gradient of information convergence in the temporal lobes," *Journal of Cognitive Neuroscience*, vol. 24, no. 8, pp. 1766–1778, 2012. [Online]. Available: https://doi.org/10.1162/jocn_a_00244
- [4] M. Mishkin, L. G. Ungerleider, and K. A. Macko, "Object vision and spatial vision: two cortical pathways," *Trends in Neurosciences*, vol. 6, pp. 414–417, 1983. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/016622368390190X>
- [5] A. Ishai, L. G. Ungerleider, A. Martin, J. L. Schouten, and J. V. Haxby, "Distributed representation of objects in the human ventral visual pathway," *Proceedings of the National Academy of Sciences*, vol. 96, no. 16, pp. 9379–9384, 1999, publisher: Proceedings of the National Academy of Sciences. [Online]. Available: <https://www.pnas.org/doi/abs/10.1073/pnas.96.16.9379>
- [6] T. Wei, X. Liang, Y. He, Y. Zang, Z. Han, A. Caramazza, and Y. Bi, "Predicting conceptual processing capacity from spontaneous neuronal activity of the left middle temporal gyrus," *Journal of Neuroscience*, vol. 32, no. 2, pp. 481–489, 2012, publisher: Society for Neuroscience Section: Articles. [Online]. Available: <https://www.jneurosci.org/content/32/2/481>
- [7] J. Davey, P. L. Cornelissen, H. E. Thompson, S. Sonkusare, G. Hallam, J. Smallwood, and E. Jefferies, "Automatic and controlled semantic retrieval: TMS reveals distinct contributions of posterior middle temporal gyrus and angular gyrus," *Journal of Neuroscience*, vol. 35, no. 46, pp. 15230–15239, 2015, publisher: Society for Neuroscience Section: Articles. [Online]. Available: <https://www.jneurosci.org/content/35/46/15230>
- [8] J. Davey, H. E. Thompson, G. Hallam, T. Karapanagiotidis, C. Murphy, I. De Caso, K. Krieger-Redwood, B. C. Bernhardt, J. Smallwood, and E. Jefferies, "Exploring the role of the posterior middle temporal gyrus in semantic cognition: Integration of anterior temporal lobe with executive processes," *NeuroImage*, vol. 137, pp. 165–177, 2016. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1053811916301719>
- [9] T. Larsen and J. P. O'Doherty, "Uncovering the spatio-temporal dynamics of value-based decision-making in the human brain: a combined fMRI–EEG study," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 369, no. 1655, p. 20130473, 2014, publisher: Royal Society. [Online]. Available: <https://royalsocietypublishing.org/doi/full/10.1098/rstb.2013.0473>
- [10] I. M. Balodis, C. M. Lacadie, and M. N. Potenza, "A preliminary study of the neural correlates of the intensities of self-reported gambling urges and emotions in men with pathological gambling," *Journal of Gambling Studies*, vol. 28, no. 3, pp. 493–513, 2012. [Online]. Available: <https://doi.org/10.1007/s10899-011-9259-8>

- [11] Y. Meng, W. Deng, H. Wang, W. Guo, and T. Li, "The prefrontal dysfunction in individuals with internet gaming disorder: a meta-analysis of functional magnetic resonance imaging studies," *Addiction Biology*, vol. 20, no. 4, pp. 799–808, 2015, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/adb.12154>. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1111/adb.12154>
- [12] N. K. Logothetis, J. Pauls, M. Augath, T. Trinath, and A. Oeltermann, "Neurophysiological investigation of the basis of the fMRI signal," *Nature*, vol. 412, no. 6843, pp. 150–157, 2001, number: 6843 Publisher: Nature Publishing Group. [Online]. Available: <https://www.nature.com/articles/35084005>
- [13] S. P. Kelly and R. G. O'Connell, "The neural processes underlying perceptual decision making in humans: Recent progress and future directions," *Journal of Physiology-Paris*, vol. 109, no. 1, pp. 27–37, 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0928425714000370>
- [14] M. Cossu, F. Cardinale, L. Castana, A. Citterio, S. Francione, L. Tassi, A. L. Benabid, and G. Lo Russo, "Stereo-electroencephalography in the presurgical evaluation of focal epilepsy: a retrospective analysis of 215 procedures," *Neurosurgery*, vol. 57, no. 4, pp. 706–718; discussion 706–718, 2005.
- [15] P. Sacré, M. S. D. Kerr, K. Kahn, J. Gonzalez-Martinez, J. Bulacio, H.-J. Park, M. A. Johnson, S. Thompson, J. Jones, V. S. Chib, J. T. Gale, and S. V. Sarma, "Lucky rhythms in orbitofrontal cortex bias gambling decisions in humans," *Scientific Reports*, vol. 6, no. 1, p. 36206, 2016, number: 1 Publisher: Nature Publishing Group. [Online]. Available: <https://www.nature.com/articles/srep36206>
- [16] P. Sacré, S. Subramanian, M. S. D. Kerr, K. Kahn, M. A. Johnson, J. Bulacio, J. A. González-Martínez, S. V. Sarma, and J. T. Gale, "The influences and neural correlates of past and present during gambling in humans," *Scientific Reports*, vol. 7, no. 1, p. 17111, 2017, number: 1 Publisher: Nature Publishing Group. [Online]. Available: <https://www.nature.com/articles/s41598-017-16862-9>
- [17] P. Sacré, M. S. D. Kerr, S. Subramanian, Z. Fitzgerald, K. Kahn, M. A. Johnson, E. Niebur, U. T. Eden, J. A. González-Martínez, J. T. Gale, and S. V. Sarma, "Risk-taking bias in human decision-making is encoded via a right-left brain push-pull system," *Proceedings of the National Academy of Sciences*, vol. 116, no. 4, pp. 1404–1413, 2019, publisher: Proceedings of the National Academy of Sciences. [Online]. Available: <https://www.pnas.org/doi/10.1073/pnas.1811259115>
- [18] C. Taylor, P. Greene, R. D'Aleo, M. S. Breault, C. Steinhardt, J. Gonzalez-Martinez, and S. V. Sarma, "Correlates of attention in the cingulate cortex during gambling in humans," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, vol. 2020, pp. 2548–2551, 2020.
- [19] M. A. Johnson, S. Thompson, J. Gonzalez-Martinez, H.-J. Park, J. Bulacio, I. Najm, K. Kahn, M. Kerr, S. V. Sarma, and J. T. Gale, "Performing behavioral tasks in subjects with intracranial electrodes," *Journal of Visualized Experiments : JoVE*, no. 92, p. 51947, 2014. [Online]. Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4672964/>
- [20] M. ter Wal, A. Platonov, P. Cardellicchio, V. Pelliccia, G. LoRusso, I. Sartori, P. Avanzini, G. A. Orban, and P. H. E. Tiesinga, "Human stereoEEG recordings reveal network dynamics of decision-making in a rule-switching task," *Nature Communications*, vol. 11, no. 1, p. 3075, 2020, number: 1 Publisher: Nature Publishing Group. [Online]. Available: <https://www.nature.com/articles/s41467-020-16854-w>
- [21] B. H. A. P. K. Je, M. S, and M. Pp, "Chronux: a platform for analyzing neural signals," *PubMed*, 2010. [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/20637804/>
- [22] G. Li, S. Jiang, S. E. Paraskevopoulou, M. Wang, Y. Xu, Z. Wu, L. Chen, D. Zhang, and G. Schalk, "Optimal referencing for stereo-electroencephalographic (SEEG) recordings," *NeuroImage*, vol. 183, pp. 327–335, 2018. [Online]. Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6495648/>
- [23] K. Fawagreh, M. M. Gaber, and E. Elyan, "Random forests: from early developments to recent advancements," publisher: Taylor & Francis. [Online]. Available: <https://www.tandfonline.com/doi/abs/10.1080/21642583.2014.956265>
- [24] J. R. Binder, R. H. Desai, W. W. Graves, and L. L. Conant, "Where is the semantic system? a critical review and meta-analysis of 120 functional neuroimaging studies," *Cerebral Cortex*, vol. 19, no. 12, pp. 2767–2796, 2009. [Online]. Available: <https://doi.org/10.1093/cercor/bhp055>
- [25] C. Whitney, M. Kirk, J. O'Sullivan, M. A. Lambon Ralph, and E. Jefferies, "The neural organization of semantic control: TMS evidence for a distributed network in left inferior frontal and posterior middle temporal gyrus," *Cerebral Cortex*, vol. 21, no. 5, pp. 1066–1075, 2011. [Online]. Available: <https://doi.org/10.1093/cercor/bhq180>