

Supplementary File

S1. Map use experiment

S1.1. Participants

The study complied with the guidelines of the Ethical Review Board of XXX University. We recruited 50 individuals (25 females; age 20-34 years, $M = 25.4$ years, $SD = 3.35$ years) for the experiment. All participants had a normal or corrected-to-normal vision and no history of neurological disorders. They provided informed consent and completed all experimental procedures. They received €10 as compensation for their participation.

S1.2. Map use tasks and stimuli

In this study, participants performed four daily map use tasks (i.e., map activities), which are common activities people perform on Google Maps (or other web map services):

- Global search (GS): Participants were asked to search for one food or drink type point of interest (POI) on the map.
- Distance comparison (DC): Participants were required to determine the POI with the smallest Euclidean distance from their current location out of four potential targets.
- Route following (RF): Participants were asked to count the number of intersections along a route marked on the map.
- Route planning (RP): Participants were asked to identify the shortest path from their current location to a given destination, both marked on the map.

To ensure ecological validity, we employed 16 state-of-the-art static Google Maps (1920 x 1080 screen resolution) as experimental stimuli. To prevent participants from having prior knowledge of the map area and to ensure a consistent language for map labels (i.e., English), all 16 maps were selected from North America, South America, and Oceania – regions that were unfamiliar to the participants, which was confirmed in the interviews after the experiment. The complexity of the map was quantified using Feature Congestion (Schnur et al., 2018) before selection, which describes a condition in which a given area of the visual scene is so densely populated with features that it becomes difficult to identify individual elements. This measure ensures that the content and information of these 16 maps remained at a similar complexity level (FC range: 4.96-5.41, $M = 5.14$, $SD = 0.137$). All maps had the same zoom level (street level: 16 of the Google Maps) to maintain a consistent amount of map information across all four tasks.

S1.3. Experimental procedure

The experiment consisted of three main phases: the learning phase, the test phase, and the post-test phase (Supplementary Figure A1). During the learning phase, participants were given two trials per task to ensure they fully understood the procedure. In the test phase, each participant performed 64 trials (16 maps with 4 tasks each) in 4 runs, with breaks between runs. The 16 maps were presented in a fixed order to minimize the learning effects of the same map, and all trials followed a Latin square design to minimize the effects of trial order on the experiment. Each trial began with a 5-second instruction

period, followed by a 3-second baseline period, and a maximum of 30-second stimuli period in which participants engaged with the map. They were instructed to press the 'space' key to move on once they found the answer, and then to select their answer using the number keys 1, 2, 3, or 4 during the response period. We asked them to complete tasks as fast and accurate as possible. After the test phase, participants were interviewed about their task-solving strategies and asked to complete the NASA-TLX scale and questionnaire in the post-test phase.

S1.4. ET and EEG data acquisition and preprocessing

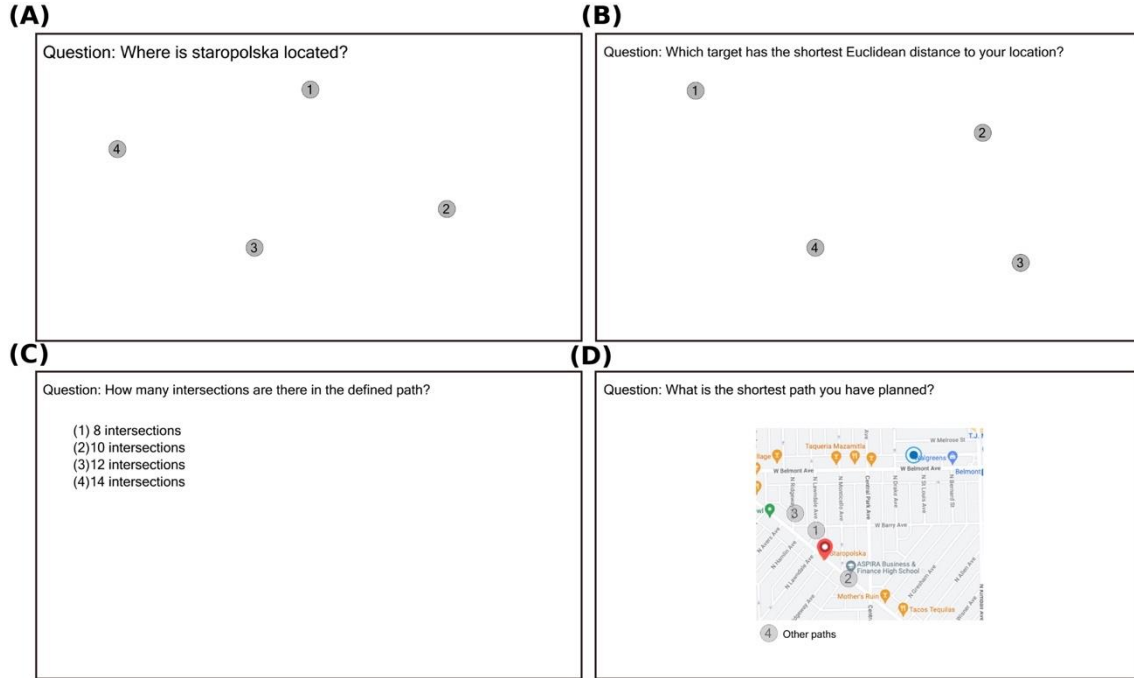
We collected eye-tracking data using a Tobii Pro Fusion eye tracker with a sampling rate of 250Hz. Only the recording data during the stimuli period (see Figure 2) was used for map activity recognition. The Tobii standard algorithm I-VT filter (Olsen, 2012) with a velocity threshold of 30 degrees/second was used to segment fixations and saccades.

Throughout the experiment, EEG data were recorded continuously using a 32-gel electrode cap following the extended 10-20 international layout connected to the Enobio NIC2 System. The raw EEG data were bandpass filtered between 1 and 50 Hz. Poor-quality electrodes ($M = 1.9$, $SD = 3.25$) were visually inspected and interpolated using the spherical spline method. All electrodes were then re-referenced to the average. Independent component analysis (ICA) was performed using fastICA to correct for artifactual components, which were manually detected based on time course, topography, and power spectral density of the components. Preprocessing of the EEG data was performed using the Python programming language and the MNE library (Gramfort et al., 2013).

To align the ET and EEG data on the same timeline, we used the predefined keyboard event (numeric keys 6,7,8,9) as markers (start timestamp and end timestamp of four runs) in the two-instrument software. In this way, ET metrics (such as the timestamp when the fixation was first located on the cAOI) and keyboard responses (such as the 'space' key at the end of the trial) can be used as events in EEG time course signals.



Supplementary Figure A1. The experimental framework and procedure (Note that the target for the instruction period of the global search task was a food or drink POI on the map, ‘staropolaska’ in this figure). The high resolution of response period stimuli is shown in the Supplementary Figure A2.



Supplementary Figure A2. Subplot A: A response period stimulus for a global search task; Subplot B: A response period stimulus for a distance comparison task; Subplot C: A response period stimulus for a route following task; Subplot D: A response period stimulus for a route planning task.

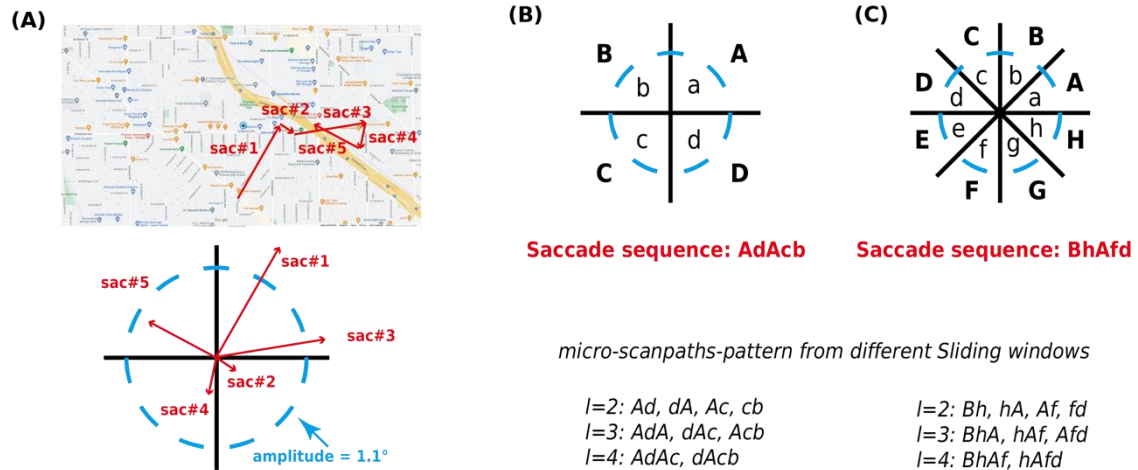
Supplementary Table A1. Behavioral results (mean, standard error and 95% of confidence intervals for response time (RT) and accuracy) of the 2073 trials for the four different tasks

	RT (ms)			Accuracy		
	Mean	SE	95% CI	Mean	SE	95% CI
Global search	7126.6	153.6	(6825.6,7427.7)	0.992	0.004	(0.984,1.000)
Distance comparison	6691.8	137.0	(6423.2,6960.4)	0.899	0.013	(0.874,0.924)
Route following	12009.5	145.5	(11724.4,12294.6)	0.726	0.020	(0.687,0.765)
Route planning	9334.9	181.2	(8979.8,9690.0)	0.664	0.021	(0.623,0.705)

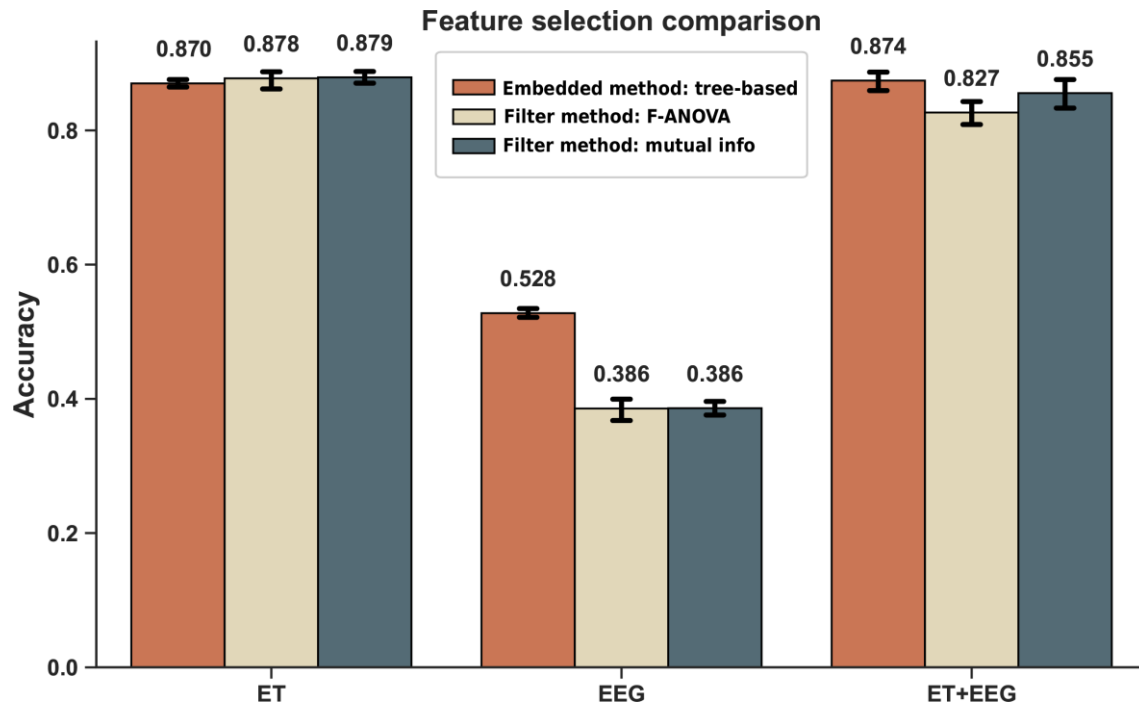
Supplementary Table A2. Default hyperparameter settings for 9 classifiers.

Classifiers	Hyperparameters
<i>LogisticRegression</i>	penalty = 'l2'; C = 1.0; solver = 'lbfgs'
<i>KNeighborsClassifier</i>	n_neighbors = 5; weights = 'uniform'; leaf_size = 30; p = 2; metric = 'minikowski'
<i>LinearDiscriminantAnalysis</i>	solver = 'svd'

<i>SVC</i>	$C = 1.0$; kernel = 'rbf'; degree = 3
<i>DecisionTreeClassifier</i>	criterion = 'gini'; splitter = 'best'; min_samples_split = 2; min_samples_leaf = 1; min_weight_fraction_leaf = 0.0
<i>RandomForestClassifier</i>	n_estimators = 100; criterion = 'gini'; min_samples_split = 2; min_samples_leaf = 1; min_weight_fraction_leaf = 0.0
<i>AdaBoostClassifier</i>	estimator = <i>None</i> ; n_estimators = 50; learning_rate = 1.0; algorithm = 'SAMME.R'
<i>GradientBoostingClassifier</i>	loss = 'log_loss'; learning_rate = 0.1; n_estimators = 100; subsample = 1.0; criterion = 'friedman_mse'; min_samples_split = 2; min_samples_leaf = 1; min_weight_fraction_leaf = 0.0
<i>MLPClassifier</i>	activation = 'relu'; solver = 'adam'; alpha = 1e-4; learning_rate = 'constant'; max_iter = 500
<i>XGBClassifier</i>	Booster = 'gbtree'; learning_rate = 0.3; min_split_loss = 'gamma'; subsample = 1; colsample_bytree = 1
<i>LGBMClassifier</i>	n_estimators = 100; boosting = 'gbdt'; learning_rate = 0.1; num_leaves = 31; max_depth = -1; subsample = 1; colsample_bytree = 1; min_child_samples = 20

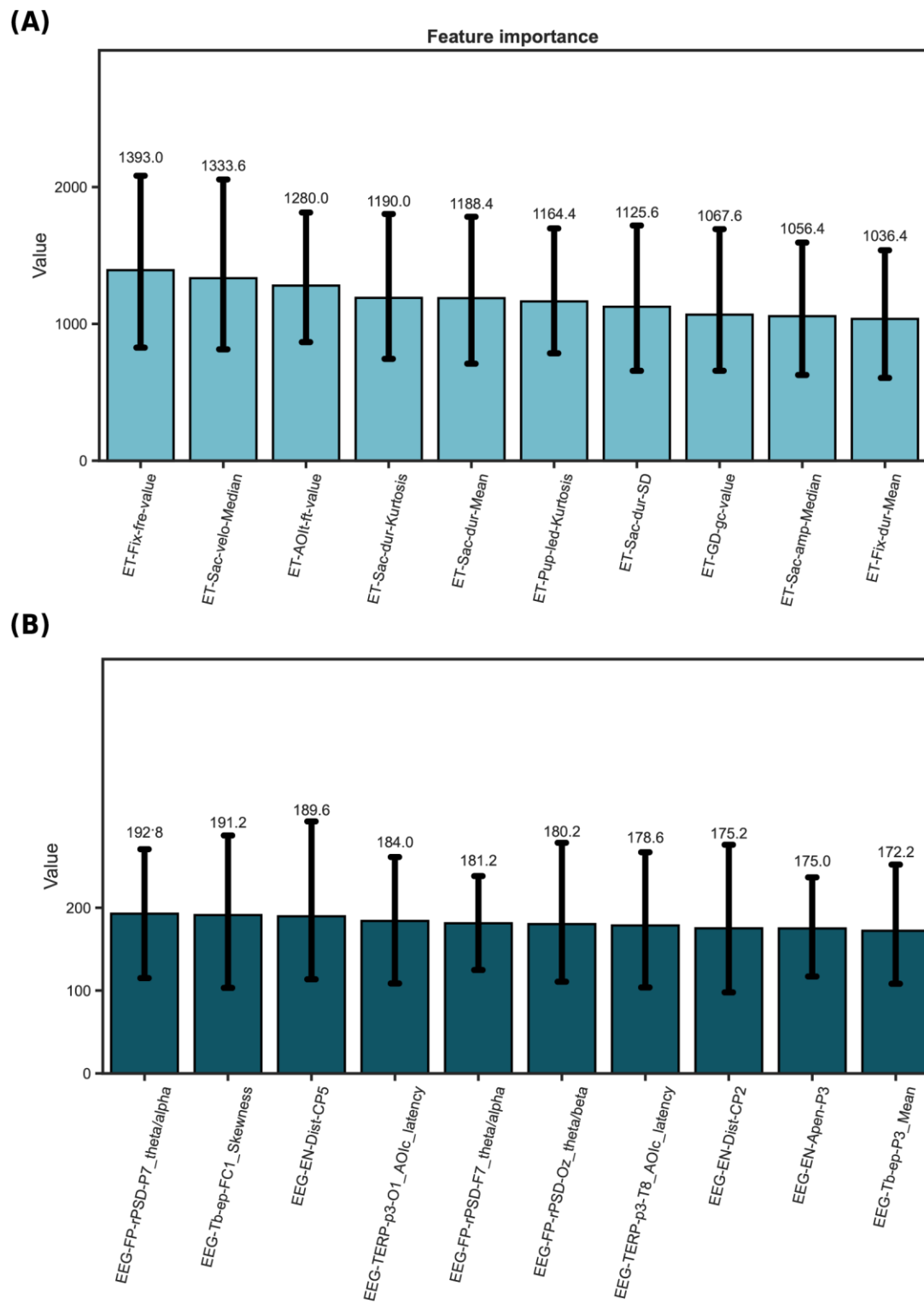


Supplementary Figure A3. Subplot A shows the illustration of a saccade sequence (the number of saccades = 5). Subplots B and C show the 4-directional and 8-directional schemes for encoding the saccade sequence, respectively.

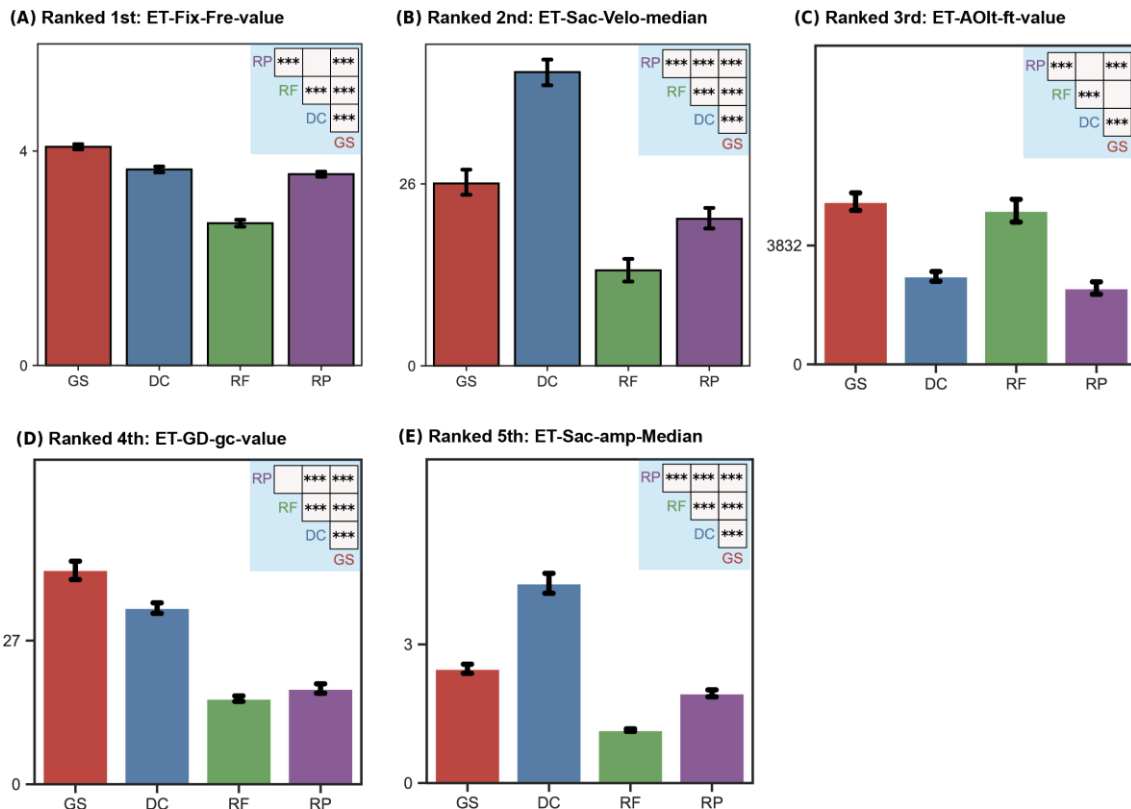


Supplementary Figure A4. The recognition accuracy for 3 feature selection methods.

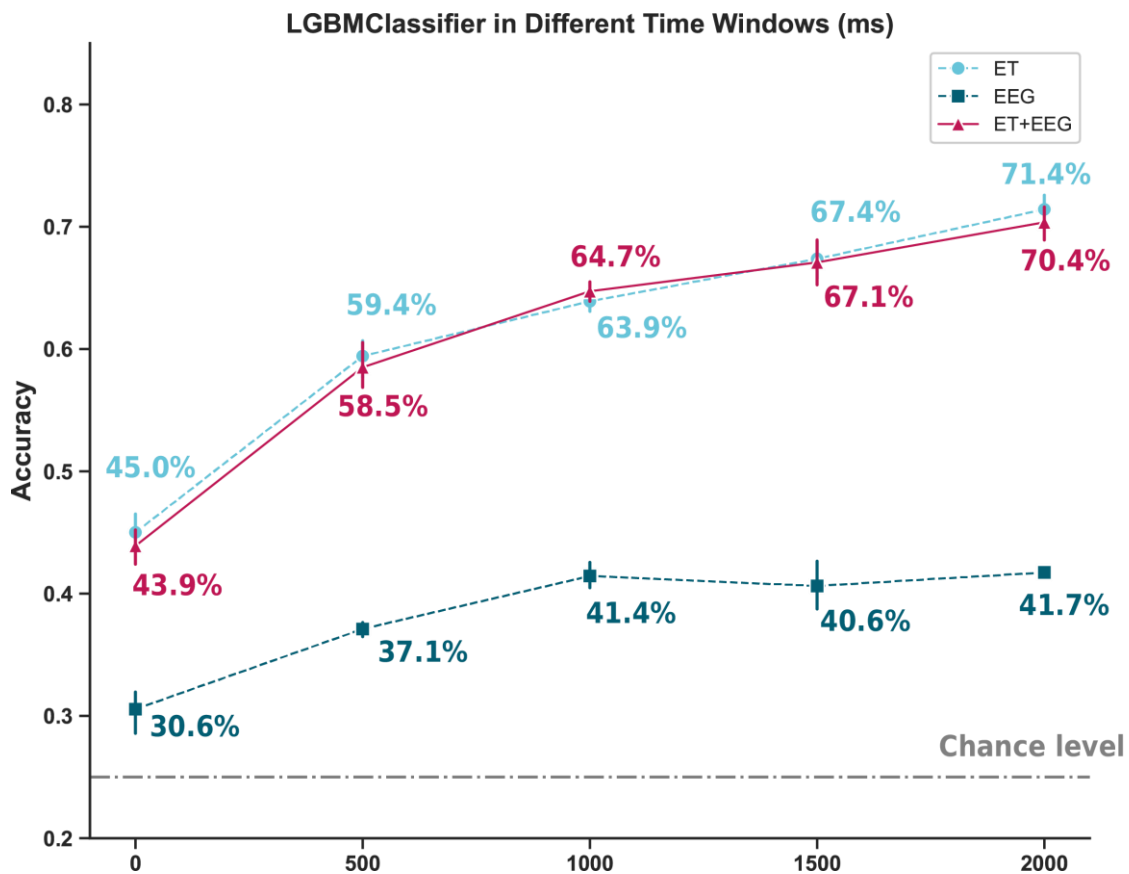
The embedded tree-based feature selection method achieves the highest average accuracy when using EEG only (52.8%) and ET+EEG features (87.4%), and the accuracy when using only ET (87.0%) was comparable to the highest accuracy (87.9%), across five training/test splits.



Supplementary Figure A5. The feature importance (top 10) ranking for recognition using ET-only features (A) and EEG-only features (B).



Supplementary Figure A6. The values of selected important features (top 5) for different map activities (Upper right subplots reflect the differences between the pairwise tasks. $p < 0.001$: ***; $p < 0.01$: **; $p < 0.05$: *; $p > 0.05$: blank).



Supplementary Figure A7. The recognition accuracy for five different (overlay) time windows: (0-1000 ms; 500-1500 ms; 1000-2000 ms; 1500-2500 ms; 2000-3000 ms)

Reference

- Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., ... & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in neuroscience*, 267.
- Olsen, A. (2012). The Tobii I-VT fixation filter. *Tobii Technology*, 21, 4-19.
- Schnur, S., Bektaş, K., & Çöltekin, A. (2018). Measured and perceived visual complexity: A comparative study among three online map providers. *Cartography and Geographic Information Science*, 45(3), 238-254.