Supplementary Materials for “Age differences in neural discriminability of rumination and worry” by Masaya Misaki, Aki Tsuchiyagaito, Salvador M. Guinjoan, and Martin P. Paulus

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Supplementary Table S1. AUC and age correlations (Spearman's *rho*) with self-reports of task evaluation and distress levels related to rumination and worry events. P-values are uncorrected.

	Rumination-Worry		Rumination-Positive		Worry-Positive		Age	
	rho	*p*	*rho*	*p*	*rho*	*p*	*rho*	*p*
difficulty	-0.111	0.525	-0.190	0.273	-0.291	0.089	-0.415	**0.013**
success	0.054	0.756	0.174	0.318	0.254	0.141	0.377	**0.025**
sleepiness	-0.151	0.386	-0.273	0.113	-0.275	0.110	-0.568	**0.000**
emotional exhaustion	0.099	0.573	0.050	0.776	0.076	0.665	-0.187	0.283
tiredness	-0.178	0.306	-0.262	0.128	-0.210	0.225	-0.525	**0.001**
distress rumination	0.034	0.848	0.168	0.336	0.229	0.186	0.111	0.524
distress worry	0.280	0.103	0.238	0.168	0.184	0.290	0.196	0.258

Frequency of Negative Thinking Instructions

For each of the four negative events in the rumination and worry conditions, participants selected one of three predefined instruction types. These choices may reflect the kinds of events participants recalled, which could vary by age, sex, or affective traits. For example, older adults may be more inclined to reflect on broader life implications (e.g., "Why did that happen to you?" and "How would this affect your life?"), whereas younger adults may focus more on their own actions or emotional responses (e.g., "Why did you do that?" or "How would you feel if that happened?"). To explore this possibility, we examined whether instruction selection was systematically associated with individual differences.

We tested associations between the frequency of each instruction type and participants' age, sex, and affective trait scores (RRS, PSWQ, STAI-T, and SCI-QOL Positive Affect). Spearman correlations were used for continuous variables, and independent-samples t-tests were conducted for sex. Supplementary Table S1 presents the mean frequency of each instruction type and the corresponding test statistics.

No associations reached statistical significance (all uncorrected *p* values were greater than 0.05), suggesting that instruction selection (and by extension, the types of autobiographical events recalled) did not systematically vary with age, sex, or affective traits.

Supplementary Table S2. Mean frequency of selected instructions and their associations with participant age, sex, and affective trait scores. The table shows the mean frequency with which each instruction type was selected for rumination and worry tasks, along with Spearman correlation coefficients (*rho*) for age and affective traits, and Mann-Whitney-Wilcoxon test statistics for sex (Female - Male). No associations were statistically significant (all uncorrected $p > 0.05$).

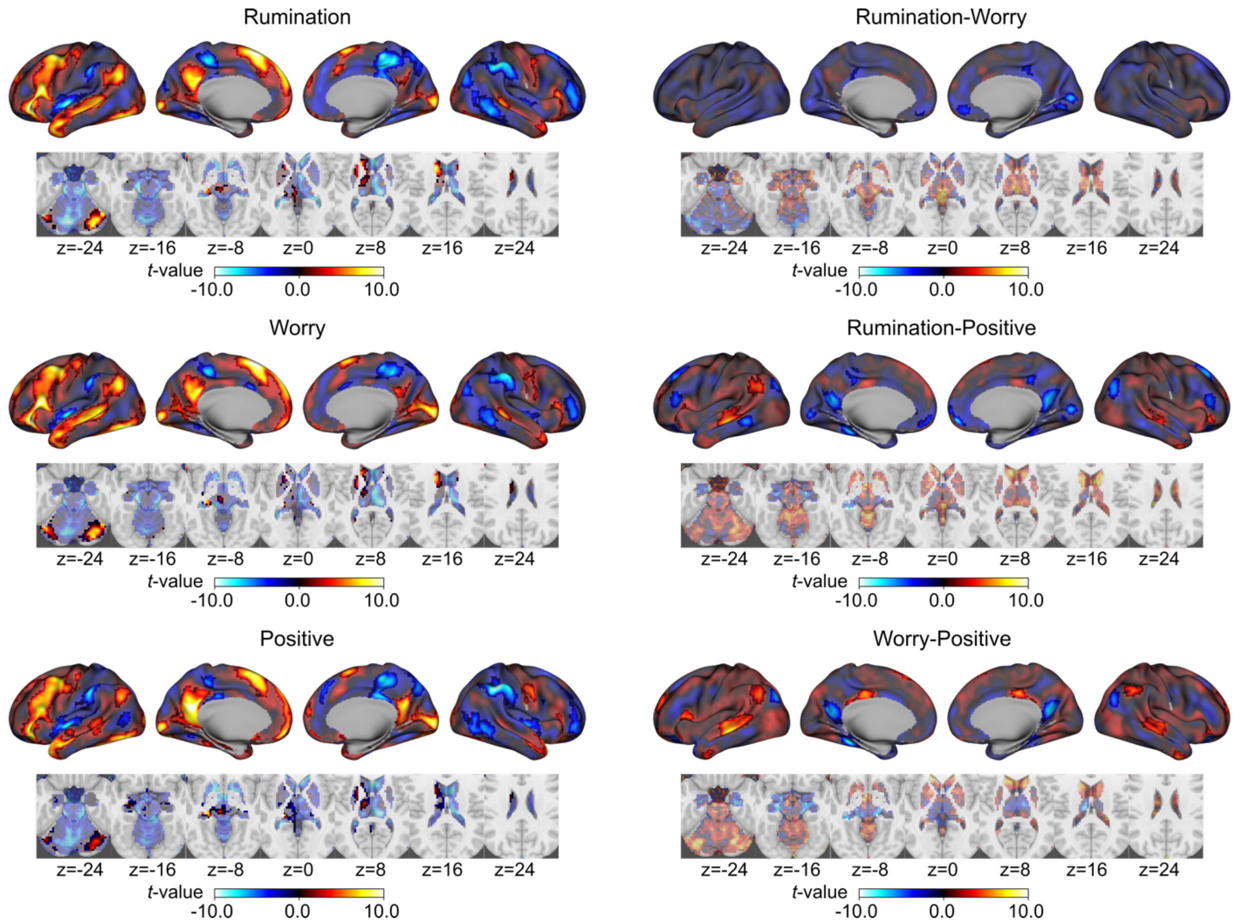
Instruction	Mean Frequency	Age (*rho*)	Sex (*W*)	RRS (*rho*)	PSWQ (*rho*)	STAI-T (*rho*)	SCI-QOL Positive (*rho*)
Rumination:							
Why did that happen to you?	1.857	0.066	162.5	-0.190	-0.208	-0.163	0.073
Why did you do that?	1.171	-0.232	113	0.125	0.078	0.065	0.076
Why did you react that way?	0.971	0.184	121	0.182	0.305	0.229	-0.168
Worry:							
How would this affect your life?	1.771	0.044	169.5	0.079	0.155	-0.106	0.136
How would you feel if that happened?	1.229	-0.247	115	0.009	-0.144	0.145	-0.066
What would you do if that happened?	1.000	0.077	97	-0.015	0.004	0.119	-0.118

RRS, Ruminative Response Style; PSWQ, Penn State Worry Questionnaire; STAI-T, State-Trait Anxiety Inventory Trait score; SCI-QOL Positive, Spinal Cord Injury – Quality of life index positive affect and well-being score.

Supplementary Table S3. ANOVA table for the linear mixed-effects (LME) model analysis of decoding probability with time and age. Time was entered as a factor variable to account for potential nonlinear changes across the time course. Only the time points used during model training (6–22 s from the onset of the think block) were included in the analysis.

	Rumination		Worry		Positive	
	F	*p*	*F*	*p*	*F*	*p*
Time	0.409	0.916	2.664	**0.006**	1.154	0.3223
Age	11.352	**0.002**	13.356	**0.001**	8.872	**0.005**
Time x Age	1.198	0.296	3.863	**< 0.001**	0.513	0.847

Validation of Decoder-Derived Time Series



Supplementary Figure S1. Brain activation patterns associated with the thought states and their contrasts, evaluated using block-wise response models. The maps are displayed on the inflated cortical surface, while subcortical and cerebellar regions are shown on axial slice maps. Clusters with voxel-wise $p < 0.001$, corrected for cluster extent at $p < 0.05$, are highlighted with opaque colors.

Instructions for collecting personal events related to rumination, worry and positive thinking

Rumination: Four Negative Thoughts About the Past. Sometimes people think about things that happened to them in the past that made them feel bad, embarrassed, sad, or afraid. When people think about these things, it can be hard to stop thinking about them. We would like you to try and remember four different thoughts you have had about the past that make you feel bad, embarrassed, sad, or afraid when you think about them, and that may be hard to stop thinking about. Sometimes these thoughts are about situations that you did not handle well, relationships that ended poorly, work goals that you did not accomplish, or recreational activities that went wrong. This should be kept in private; you do not need to tell us details. Now, let's write keywords referencing this thought that you can recognize in the MRI so that you may immediately engage with this thought in the scanner. Two or three keywords that remind you about the situation and your feelings would be helpful. For example: Colleague: Comparison.

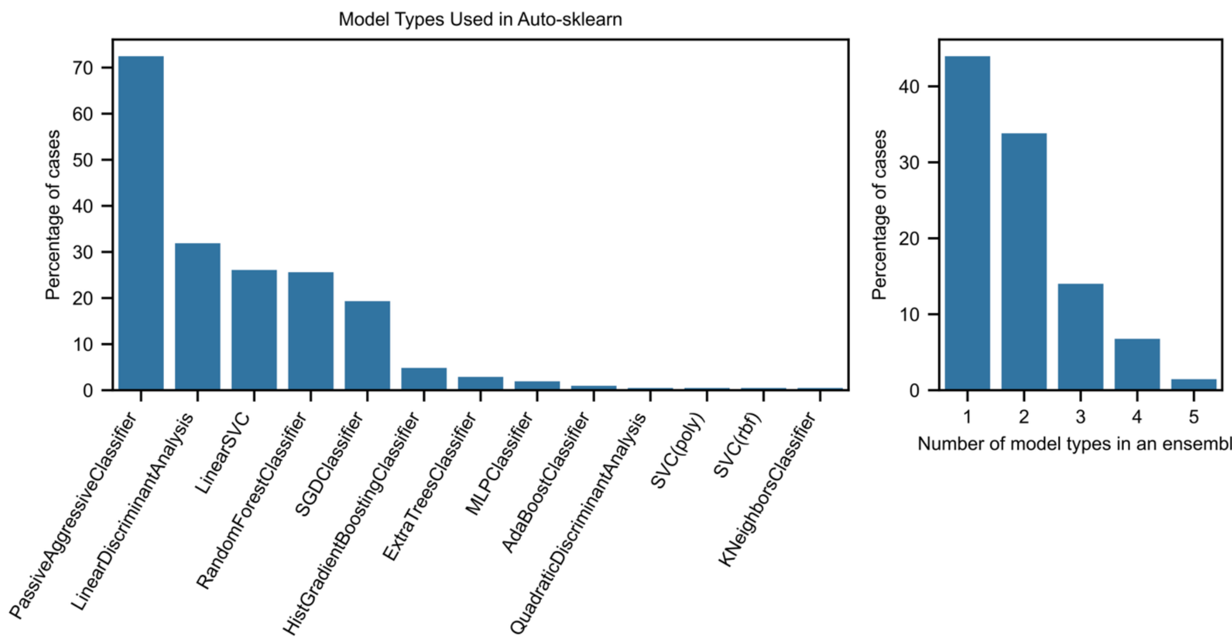
Worry: Four Worrying Thoughts About the Future. Sometimes people think about something that may happen but has not happened yet. We would like for you to come up with four different thoughts that may make you anxious, nervous, tense, or irritable. Just as with the thoughts you described on the previous page, sometimes it is difficult to get these thoughts out of your mind. These thoughts could be about bad, annoying, dangerous, or uncomfortable situations that may happen to you. This should be kept in private; you do not need to tell us details. Just like we did on the previous page, let's write down keywords referencing the thought. For example: Airport: miss the flight.

Positive: Four Positive Thoughts About the Past. We would like you to try and remember four different thoughts you have had about the past that make you feel good, you enjoy thinking about, and are happy, positive, fulfilling or exciting events in your life. This should be kept in private, and you do not need to tell us details. Just like we did on the previous page, let's write down keywords referencing the thought. For example: Beach: sunset.

Model Profiles in Auto-sklearn Classifier Training

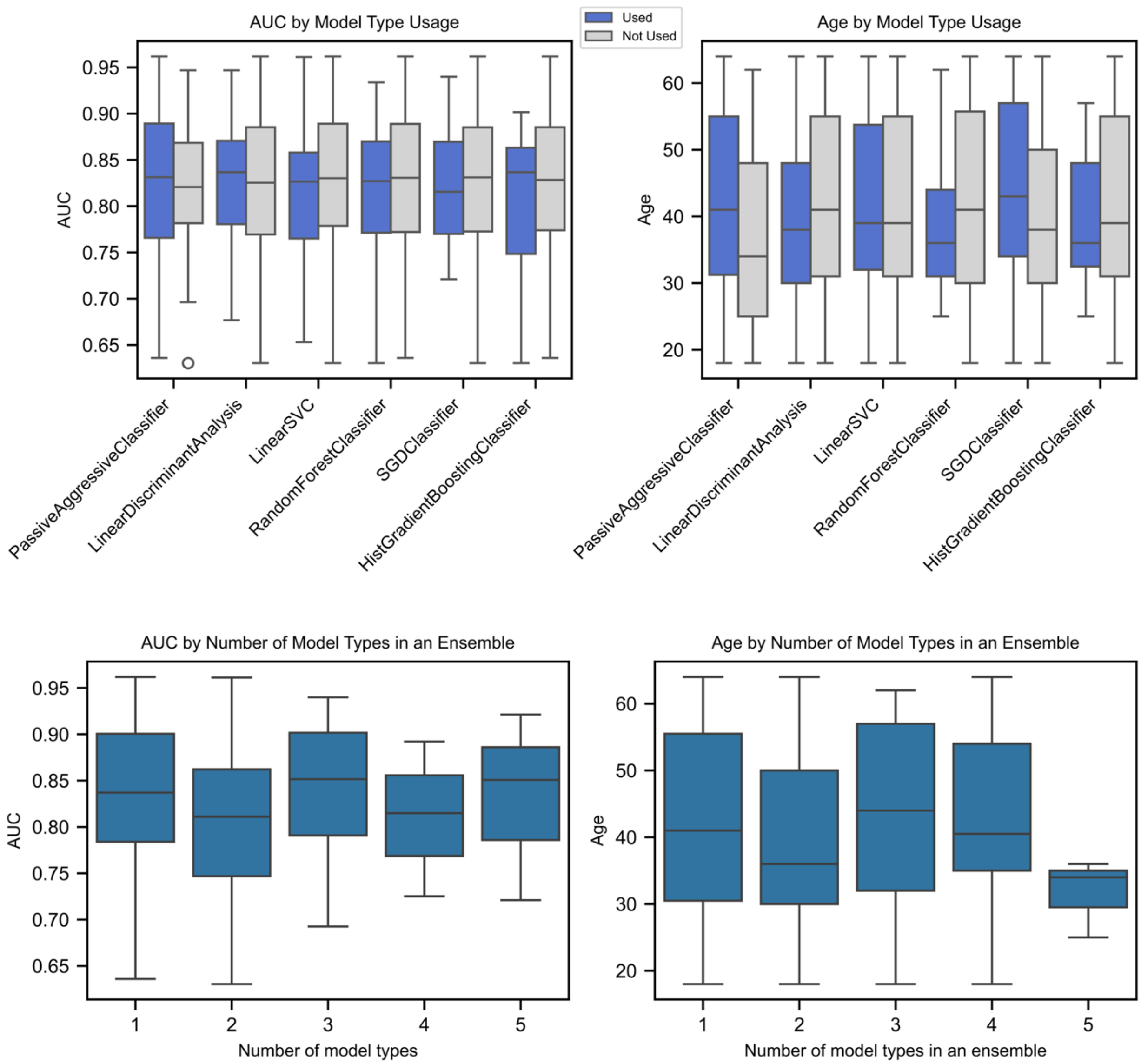
Supplementary Figure S2 shows the percentage of cases in which each model type was used (left), as well as the number of different model types included in the ensemble classifiers (right). Model names correspond to class names in the scikit-learn toolbox. Because multiple model types can be combined within a single cross-validation instance as an ensemble model, the total percentage exceeds 100% in the right panel.

Notably, the Passive-Aggressive Classifier was selected as the top-performing model in the majority of cases (>70%) by auto-sklearn. This algorithm belongs to a family of online learning methods for large-margin classification. It seeks to maintain a large classification margin and updates its parameters only when a prediction error occurs or when the margin constraint is violated. This model is a linear classifier and the other two most frequently selected models, Linear Discriminant Analysis and Linear Support Vector Classifier (SVC), are also linear classifiers. The consistent selection of linear models suggests that, in the context of high-dimensional fMRI data with limited training samples, linear decision boundaries may offer a favorable balance between model complexity and generalizability.



Supplementary Figure S2. Percentage of cases in which each model type was used (left), and the number of different model types included in an ensemble classifiers (right). PassiveAggressiveClassifier, Passive-Aggressive classifier [2]; LinearDiscriminantAnalysis, Linear Discriminant Analysis [3]; LinearSVC, Linear Support Vector Classification [4]; RandomForestClassifier, Random forest classifier [5]; SGDClassifier, regularized linear models with stochastic gradient descent (SGD) learning [6]; HistGradientBoostingClassifier, Histogram-based Gradient Boosting Classification Tree [7]; ExtraTreeClassifier, Extremely randomized tree classifier [8]; MLPClassifier, Multi-layer Perceptron classifier [9]; AdaBoostClassifier, AdaBoost classifier [10]; QuadraticDiscriminantAnalysis, Quadratic Discriminant Analysis [11]; SVC(poly), Support Vector Classification with polynomial kernel [12]; SVC(rbf), Support Vector Classification with radial basis function kernel [12]; KNeighborsClassifier, Classifier implementing the k-nearest neighbors vote [13].

Supplementary Figure S3 shows the relationship between model selection, AUC performance, and participant age. Only models that were selected in more than ten cross-validation instances are included. No significant associations were found between model type, ensemble size, and classification performance. Similarly, model selection did not vary systematically with participant age. These results suggest that the Auto-sklearn framework selected classifiers in a participant-specific manner, without systematic bias related to decoding accuracy or demographic variables.



Supplementary Figure S3. Associations between model selection and both model performance (Area Under the ROC Curve; AUC) and participant age. The upper panels show associations for individual model types (limited to those used in more than 10 cross-validation instances). The lower panels show the relationship between the number of model types included in an ensemble and AUC or participant age. No significant associations were found for any model types or for the number of models included in an ensemble, based on linear mixed-effects model analyses with AUC or age as the dependent variable and participant as a random intercept.

References

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