Brain neuromarkers predict self- and other-related mentalizing across adult, clinical, and developmental samples

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Abstract

Human social interactions rely on the ability to reflect on one's own and others' internal states and traits—a psychological process known as mentalizing. Impaired or altered self- and other-related mentalizing is a hallmark of multiple psychiatric and neurodevelopmental conditions. Yet, replicable and easily testable brain markers of mentalizing have so far been lacking. Here, we apply an interpretable machine learning approach to multiple datasets (total *N*=281) to train and validate fMRI brain signatures that predict 1) mentalizing about the self, 2) mentalizing about another person, and 3) both types of mentalizing. We test their generalizability across healthy adults, adolescents, and adults diagnosed with schizophrenia and bipolar disorder. The classifier trained across both types of mentalizing showed 98% predictive accuracy in independent validation datasets. Self-mentalizing and other-mentalizing classifiers had positive weights in anterior/medial and posterior/lateral brain areas respectively, with accuracy rates of 82% and 77% for out-of-sample prediction. Classifier patterns across cohorts revealed better self/other separation in 1) healthy adults compared to individuals with schizophrenia and 2) with increasing age in adolescence. Together, our findings reveal consistent and separable neural patterns subserving mentalizing about self and others—present at least from the age of adolescence and functionally altered in severe neuropsychiatric disorders. These mentalizing signatures hold promise as mechanistic neuromarkers to measure social-cognitive processes in different contexts and clinical conditions.

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Introduction

Mentalizing—representing and inferring the psychological states of oneself and others—is a fundamental process for adaptive navigation through the social world (Moore & Frye, 1991; Wellman, 2014). Delineating the brain systems involved in mentalizing about self and others is important for understanding brain health and dysfunction, as atypical mentalizing patterns underlie many neurodevelopmental and psychiatric conditions (Brüne & Brüne-Cohrs, 2006; Debbane et al., 2016; Gray et al., 2011; Luyten et al., 2020; Sharp, 2006; Sloover et al., 2022; Johnson et al., 2022).

Many studies have examined the neural correlates of mentalizing, suggesting an interplay of different brain regions, including medial prefrontal cortex (mPFC), temporoparietal junction (TPJ), and precuneus (Frith & Frith, 2006; Saxe, 2006; Schurz et al., 2021; Van Overwalle & Baetens, 2009; Yang et al., 2015). However, predictive brain measures of mentalizing that can be applied to individuals to decode the degree of self-related and other-related processing are still lacking. Most cognitive and affective processes cannot be captured by activity in individual brain regions, as they are reflected in patterns of brain activity distributed across multiple regions and systems, which can be harnessed in decoding (Kragel et al., 2018; Rosenberg et al., 2018). For instance, recent work demonstrates that distributed brain activity and connectivity patterns as indexed by fMRI enables us to decode the intensity of pain (Wager et al., 2013), drug and food craving (Koban et al., 2023), sustained attention (Rosenberg et al., 2016), depressive rumination (Kim et al., 2023), and clinically relevant behaviors and outcomes (Gabrieli et al., 2015). These predictive brain activity patterns or '*brain signatures'* are multivariate models that utilize data across the whole brain to make formally testable population-level predictions across subjects and datasets (Kragel et al., 2018; Woo et al., 2017). The predictions address the involvement and/or the intensity of a mental process. Here, we apply this 'signature' approach to predict mentalizing about oneself or other people.

Mentalizing, as a hidden state, would arguably benefit from such an approach. Thinking about self and others is inherently multilayered and multidimensional (Schurz et al., 2021; Tamir & Thornton, 2018; Qin et al., 2020). Recent conceptualizations of self- and social-cognition point to multiple dimensions, such as about self versus others, affective versus cognitive (Corradi-Dell'Acqua et al., 2014; Luyten et al., 2020; Schurz et al., 2021) and multiple layers, such as observing behaviours, and processing at the state and trait levels (Tamir & Thornton, 2018). Moreover, social cognition terms, including but not limited to mentalizing (e.g., empathy, perspective taking) suffer from inconsistent usage in the literature and lack of consensual definitions (Quesque et al., 2024). Developing brain signatures of mentalizing could potentially help account for this heterogeneity, offering the possibility of testing whether the proposed subdimensions of mentalizing are subserved by dissociable neurobiological patterns. In turn, these signatures carry the potential for validating the multiple facets of mentalizing (Kragel et al., 2018). However, it remains unclear—especially considering the complexity of the mentalizing construct—whether distributed neural patterns can reliably predict mentalizing using brain images.

A central question is whether mentalizing about oneself and mentalizing about others (self- and other-mentalizing hereafter) are reliably distinguishable based on brain activity. Recent electrophysiological evidence suggests that self- and other-mentalizing activate overlapping cortical areas following a similar temporal sequence: Temporoparietal junction (TPJ), medial temporal gyrus (MTG)/temporal poles (TP), precuneus/posterior cingulate cortex (PCC), medial prefrontal cortex (mPFC) in a roughly posterior to anterior temporal order (Tan et al., 2022; Wang et al., 2021). Conversely, differences in brain activity between self- and other-mentalizing have also been observed. In mPFC, more dorsal areas coincide with other-related processing and ventral areas with self-related processing, with research initially supporting a linear (Denny et al., 2012) but more recently a curvilinear (Parelman et al., 2021) ventral-to-dorsal gradient for self versus other within mPFC. Further, self-referential thought typically elicits activation in cortical midline structures, such as anterior cingulate cortex (ACC), subcortical areas, including thalamus, striatum and caudate nucleus, and, to a lesser extent, in insula, temporal poles and ventrolateral prefrontal cortex (vlPFC; Fossati et al., 2003; Denny et al. 2012; Murray et al., 2014; Northoff et al., 2006; Parelman et al., 2021; Van der Meer et al., 2010). In contrast, other-referential thought typically elicits activation in TPJ, middle and superior temporal gyri extending to temporal poles (Arioli et al., 2023; Frith & Frith, 2006; Parelman et al., 2021; Saxe, 2006; Tamir et al., 2016; Wagner et al., 2019), and to a lesser degree in supplementary motor area (SMA), left inferior and medial frontal gyri (IFG/MFG) and medial orbitofrontal cortex (Arioli et al., 2021; Murray et al., 2014). Collectively, the literature remains inconsistent regarding the separation between self- and other-mentalizing and it is unclear whether generalizable brain models of self- versus other-mentalizing can be identified.

To address these gaps, we leverage fMRI and machine learning to develop three distinct brain signatures, 1) the Mentalizing Signature (MS) for mentalizing overall (i.e., thinking about either the self or another person versus non-mentalizing control conditions), 2) the Self-Referential Signature (Self-RS) to detect specifically self-related thought (here referred to as “self-mentalizing”), and 3) the Other-Referential Signature (Other-RS) to detect other-related thought (here referred to as “other-mentalizing”). This allowed us to test whether dissociable and generalizable neural patterns underlie distinct dimensions of mentalizing.

To this end, we pooled data across nine cohorts from six independent fMRI studies. All studies included a mentalizing or a social-cognition task with three conditions: self-processing, other-related processing, and a non-social control condition. The training and validation datasets used variants of a standard trait-evaluation task, which involved reflecting on personality traits/statements describing self or another person. Conceivably, personality traits represent the enduring mental states that can be inferred from social perceptual systems (Molapour et al., 2021) across multiple observations (Schurz et al., 2021; Tamir & Thornton, 2018). Trait representations can be used to predict others’ future behavior and become the basis of the “mental-self” (Qin et al., 2020). Moreover, trait evaluations are one of the few mentalizing tasks used in the literature to include a self-condition, as other commonly used tasks (e.g., mental attribution, false-belief, perspective-taking tasks) only permit mentalizing about others. Thus, trait evaluation is an ideally suited task to study a key mentalizing process, namely representing stable psychological states of self and others.

We first used standard machine learning algorithms—support vector machines—to develop and cross-validate multivariate classifiers (signatures) of mentalizing in a sample of healthy adults. In a second step, we then further validated these signatures in seven completely independent test datasets from different laboratories, countries, and scanners, and with different sample characteristics (healthy, adolescent, and clinical populations), allowing us to test their generalizability and predictive validity in adolescent and clinical populations. Third, we tested the signatures in yet another independent dataset that used a different social cognition task to see whether mentalizing signatures would generalize to other contexts in which mentalizing is not directly instructed but likely to implicitly occur. Finally, we assessed whether local patterns of brain activity in several regions of interest (ROIs) contain sufficient information to predict self- and other-referential mentalizing. Together, the results of these analyses inform us about the functional neural organization of self- versus other-related mentalizing and provide us with distributed brain signatures of mentalizing that can be used as brain targets for monitoring and intervening on mentalizing-related brain processes in future studies.

Results

Data overview

The study included a total of 904 contrast images from 281 participants and nine independent cohorts, including four samples of healthy adults (*n*=118), two samples of healthy adolescents (*n*=105; M_{age}=12.9 and 16), and three samples of adults with clinical diagnosis of either schizophrenia (*n*=40) or bipolar disorder (*n*=18; see Fig. 1a and Table S1). Thus, this study combined six independent studies that constituted the training dataset, validation datasets, and the extension dataset (see Fig 1a). The training and validation datasets included participants completing variants of a self- and other-referential judgement task. The extension dataset included images of participants performing a social feedback task. All tasks included three conditions, namely a Self-condition, an Other-condition, and a non-social Control condition. Contrast images were computed for each condition (versus implicit baseline) and rescaled using L2-norm to standardize the scale of beta weights across participants, studies, and scanners.

Training and cross-validation results

The training dataset (Study 1a) consisted of *n*=21 adult participants who completed a trait-evaluation task using a block design (similar to Kelley et al., 2002; see Fig. 1c). In each block, participants were presented with several trait adjectives: In blocks of the Self-reflection condition, they were asked to rate the degree to which each trait adjective described themselves. In the Other-reflection condition, they had to rate how much each adjective described another person—a confederate with whom the subject had previously interacted during a decision-making task (Koban et al., 2014). In the non-mentalizing Control condition, participants indicated the number of syllables in the trait adjectives. To reduce the influence of non-mentalizing-related brain regions (e.g., visual cortex) and opportunistic classification based on features not related to mentalizing, we used an inclusive mask of brain regions related to social processing (see Fig. 1B).

We used support vector machines (SVM) using default parameters (to avoid overfitting) and 10-fold cross-validation (Scheinost et al., 2019) to train three distinct mentalizing signatures using the masked contrasts images from the training dataset. The Self-Referential Signature (Self-RS) was trained to detect Self-reflection (versus the two-remaining conditions), the Other-Referential Signature (Other-RS) to detect Other-reflection (versus the two-remaining conditions), and the Mentalizing Signature (MS) to detect both types of mentalizing versus the Control condition (see Fig. 1c).

All three signatures showed excellent cross-validated (out-of-sample) prediction accuracy (100% accuracy in two-alternative forced-choice tests, $p<.001$, averaged *Cohen's d* for Self-RS = 3.18, for Other-RS = 2.45, for MS = 4.92). To identify which voxels contributed most reliably to the mentalizing signatures, we used bootstrapping (5000 samples) to obtain one p-value per voxel and displayed the thresholded weight maps using false discovery rate (FDR) correction at $q < .05$ and cluster extent $k > 10$ voxels. Brain regions with significant positive voxel weights for the Self-RS (see Fig. 2) included the vmPFC, dmPFC, frontal eye fields, ventral ACC, frontal operculum, anterior insula, thalamus, caudate nucleus (see Table S2). For the Other-RS, significant positive weights were found in left vlPFC, left STS, bilateral TPJ, and precuneus/PCC (see Fig. 2 and Table S3). The MS had significant positive clusters in mPFC (both dorsal and medial), bilateral vlPFC, dorsal ACC (dACC), frontal operculum, bilateral SMA, bilateral MTG, bilateral TP, left STS, middle cingulate gyrus (MCC), bilateral posterior cingulate cortex (PCC), precuneus, bilateral angular gyrus/temporoparietal junction, and subcortical areas, including right caudate nucleus, left anterior insula (AI), bilateral thalamus (see Fig. 2 and Table S4).

For completeness, we trained a Self-versus-Other Classifier following the same training and validation pipelines (see Supplementary Figure 1). For the purposes of simplicity and because the pattern of results is in line with the main three signatures, we report the results pertaining to this signature only in the supplementary figure.

Validation in independent samples

Next, we validated the three brain signatures on several completely independent studies: two samples of healthy adults (Study 4a & 5a), two adolescent samples (Study 2 & 3), one cohort of participants with bipolar disorder (Study 5c), and two cohorts of participants with schizophrenia (Study 4b & 5b). All datasets included comparable trait evaluation tasks and fMRI block designs with three conditions, with some small variations in task designs between studies (see Fig 1a). To obtain pattern expression values, we computed the matrix dot product between the mentalizing signatures and each subject-level contrast images from these datasets, yielding one scalar value per individual contrast image and per signature (see Fig. 1c). These pattern expression values were then used to test the predictions of the mentalizing signatures. The average prediction accuracy in two-choice tests, across all independent validation datasets, was 81.52% for the Self-RS (+/- 6.17% average STE; significant in 10 out of 14 validation tests [7 samples*2 comparisons]), 77.25% for the Other-RS (+/- 6.02% average STE; significant in 12 out of 14 tests), and 97.87% for the MS (+/- 01.79% average STE; significant in all 14 tests), suggesting overall high prediction accuracy of the three signatures, even in new samples, although with some variations between datasets (see Fig. 2 & Table S5).

Better self/other separation in healthy adults compared to participants with schizophrenia

The results above show that the signatures significantly predicted mentalizing in most samples, including clinical samples. Yet, schizophrenia in particular is often associated with impaired social cognition and altered self-perception (Bora et al., 2009; Sprong et al., 2007). Thus, we next tested how well the signatures separated self- from other-related mentalizing in two of the validation studies (Study 4 & Study 5) that included both participants with schizophrenia (total n=40) and matched healthy participants (total n = 48). As expected, both the Self-RS (M_{HC} = .32, M_{SCZ} = .12; β = .21, STE = .07, CI = [.07, .35], p = .004) and the Other-RS (M_{HC} =.43, M_{SCZ} = .24; β = .19, STE = .07, CI = [.04, .33], p = .01) showed better discrimination between self- and other-referential mentalizing (i.e., a greater positive difference between Self-RS responses in the Self compared to the Other condition, and a greater difference between Other-RS responses for the Other compared to the Self condition) in healthy adults, compared to adults with schizophrenia. No group differences were found in the correct discrimination of mentalizing versus Control by the MS (p = .28, see Fig. 3). These results indicate that, compared to healthy adults, participants with schizophrenia have less differentiated brain patterns between self- and other-related thought, indicating the potential clinical utility of the signatures.

For completeness, we also compared the discrimination of self- versus other-related mentalizing activity in participants with bipolar disorder (n=18) versus healthy adults (n=15) using data from Study 5. However, participants with bipolar disorder did not differ significantly from controls for any of the signatures.

Better self-other separation with increasing age in adolescents

Next, we explored potential developmental differences in the classifier performances, by testing whether the ability of the classifiers to separate self- from other-related mentalizing depended on the age of the participants in the two adolescent samples (Studies 2 and 3, total N = 105). We combined data from Study 2 (age 12-18 years; M_{age} = 16) and Study 3 (age 11-14 years; M_{age} = 12.9). We found that (controlling for study) older adolescents had better self/other separation both for the Self-RS (β = .08, *STE* = .03, *CI* = .012 to .018, p = .01) and the Other-RS (β = .06, *STE* = .03, *CI* = .001 to .12, p = .047; see Fig. 4). In contrast, there were no significant associations between age and performance of the MS. These results suggest that, with increasing age, adolescents' brain activity becomes more differentiated for self- versus other-related mentalizing.

Testing the mentalizing signatures in a social feedback task

So far, we have shown that the signatures performed well in several independent datasets from different labs, but all using a similar explicit mentalizing task. In order to examine how the signatures would respond to other types of social tasks, especially those without any explicit mentalizing demands, we next tested their performance in an fMRI dataset (Study 6) of $n = 49$ romantic partners performing a social feedback task. Participants were instructed that their task was to read other participants' likability ratings about themselves and about their romantic partners. Thus, participants viewed the positive and negative ratings targeted to themselves (Self-feedback) and to their partners (Partner-feedback). Participants were informed that their partners would see the same material, establishing a sense of shared experience. As the control condition, participants viewed others' feedback without any ratings, which was ostensibly due to technical errors.

Here, we tested whether the signatures' responses paralleled the target of the feedback conditions. For instance, to provide evidence of successful extension, the Self-RS should show higher pattern expression values in the self-feedback condition as opposed to other two conditions. As expected, the Self-RS had different response levels across task conditions in favor of the Self-condition, $F(2,96)$= 14.214, p < .001, η_p^2 = .23 (Fig. 5). Bonferroni-corrected pairwise comparisons showed that the Self-feedback condition (M= .16) had significantly higher Self-RS expression scores than both the Partner-feedback (M= -.09, p=.01) and Control (M= -.36, p<.001) conditions. Additionally, Self-RS also produced higher pattern expression values for the Partner-feedback (M= -.09) compared to Control condition (M= -.36, p = .04). Similarly, the MS successfully discriminated both feedback conditions against Control condition, $F(2,96) = 14.711$, $p < .001$, $\eta_p^2 = .24$ (Fig. 5). Bonferroni-corrected pairwise comparisons indicated that both Self-feedback ($M = .17$, $p < .001$) and Partner-feedback ($M = .12$, $p = .002$) conditions had significantly higher pattern expression scores than the Control condition ($M = -.17$). However, the Other-RS did not produce any significant differences between task conditions, $F(2,96) = 2.003$, $p = .14$ (Fig. 5). Together this suggests a modulation of the MS and the Self-RS (but not the Other-RS) even in a task where mentalizing was not directly instructed, in line with the idea that feedback to oneself or one's partner should lead to more mentalizing related brain activity.

Local patterns of self- and other-related mentalizing

Finally, we trained local classifiers in regions of interest (ROI) associated with mentalizing to gain further insight into how mentalizing-related information is processed locally and which regions can predict self- versus other-related mentalizing. The whole brain patterns indicate which regions have the most reliable positive and negative contributions to different forms of mentalizing, but they do not necessarily show which regions are *not* involved and do not inform us whether local patterns alone can predict the target of mentalizing (self or other). Training and testing classifiers for brain regions implicated in the literature can inform us in this regard.

To this end, we included ten ROIs (see Fig. 6) previously associated with mentalizing as shown in an automated term-based meta-analysis (NeuroSynth, Yarkoni, 2011): the medial prefrontal cortex (mPFC), two clusters in anterior middle temporal gyrus (aMTG) bilaterally, two clusters in temporoparietal junction (TPJ) bilaterally, a cluster covering precuneus and posterior cingulate cortex (PRE/PCC), left supplementary motor area (SMA), and three clusters in Cerebellum. We trained four types of classifiers in each of these ten ROIs. In other words, we trained each ROI to perform the four following classification tasks separately: 1) Self-mentalizing (versus the two remaining conditions); 2) Other-mentalizing (versus the two remaining conditions), 3) both mentalizing conditions (self and other) against Control condition, and 4) Self-mentalizing against Other-mentalizing. The ROI classifiers were trained and cross-validated in our training dataset (Study 1a; *n*=21) and tested in the combined sample (*n*=211) of participants from all validation datasets (including all healthy, developmental, and clinical cohorts; for detailed results see Supplementary Table 6).

As expected, all ten regions showed excellent classification accuracy as the general mentalizing classifiers in the training dataset, and all predicted mentalizing successfully in the validation dataset (see blue bars in Fig. 6). However, not all regions could significantly differentiate Self-reflection and Other-reflection conditions. While mPFC, aMTG, TPJ, and PRE/PCC were capable of differentiating self and other conditions, the Cerebellum clusters and left SMA failed at this task (see orange bars in Fig. 6). When trained for self-mentalizing (see red bars in Fig. 6), the right aMTG cluster could not capture any consistent configurations for Self-mentalizing. While TPJ subregions were successful here against control conditions, they could not predict Self- against Other-mentalizing, implying a lack of exclusive neural patterns for self-mentalizing within TPJ subregions. Finally, when trained for Other-mentalizing, the Cerebellum subregions and left SMA were incapable of picking up consistent patterns (see violet bars in Fig. 6).

Taken together, our analyses suggest that mPFC (including both vmPFC and dmPFC), TPJ, aMTG, and Precuneus/PCC clusters encode both self- and other-mentalizing, and that the left SMA and Cerebellum clusters most likely are involved in domain-general operations during mentalizing. Besides, our findings suggest that TPJ and aMTG are more strongly associated with other-mentalizing, while mPFC and Precuneus/PCC clusters are unique in the sense that they are consistently involved in both self- and other-related mentalizing.

Discussion

Mentalizing—reflecting about others' and one's own internal states—is a fundamental capacity required to function in a social world. Transdiagnostically, mentalizing deficits typify an array of psychopathological conditions (Brüne & Brüne-Cohrs, 2006; Debbane et al., 2016; Gray et al., 2011; Luyten et al., 2020; Sharp, 2006; Sloover et al., 2022; Johnson et al., 2022). Here, we developed a novel brain signature of mentalizing in general (the '*Mentalizing Signature'* or *MS*), as well as specific self- and other-related mentalizing signatures (*Self-RS* and *Other-RS*), combining data from nine independent cohorts (*N*=281). The three signatures showed good to excellent classification accuracy in independent data and provide several novel insights into the brain circuits of mentalizing. First, mentalizing appears to coincide with a specific pattern of brain activity, with reliably dissociable activation patterns for self- and other-related mentalizing, based on both whole-brain activity as well as within key nodes of the social brain, especially mPFC, precuneus/PCC, TPJ and aMTG. Second, the signatures significantly predicted mentalizing not only in healthy adults, but also in adolescents and in individuals with schizophrenia and with bipolar disorder, demonstrating its utility across different (including clinical) samples. Third, our results point to the relevance of these mentalizing signatures for a range of different research questions in social, developmental, and clinical neuroscience, by showing (i) an engagement of the MS in an independent social feedback task, (ii) that the differentiation of self- and other-related mentalizing increases as individuals transition from adolescence to adulthood, and (iii) that it is less pronounced in individuals with schizophrenia compared to healthy controls. Thus, our data provide us with clearly defined *brain models* (Kragel, et al., 2018), applicable across contexts to assess the engagement of mentalizing-related brain regions in different experimental conditions and their alteration in clinical and neurodevelopmental conditions.

The Mentalizing Signature (MS) successfully predicted mentalizing across different tasks, extending to a social feedback task that did not include any explicit mentalizing instruction. The regions that contributed to the MS most positively included mPFC, precuneus, temporoparietal junction, superior temporal sulcus, and many other regions previously associated with mentalizing (Frith & Frith, 2006; Oosterwijk et al., 2017; Van Overwalle & Baetens, 2009; Tamir et al., 2016; Tan et al., 2022), providing convincing face validity of this signature. Its exceedingly high predictive performance in validation datasets implies that mentalizing recruits consistent and reliable neural configurations in the brain, not only in healthy controls, but also clinical cohorts and developing adolescents. Interestingly, the MS also extended to other tasks predicting social feedback conditions that potentially evoke implicit mentalizing. This indicates that implicit and explicit forms of mentalizing largely share a common neural basis, in keeping with previous research (Van Overwalle & Vandekerckhove, 2013). Thus, subnetworks of mentalizing (implicit-explicit) may be building on a common anatomical architecture that is here covered by the MS.

Recent work proposes that self- and other-mentalizing activates common neural constellations or representations and recruits largely overlapping regions (Oosterwijk et al., 2017; Tan et al., 2022; Wang et al., 2021). In contrast, our findings suggest that, while they share a large common core (as evident in the MS), they can also be distinguished reliably based on both whole brain as well as local activation patterns. The Self-RS had positive weights in anterior mentalizing regions around cortical midline structures, such as mPFC, ACC, thalamus, caudate nucleus, frontal eye fields, and insula, extending to the frontal operculum. This pattern is in line with previous meta-analyses (Denny et al., 2012; Murray et al., 2014; van der Meer et al., 2010). The mPFC has been consistently related to mentalizing, and especially its ventral part with self-related processing (Fossati et al., 2003; Kelley et al., 2002; Heatherton et al., 2006; Koban et al., 2021; Wagner et al., 2019). The ventral-to-dorsal linear (Denny et al., 2012) and curvilinear gradient (Parelman et al., 2021) hypotheses propose that mPFC is involved in both self- and other-person related processing. Accordingly, our results show that mPFC is involved in both self- and other-related mentalizing with different neural configurations, and that the information encoded in mPFC seems to predict self-mentalizing more consistently. Besides, self-processing recruited reward-processing circuits (e.g., striatum), in line with the idea that introspection about oneself is intrinsically rewarding (Chavez et al., 2017; Northoff & Hayes, 2011; Tamir & Mitchell, 2012). The involvement of subcortical areas (e.g., thalamus) and cortical areas associated with interoception (e.g., insula) is in line with the previous work suggesting that one has access to affective/physiological information during self-mentalizing which are less present during mentalizing about others (Maresh & Andrews-Hanna, 2021) and that interoceptive information might be an important contribution to one's sense of self (Babo-Rebelo & Tallon-Baudry , 2018; Garfinkel et al., 2013; Qin et al., 2020).

The Other-RS subsumed more posterior and lateral regions, such as TPJ, PCC/Precuneus, STS, and vlPFC, resonating with previous findings (Arioli et al., 2023; Frith & Frith, 2006; Van Overwalle & Baetens, 2009; Parelman et al., 2021; Saxe, 2006; Tamir et al., 2016; Wagner et al., 2019). Interestingly, our results concerning the precuneus/PCC do not align with the known subdivisions of the default-mode (Andrews-Hanna et al., 2010) or mentalizing networks (Wang et al., 2021). This region is thought to be part of the midline core of the default-mode network (Andrews-Hanna et al., 2010) and of the medial subsystem of the mentalizing network (Wang et al., 2021) with stronger associations with self-processing. However, here in our results, while the precuneus/PCC cluster also contains information about self-mentalizing, it appears more strongly associated with other-related mentalizing, along with the areas that are part of the lateral subdivisions of both networks (e.g., TPJ, temporal lobes). A potential explanation here could be the involvement of precuneus in mental orientation/imagery (Peer et al., 2015; Schurz et al., 2014), which is required in a trait-evaluation task.

The mentalizing signatures generalized to data from different types of cohorts, including healthy adults, schizophrenia and bipolar samples, and adolescents. This shows that the overall neurobiological configurations of self- and other-related mentalizing are comparable across these populations and that the signatures have utility in different types of study populations. However, the Self-RS and Other-RS signatures also showed sensitivity to clinical status, since self-versus-other differentiation in the pattern responses was significantly less pronounced for both patterns in participants with schizophrenia compared to matched healthy controls. This finding is noteworthy and in line with clinical observations of alterations in self-perception, mentalizing, and the ability to discriminate between self- and other-generated thought (Bora et al., 2009; Potvin et al, 2019; Sprong et al., 2007; van der Meer et al., 2010). The responses in the bipolar sample did not differ significantly from those of the healthy adults but given the limited sample size of the bipolar group in the present analysis, future work is needed to asses more fine-grained (and potentially context-dependent) differences in mentalizing responses in bipolar disorder, as well as in other psychiatric and neurodevelopmental disorders with mentalizing deficits.

In the two adolescent samples (aged 11 to 18 years), greater age was associated with better self/other differentiation of both the Self-RS and the Other-RS. In other words, responses of these two brain signatures to self- and other-related mentalizing were more different from each other in older adolescents. Considering that the signatures were developed using an adult dataset, this reflects an ongoing development of the mentalizing neurobiology (Crone & Fuligni, 2020; Fehlbaum et al., 2022) to become more adult-like and more differentiated for different targets of mentalization, during the age span covered in our study (11-18 years). Future studies could test the role of pubertal development instead of chronological age, and test the signatures in younger children, and those with developmental disorders.

We note that the signatures' classification performance in the training and cross-validation sample is consistently higher than in the independent validation datasets. This could potentially owe to leakage of information across the different subjects in the training dataset, who all performed the same task in the same scanner and experimental settings. Alternatively, it might reflect the fact that the Other-condition in the mentalizing task was about a relatively unfamiliar other person (a confederate). This may lead to a greater difference in self- versus other-related processing compared to studies in which mentalizing was about a familiar or close person—which is often more closely related to the self and likely also engages self-referential processing. This could potentially also explain why the Other-classifier was less successful in separating other-related from self-related feedback in the sample of romantic couples (Study 6), where participants likely consider their partners as an extension of themselves. The signatures may also pick up unrelated information in control conditions, which may lead to failed predictions as observed in Study 4 for Self-RS and Study 3 for Other-RS.

Future studies may address other important research questions that were beyond the scope of the present study, such as testing whether other dimensions of mentalizing (e.g., cognitive versus affective; Luyten et al., 2020; Schurz et al., 2021) or different types of mental state content (i.e., beliefs, preferences; Defendini & Jenkins, 2023) involve distinct mentalizing signatures as well. Recent work (Kim et al., 2024; Kim Lux et al., 2022) investigated valence and self-relevance as two key components of the internal thought. It is an open question how the brain integrates valence with different targets during mentalizing. Finally, future research can also build on this work by testing the signatures in other mentalizing tasks (e.g., false-belief, emotion imagery), on a greater variety of targets (see Courtney & Meyer, 2020), and in other related mental processes (e.g., autobiographical memory retrieval).

In conclusion, we trained and validated three whole-brain signatures that predict self-related, other-related, and both types of mentalizing in multiple independent datasets that used different variants of a standard mentalizing task in different and diverse populations. Our findings imply that self- and other-mentalizing use largely dissociable neural mechanisms that build on a foundational overall mentalizing capacity. Indeed, the three mentalizing signatures possess potential for use as mechanistic neural markers of mentalizing about self and others, for example by testing how brain-circuits of mentalizing are engaged or modulated by different types of experimental conditions, and how they might be altered in different psychiatric and neurodevelopmental populations.

Methods

Participants

The present study pooled data from a total of *N*=281 participants (119 females and 162 males, M_{age}=25.5, SD_{age}=12.9) from nine cohorts participating in six independent studies (see Fig. 1a and Table S1). These nine cohorts comprised four samples of healthy (neurotypical) adult samples, two samples of healthy adolescents, and three samples of adults with a diagnosed psychiatric condition. While most of the datasets have been previously published separately, the analyses reported here were not published previously, and the six studies have not been previously combined.

The training sample (Study 1; Koban et al., 2014) consisted of *n*=21 healthy adults (10 women and 11 men, M_{age} = 23.5) who were recruited at the University of Geneva, Switzerland. One additional participant with structural abnormalities in the brain was excluded from the original study and the present analysis.

Study 2 (Debbane et al., 2017) included *n*=44 healthy adolescents (23 females and 21 males, M_{age} = 16, SD_{age} = 1.86, Age range = 12.01 to 18.84) who were recruited from secondary schools in Geneva, Switzerland. In the original study, one additional subject was excluded due to structural abnormalities in the brain, three due to incompletion of the paradigm, one due to signs of substance use, and five due to excessive movement.

Study 3 (van Buuren et al., 2020) included *n*=61 healthy adolescents (27 females and 34 males, M_{age} = 12.9, SD_{age} = 0.43, Age range = 11.61 to 14.22) who were recruited for a longitudinal project from secondary schools in the Netherlands. An additional 18 participants were excluded from the original study due to excessive movement, incorrect task completion, or measurement errors.

Study 4 (Fuentes-Claramonte et al., 2019; Fuentes-Claramonte et al., 2020) included n=33 healthy adults (14 women and 19 men, M_{age} = 41.7) and *n*=23 adults with schizophrenia (7 women and 16 men, M_{age} = 37). The two cohorts were matched on age, sex, and a measure of general intelligence. The patients were recruited from a local psychiatric hospital in Barcelona, Spain based on diagnostic interviews. The schizophrenia diagnosis was confirmed using the Structured Clinical Interview for DSM Disorders (SCID; First, 2015).

Study 5 (Zhang et al., 2015) included three types of cohorts: Healthy adults (*n*=15, 6 women and 9 men, M_{age} = 33.3), adults with schizophrenia (SZ, *n*=17, 6 women and 11 men, M_{age} = 35.5), and adults with bipolar disorder (BD, n=18, 9 women and 9 men, M_{age} = 40.3). The clinical cohorts were recruited from a local hospital in the north of the Netherlands. The diagnoses of the patients were confirmed using the Mini International Neuropsychiatric Interview-Plus 5.0.0 (MINI-Plus; Sheehan et al., 1998). All BD patients were chosen among those who had a history of at least one psychotic episode. All three cohorts were matched with one another on age, sex, level of education, and a measure of general intelligence. The SZ and BP patients were additionally matched on the level of cognitive and clinical insight as measured by the Schedule of Assessment of Insight-Expanded version (SAI-E, clinical insight; Kemp & David, 1997) and the Beck Cognitive Insight Scale (BCIS, cognitive insight; Beck et al., 2004).

Study 6 included 56 healthy adults in romantic relationships recruited from the Tucson, Arizona community and surrounding areas. Seven participants were excluded from the study due to missing or inadequate imaging data, yielding a final sample size of *n*=49 (26 women and 23 men, M_{age} = 22.6). Community members were eligible to participate if they had been in a romantic relationship for at least six months, had no contraindications for MRI scanning, and did not meet criteria for active psychosis or mania at the time of screening. Both members of the couple completed all components of the study including the social feedback fMRI task.

All participants gave written informed consent and were compensated for their participation via monetary means or gifts. All studies were approved by the respective institutional ethics committees. For additional information, please refer to the original studies and Supplementary Table 1.

Tasks

Training dataset

We used a trait evaluation task, adapted from Kelley et al. (2002) as the training mentalizing task. Participants were asked to rate the extent to which certain personality adjectives (e.g., 'talkative', 'daring') described themselves (Self-condition) or a same-sex confederate (Other-condition), with whom they thought they were interacting in a preceding decision-making task (Koban, et al., 2014). In the Control condition, they were asked to count the syllables for each trait adjective.

Participants met the confederate in person at the beginning of the experimental session where they were briefed that one of them would be tested in the scanner, the other one in a separate room, and that they would interact via computer interface. They first participated in a social decision-making task resembling a serial dictator paradigm whereby the participant was given the choice to share or keep the resources with the confederate in a series of trials (Koban, et al., 2014). After this task, participants were introduced to the trait-evaluation task and were asked to rate their co-player.

The task consisted of 150 trials in total presented in 30 blocks (ten per condition). Each block contained five trials and lasted for 20 seconds, with an inter-block-interval (fixation cross) of 8s. Half of the blocks only contained negative and the other half only positive adjectives. Each word appeared once for each condition (50 adjectives were used in total).

Each trial started with a 3s cue above the fixation cross reminding the condition (self, other, or syllables) which was followed by the presentation of the adjective and a Likert scale (1-4) on which the participant was expected to select using a button press device. A word was presented every 4 seconds. If the participant made a choice sooner, the word would disappear for the remaining time of the 4 seconds before the next trial. The order of the blocks and words displayed in each block was randomized.

Validation datasets

All validation datasets included similar mentalizing tasks with the same three conditions (Self, Other, Control) as the training task and utilized a block design (for an overview, see Fig. 1a and Table S1). The main difference between validation tasks was the stimuli that were presented: Studies 2 and 3 used trait adjectives, Study 4 (with two cohorts) used trait statements, Study 5 (with three cohorts) used a mix of trait and physical statements, and Study 6 used positive and negative feedback about the likeability of participants' romantic partners, information which was assumed by participants to be accessible to their partner. The studies also used a variety of *others* in the Other-condition: Best/close friend (Study 2), similar and dissimilar classmate (Study 3), relative or close friend (Study 5), romantic partner (Study 6), and acquaintance (Study 4). Studies 2 and 5 collected responses using Likert scales and Studies 3 and 4 asked for binary choices (yes/no). Study 6 was primarily a passive viewing task, promoting spontaneous empathy when feedback was directed to participants' romantic partners (or self). Finally, the Control conditions also varied between studies. Studies 4 and 5 presented general knowledge statements; Study 3 asked participants to search for the letter in words; Study 2 asked them to count the syllables in words; and Study 6 presented no feedback during control trials.

fMRI data acquisition and pre-processing

Training dataset

The training MRI images were acquired on a 3T Magnetom TIM Trio whole-body scanner (Siemens, Germany) with the product 12-channel head coil. A T1-weighted MPRAGE sequence (TR = 1900ms, TI = 900 ms, TE = 2.27 ms, voxel size 1 x 1 x 1 mm) was used to acquire structural anatomical images. Functional images were obtained using a standard T2-weighted echo-planar imaging sequence (2D-EP, TR = 2100 ms, TE = 30 ms, flip angle 80°, voxel size 3.2 x 3.2 x 3.2 mm) that scanned the whole brain in 36 sequential slices. An automated shimming procedure was included to minimize magnetic field inhomogeneities.

SPM8 (Wellcome Department of Imaging Neuroscience, UCL, London, UK) and Matlab® (The MathWorks Inc.) were used for image preprocessing and first-level analysis. A standard preprocessing pipeline was performed, that included spatial realignment and reslicing, coregistration, unified segmentation and normalization to the standard Montreal Neurological Institute (MNI) echo planar imaging template (voxel size: 2 mm^3), and finally spatial smoothing using an 8 mm Full Width at Half Maximum (FWHM) Gaussian kernel.

During first-level analysis, we included six task (block) regressors that were composed of 3 task conditions by positive and negative valence. The task regressors were convolved with a canonical hemodynamic response function. We also included six additional regressors for motion parameters. A high-pass frequency filter (128s) and autocorrelation corrections (using restricted maximum likelihood and an autoregressive model) were used in model estimation.

Validation dataset

We conducted a non-systematic literature review to identify recent fMRI studies of comparable mentalizing tasks with at least three conditions (Self, Other, and non-mentalizing Control condition) and in which participants rated whether trait adjectives or statements. We emailed the authors of seven studies that we identified and received positive responses from four of them. Data from these four studies were included in the current study as validation datasets. In addition, to test the signatures in a different type of task, we included an unpublished dataset by one of the co-authors (JAH) as the extension dataset (Study 6). Please refer to the original studies (see Supplementary Table 1) for details of image acquisition, preprocessing, and first-level analysis.

The authors provided the person-level contrast images of three conditions (versus implicit baseline). Voxel weights were normalized using L2-norm. These contrast images were resampled onto the same image space as the training dataset using linear resampling. For Study 3, which included two different Other-conditions (similar and dissimilar classmates), we averaged the contrast images across these two conditions, resulting in a single Other-condition, as in the training and the other validation datasets (analyzing them separately did not alter the results).

Data Analysis

Training and cross-validation

Using 10-fold cross-validation, we trained three support-vector-machine (SVM) classifiers in Study 1 that discriminate each condition from the other two conditions: The Self-RS was trained to separate the Self-condition from Other and Control conditions, the Other-RS to separate the Other-condition from Self and Control conditions, and the MS was trained to separate both mentalizing conditions (Self and Other) from the Control condition. To reduce the possibility that classifiers opportunistically used non-mentalizing related processes (e.g., visual information), we applied a mask in the training dataset that includes key social-cognition regions (see Fig. 1b). This mask was computed as the union of six term-based meta-analytic maps (association and uniformity maps for "mentalizing", "self-referential", and "social", downloaded from NeuroSynth [Yarkoni et al., 2011; https://neurosynth.org] on 06/06/2024).

SVM were chosen based on their high performance for binary linear classification problems in high dimensional data. The algorithm fits a hyperplane that classifies true and false classes by assigning weights for each feature (i.e., each voxel). The fitting is performed for each of 10 folds, in which the data of 90% of participants are used for fitting the classifier and the resulting classifier is tested on the remaining 10% hold out participants' data, allowing to assess its classification performance in independent hold-out data. Because using a one versus the rest approach in SVM (e.g., Self versus Other and Control, see Fig. 1c) may add bias into the model by favoring the majority class, we fitted weighted SVM models with a ridge amount of .5. To avoid overfitting, the SVMs were otherwise trained using default parameters (regularization parameter C = 1). The cross-validated distance from the hyperplane of hold-out images was used to calculate the receiver operating characteristic (ROC) curves and the accuracy for each classification. Each SVM results in a weight map with one value per voxel. These voxel weights are effectively the predictive weights of the true class, yielding brain signatures of mentalizing that can be applied to other brain images to obtain a single pattern expression score per image.

We used bootstrapping to illustrate the regions that most significantly contribute to the classification. Statistical weight maps were calculated using 5000 bootstrapped samples that yielded two-tailed, uncorrected p-values for each voxel. These maps were then thresholded using FDR-correction at $q < .05$ with a minimum cluster size of 10 voxels. Note that corrected maps were only used to illustrate the most important contributing regions of each signature. Unthresholded weight maps are used for classification and hence constitute the brain signatures used for all further steps of the present analyses and which can be used in future tests in other studies. The classification accuracies in training dataset were tested using two-alternative forced-choice predictions and binomial tests.

Validation in independent datasets

The three mentalizing signatures were applied to the validation datasets by computing the pattern similarity values as the matrix dot product between mentalizing signatures and the person-level (1st level) contrast images of each study, yielding one scalar value per condition and participant and signature. The predictions followed a binary forced-choice principle using paired observations. Lastly, the signatures' classification accuracies were assessed using Receiver Operating Characteristic (ROC) analysis and binomial tests using a two-sided significance threshold of $p < .05$.

Group comparisons of pattern expression values. To quantify how well signatures discriminate Self versus Other conditions and to easily compare self/other separation across groups, we calculated a 'true minus false class score' for each signature by subtracting the pattern expression values of the false condition images from the true condition images (i.e., responses of the Self-RS for the Self minus Other condition, responses of the Other-RS for Other minus Self condition, responses of the MS for the mean of Self and Other conditions minus Control condition). For statistical comparisons between participants with schizophrenia and healthy controls, we ran linear mixed effects models for each of the signatures, with self-other discrimination ('true minus false class score') as the dependent variable. The group constituted the fixed effect variable (healthy controls [n=48] versus schizophrenia sample [n=40]). Because the data came from two different studies (Study 4 and Study 5), study was included as a random effect variable. Therefore, the model equation was "*true_minus_false_class_score ~ group + (1|study)*". To test whether the bipolar sample (n=18) differed from healthy adults (n=15) in Study 5 regarding their pattern expression values, we performed independent samples t-test for each of the signatures consecutively. The dependent variable was the "true minus false class score" mentioned above.

Associations with age. We tested whether the adolescents' age was associated with self-other discrimination using linear mixed effects models. We included age as the fixed effect, and Study (Study 2 and Study 3) as a random effect. The dependent variable was the difference of the true minus false classes for each of the signature, as detailed above. Therefore, the model formula was "*true_minus_false_class_score ~ ages + (1|study)*".

Testing the signature in an extension task (social feedback, Study 6)

The signatures were applied to the subject-level contrast images for three experimental conditions (feedback to the self, feedback to the partner, no feedback), by computing their dot products. The resulting pattern expression values were subjected to repeated-measures ANOVAs to test for differences across the three conditions of the social-feedback task. Bonferroni-corrected t-tests were used for subsequent pairwise comparisons.

Region-of-Interest (ROI) Analyses

To test the ability of local patterns to predict mentalizing and to separate self-related versus other-related mentalizing, we trained and cross-validated region-of-interest (ROI) classifiers using a parallel approach to the whole-brain classifiers. We downloaded a term-based meta-analytic map for 'Mentalizing' from NeuroSynth on 14/09/2022 that included 151 studies. We selected clusters that contained more than 200 voxels, resulting in the following ten ROIs: mPFC, bilateral TPJ, bilateral anterior MTG, precuneus/PCC, right SMA, and three clusters in the cerebellum. In each ROI, we trained and 10-fold cross-validated four classifiers in the training dataset and validated them in the remaining datasets, to (i) predict Self-mentalizing (versus the two remaining conditions), (ii) predict Other-mentalizing (versus the two remaining conditions), (iii) predict mentalizing (Self- and Other-mentalizing versus Control condition), and (iv) differentiate Self- versus Other-processing. We tested these ROI classifiers in the validation datasets using the same parameters and analytic approach as outlined above in the main whole-brain analyses.

General statistical approach

All data analysis was performed using Matlab® R2022b software and the Canlab toolbox (https://github.com/canlab). Statistical inference used a significance threshold of $p < 0.05$, unless otherwise noted.

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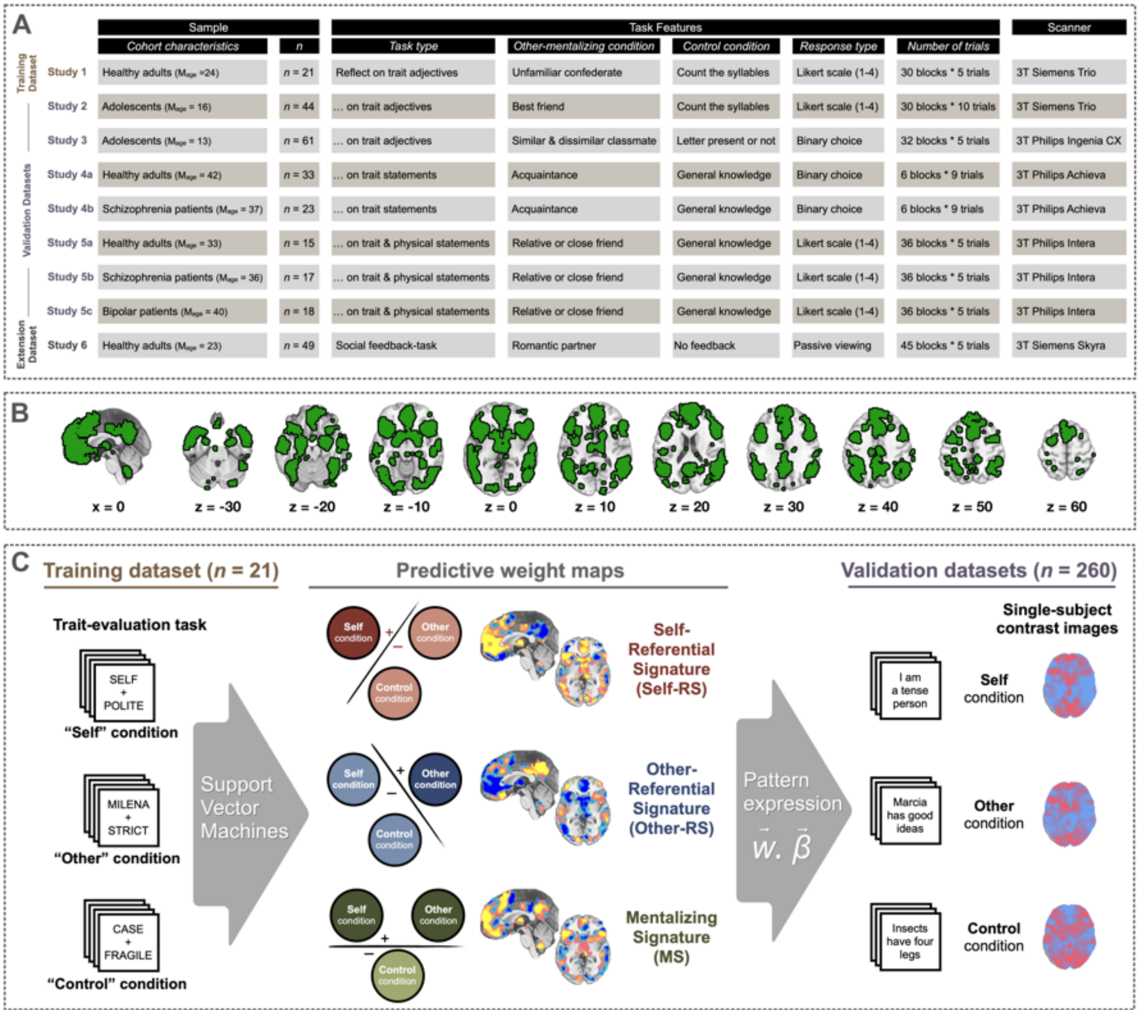
Figures



		Sample		Task Features					Scanner
		Cohort characteristics	n	Task type	Other-mentalizing condition	Control condition	Response type	Number of trials	
Training Dataset	Study 1	Healthy adults (M_{age} =24)	n = 21	Reflect on trait adjectives	Unfamiliar confederate	Count the syllables	Likert scale (1-4)	30 blocks * 5 trials	3T Siemens Trio
Validation Datasets	Study 2	Adolescents (M_{age} = 16)	n = 44	... on trait adjectives	Best friend	Count the syllables	Likert scale (1-4)	30 blocks * 10 trials	3T Siemens Trio
	Study 3	Adolescents (M_{age} = 13)	n = 61	... on trait adjectives	Similar & dissimilar classmate	Letter present or not	Binary choice	32 blocks * 5 trials	3T Philips Ingenia CX
	Study 4a	Healthy adults (M_{age} = 42)	n = 33	... on trait statements	Acquaintance	General knowledge	Binary choice	6 blocks * 9 trials	3T Philips Achieva
	Study 4b	Schizophrenia patients (M_{age} = 37)	n = 23	... on trait statements	Acquaintance	General knowledge	Binary choice	6 blocks * 9 trials	3T Philips Achieva
	Study 5a	Healthy adults (M_{age} = 33)	n = 15	... on trait & physical statements	Relative or close friend	General knowledge	Likert scale (1-4)	36 blocks * 5 trials	3T Philips Intera
	Study 5b	Schizophrenia patients (M_{age} = 36)	n = 17	... on trait & physical statements	Relative or close friend	General knowledge	Likert scale (1-4)	36 blocks * 5 trials	3T Philips Intera
	Study 5c	Bipolar patients (M_{age} = 40)	n = 18	... on trait & physical statements	Relative or close friend	General knowledge	Likert scale (1-4)	36 blocks * 5 trials	3T Philips Intera
Extension Dataset	Study 6	Healthy adults (M_{age} = 23)	n = 49	Social feedback-task	Romantic partner	No feedback	Passive viewing	45 blocks * 5 trials	3T Siemens Skyra

Figure 1. Study design and analytic approach. A) The present study included data from six independent studies (nine cohorts, total N = 281). All studies used a task that included a Self-condition, an Other-condition), and a non-social Control condition. B) Display of the inclusive mask of brain areas related to social cognition. C) The training dataset (Study 1) included contrast images of n = 21 participants performing a trait-evaluation task with three conditions (Self, Other, Control). We used 10-fold cross-validated linear SVM to train three mentalizing signatures. The Self-Referential Signature (Self-RS) was trained to predict the Self condition versus the two remaining conditions. The Other-Referential Signature (Other-RS) was trained to predict the Other condition versus two remaining conditions. The mentalizing signature (MS) was trained to separate the Self and Other conditions from Control condition. For the validation in independent datasets, we applied the signatures to the single-subject contrast images from Studies 2-6, by computing the dot product between the weight maps and the contrast images.

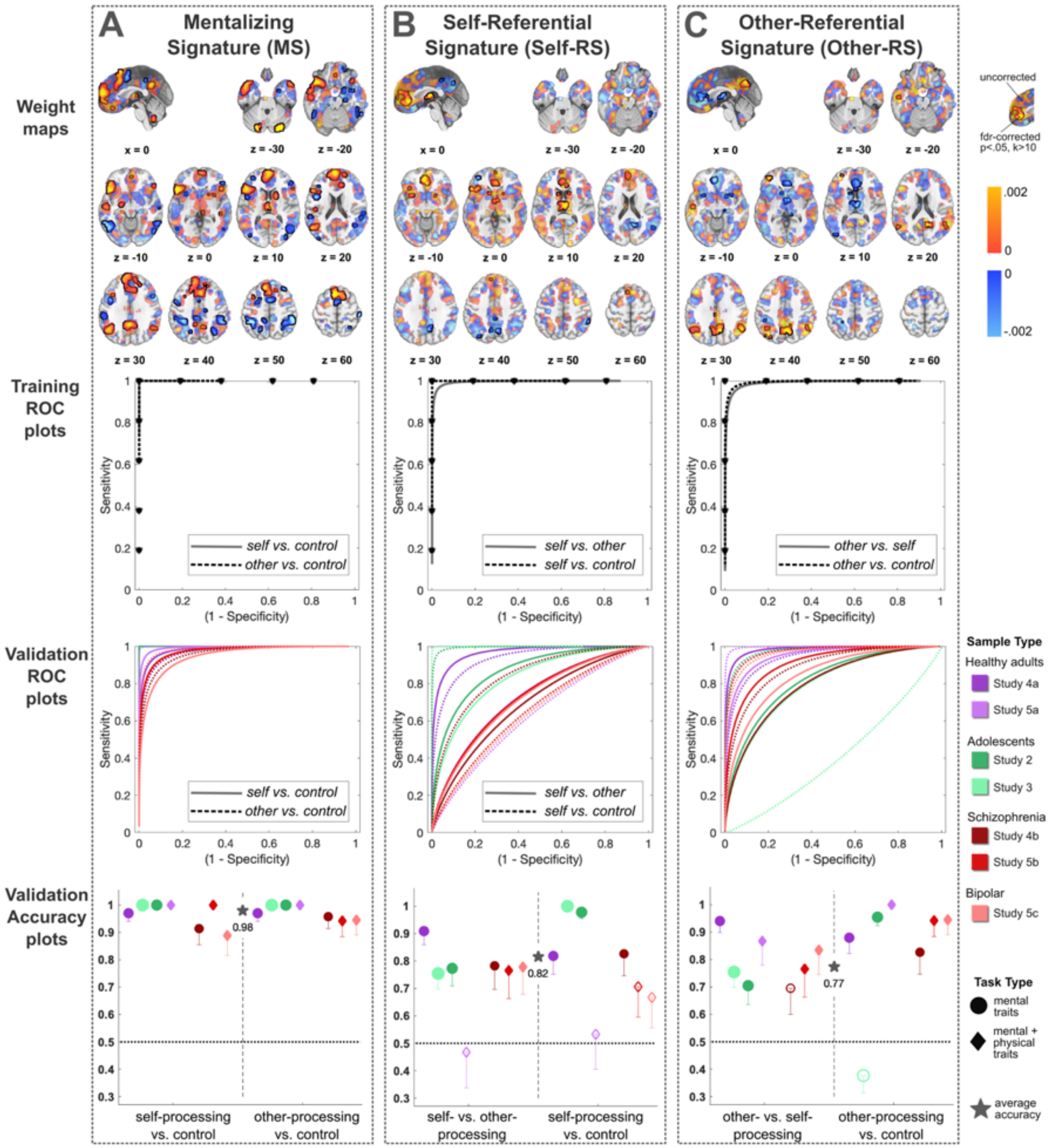


Figure 2. Model weights, training and validation results of the mentalizing signatures. On the top row, weight maps illustrate the positive and negative weights of a) the Mentalizing Signature (MS), b) the Self-Referential Signature (Self-RS), and c) the Other-Referential Signature (Other-RS). Voxels significant at an FDR-corrected threshold ($q < .05$, minimum cluster size of $k = 10$) are highlighted by black outlines. The two middle rows depict the receiver operation characteristics (ROC) plots from the i) cross-validated training and ii) validation datasets. The last row shows the accuracies of all three mentalizing signatures in each validation dataset separately, with color representing the study, and shape illustrating the type of sample.

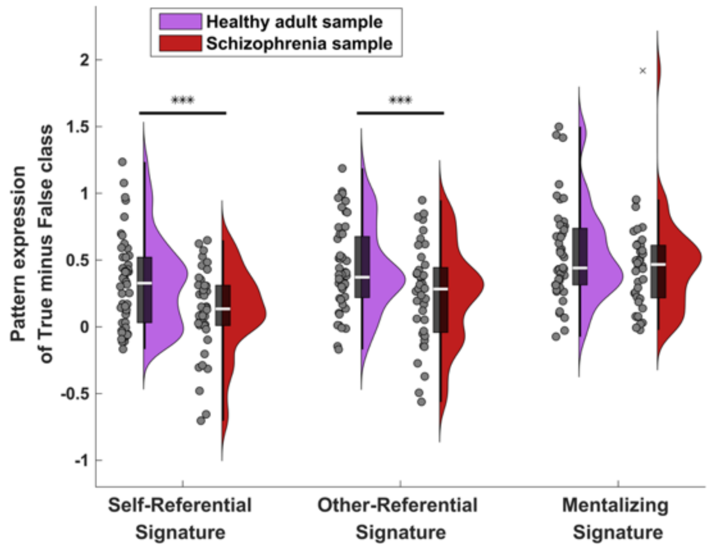


Figure 3. Self/other discrimination based on classifier responses in healthy adults versus individuals with schizophrenia. Self/other discrimination is measured as the pattern expression of true minus false class, separately for each signature and healthy adults (*n*=48, in red) versus individuals with schizophrenia (*n*=40, in red). Dots indicate values per person, boxplots mark the median, lower, and upper quartiles. Whiskers extend from the minimum to maximum data points excluding outliers. Linear mixed effects are used to test the group differences controlling for different cohorts. Self-RS: β = .21, STE = .07, CI = [.07, .35], p = .004). Other-RS: β = .19, STE = .07, CI = [.04, .33], p = .01.

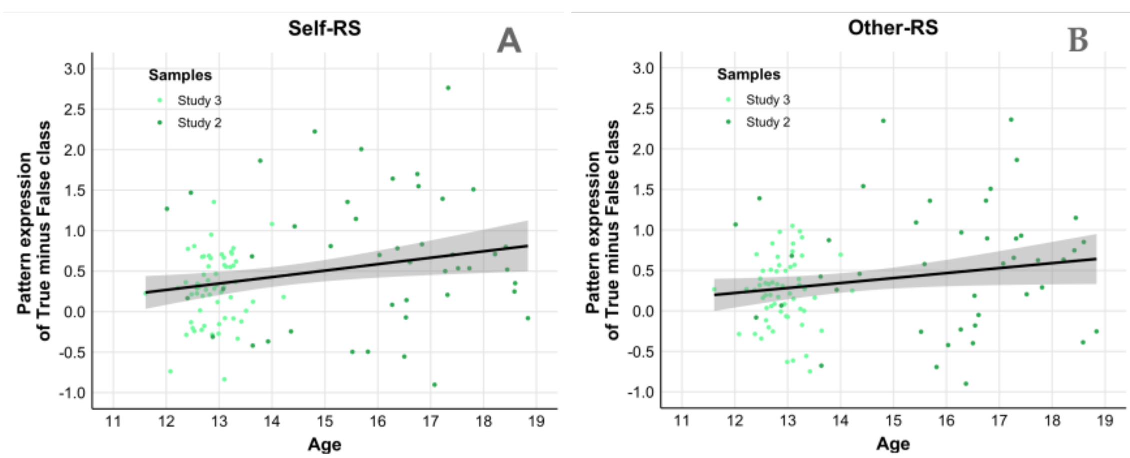


Figure 4. Association between self/other discrimination and age of adolescents (n = 105). Older age was significantly associated with better differentiation of self- and other-related mentalizing, controlling for cohort (Self-RS [β = .08, STE = .03, CI = .012 to .018, p = .01]; Other-RS [β = .06, STE = .03, CI = .001 to .12, p = .047]). Black lines display the linear regression fits, shaded areas the %95 confidence intervals.

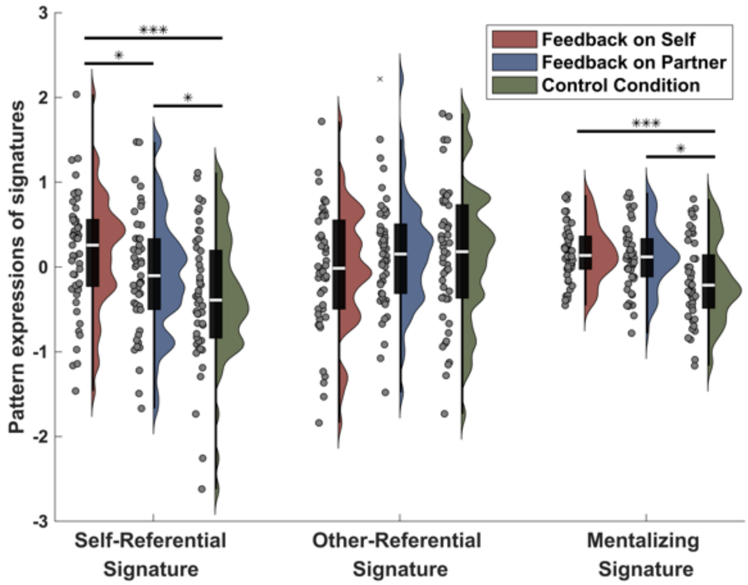


Figure 5. Signature responses in an independent social feedback task (n=49). Participants received feedback for themselves, for their partners, or no feedback (Control condition) and we computed pattern expression scores of each signature on each of these three conditions. Asterisks indicate significant Bonferroni-corrected pairwise comparisons following an initial repeated measures ANOVA test within each signature. *p<.05; ***p<.001.

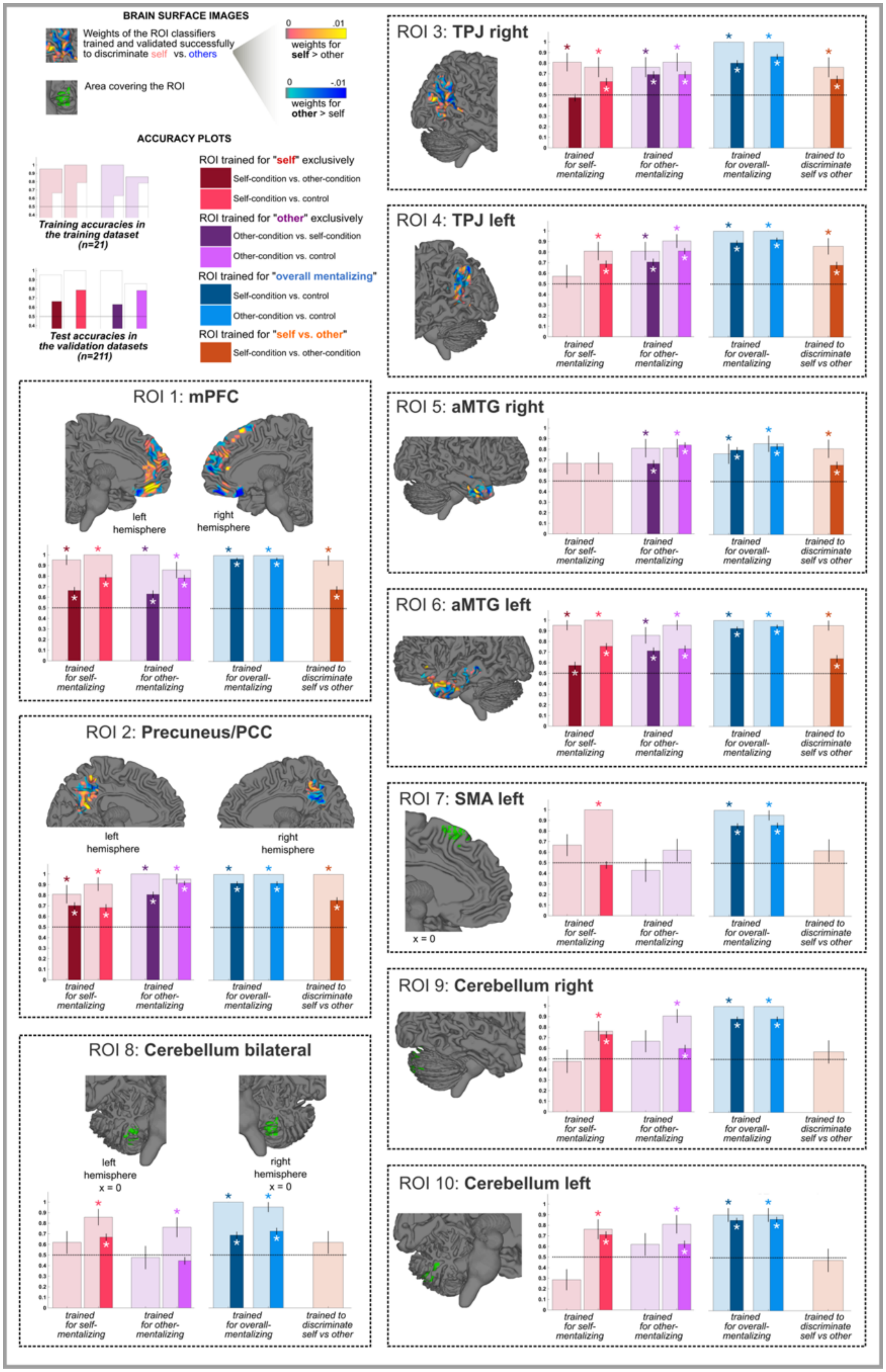

BRAIN SURFACE IMAGES
Weights of the ROI classifiers trained and validated successfully to discriminate self vs. others
Area covering the ROI
weights for self > other
weights for other > self
ACCURACY PLOTS
Training accuracies in the training dataset (n=21)
Test accuracies in the validation datasets (n=211)
ROI trained for "self" exclusively
Self-condition vs. other-condition
Self-condition vs. control
ROI trained for "other" exclusively
Other-condition vs. self-condition
Other-condition vs. control
ROI trained for "overall mentalizing"
Self-condition vs. control
Other-condition vs. control
ROI trained for "self vs. other"
Self-condition vs. other-condition
ROI 1: mPFC
ROI 2: Precuneus/PCC
ROI 3: TPJ right
ROI 4: TPJ left
ROI 5: aMTG right
ROI 6: aMTG left
ROI 7: SMA left
ROI 8: Cerebellum bilateral
ROI 9: Cerebellum right
ROI 10: Cerebellum left
left hemisphere
right hemisphere
x = 0
trained for self-mentalizing
trained for other-mentalizing
trained for overall-mentalizing
trained to discriminate self vs other

Figure 6. Results of the ROI analysis. Training and validation results for ten ROIs derived from a term-based meta-analysis ('mentalizing', NeuroSynth, Yarkoni, et al. 2011): mPFC, precuneus/posterior cingulate cortex (PCC), temporoparietal junction (TPJ) right, TPJ left, anterior middle temporal gyrus (aMTG) right, aMTG left, supplementary motor area (SMA) left, cerebellum right, cerebellum left, and a bilateral cerebellum cluster. Four different classifiers were trained for each ROI: (i) to predict Self exclusively, (ii) to predict Other exclusively, (iii) to predict overall mentalizing, and (iv) to discriminate the Self versus Other. If an ROI classifier had significant accuracy in the cross-validated training dataset, it was further tested across the validation datasets. The cross-validated training accuracies are illustrated by the wider bars in the background. The validation accuracies are illustrated by the thinner bars at the front. Classification performances significantly above the chance level (50%) are marked with asterisks. The surface images illustrate the weights of the classifiers that were trained to discriminate Self versus Other. Orange-yellow colors show areas with positive weights towards Self, blueish colors show areas associated with positive weights towards Other. If a specific ROI did not yield significant training and independent classification accuracy for this task, then the area covering this ROI is displayed in green color.

Supplementary Materials

Brain neuromarkers predict self- and other-related mentalizing across adult, clinical, and developmental samples

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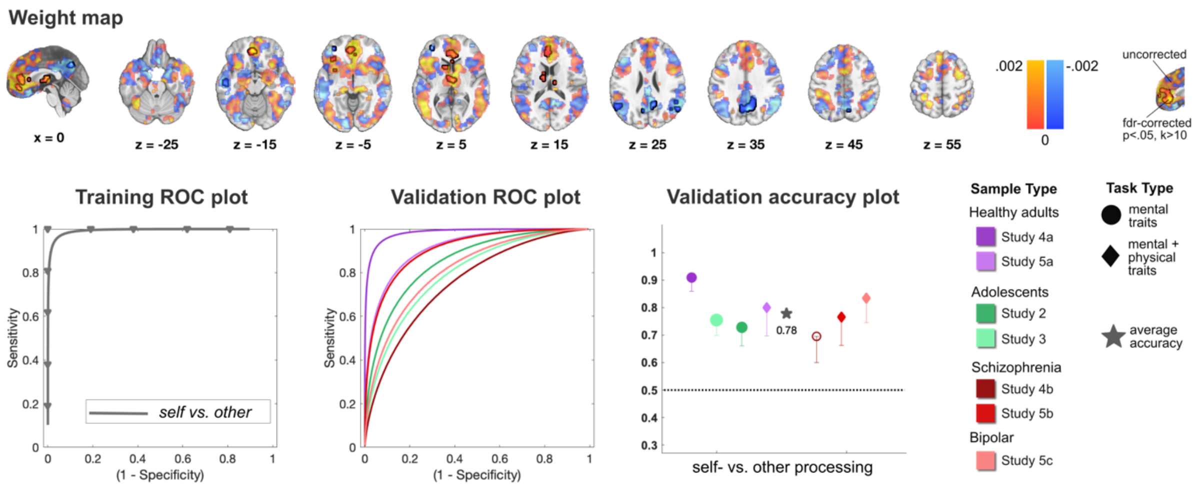

Figure S1. Model weights, training, and validation results of the Self-vs-Other Classifier. A classifier trained to separate self- versus other-related mentalizing (the *Self-vs-Other Signature*) showed 100% accuracy in cross-validated (out-of-sample) predictions in the training dataset (two-alternative forced-choice test, p<.001, Cohen's d = 2.45). The average prediction accuracy in the validation datasets was %78 (+/- %7.1 STE) and predicted the conditions above chance level in 6 out 7 samples. Brain regions with significant positive voxel weights (associated with Self Condition) included ventromedial and ventrolateral prefrontal cortex, anterior cingulate cortex, left anterior insula, left inferior frontal gyrus, left caudate nucleus, left middle temporal cortex, and bilateral thalamus. Significant negative clusters (associated with Other Condition) were found in precuneus, bilateral temporoparietal junction/angular gyrus, right posterior cingulate cortex, left superior temporal sulcus, left middle frontal gyrus, and left supramarginal gyrus. The weight map (first row) illustrates the positive and negative weights, as well as the voxels significant at an FDR-corrected threshold (q < .05, minimum cluster size of k = 10). The second row depict the receiver operation characteristics (ROC) plots from the i) cross-validated training and ii) validation stages, and iii) the accuracies of Self vs Other Classifier in each validation dataset. Shapes in the validation accuracy plot encode different task types.

Table S1

Demographics

Study	Population	n	Gender (females)	Age mean (SD)	Handedness (left)	Education (in years)	Place	References
Study 1	Healthy adults	21	10	23.7 (7.4)	2	NA	Switzerland	Koban et al., 2014
Study 2	Adolescents	44	23	16.0 (1.9)	0	NA	Switzerland	Debbane et al., 2017
Study 3	Adolescents	61	27	12.9 (0.4)	11	NA	The Netherlands	van Buuren et al., 2020
Study 4a	Healthy adults	33	14	41.7 (11.7)	0	12.7	Spain	Fuentes-Claramonte et al., 2019 & 2020
Study 4b	Schizophrenia patients	23	7	37.0 (8.1)	0	10.4		
Study 5a	Healthy adults	15	6	33.3 (11.3)	2	17.2	The Netherlands	Zhang et al., 2015
Study 5b	Schizophrenia patients	17	6	35.5 (9.7)	1	16.6		
Study 5c	Bipolar patients	18	9	40.3 (12.7)	0	17.0		
Study 6	Healthy adults	49	26	22.7 (3.9)	6	13.0	Arizona, USA	Ma et al., 2024
Overall		**281**	**128**	**25.5 (12.9)**	**22**			

Note. NA = not assessed. Links to the published studies are as follows: Study 2 (doi.org/10.3758/s13415-017-0497-9); Study 3 (doi.org/10.1016/j.neuroimage.2020.117060); Study 4, 2019 (doi.org/10.1371/journal.pone.0209376); Study 4, 2020 (doi.org/10.1016/j.nicl.2019.102134); Study 5 (doi.org/10.1016/j.nicl.2015.04.010); Study 6 (doi.org/10.31234/osf.io/qcj45)

Table S2

Significant clusters of the Self-RS

Labeled Name	Atlas region (see note)	x	y	z	Voxel number	Max(z)
Cerebellum	Cblm Crus II R	26	-80	-38	54	0.00035
Ventral Anterior Cingulate Cortex (vACC) / ventromedial prefrontal cortex (vmPFC) (incl. dorsomedial and frontopolar prefrontal cortices)	Multiple regions	-2	44	0	933	0.00068
Anterior insula (AI)	AAIC L	-34	10	-10	33	0.00043
Caudate nucleus	Caudate Ca R	18	10	-6	13	0.00033
Inferior frontal gyrus (IFG)	45 L	-46	24	2	162	0.00057
Thalamus	Multiple regions	0	-12	10	311	0.00068
Caudate nucleus	Caudate Ca R	12	14	8	17	0.00031
Caudate nucleus	Caudate Ca L	-14	14	6	32	0.00035
Dorsolateral prefrontal cortex (dlPFC)	9m L	-8	48	38	21	0.00037
Superior frontal lobule/ dorsomedial prefrontal cortex (dmPFC)	SFL L	-8	22	56	46	0.00040
Temporal pole	TGd L	-34	14	-34	13	-0.00050
Inferior temporal gyrus/sulcus	TE2p R	46	-46	-22	27	-0.00045
Posterior temporal cortex	PH R	52	-54	-14	21	-0.00054
dlPFC	a9 46v L	-38	48	4	26	-0.00072
Posterior cingulate cortex (PCC)	POS2 R	6	-60	32	270	-0.00070
Inferior parietal cortex (IPC) / Temporoparietal junction (TPJ)	PGi R	52	-62	22	52	-0.00046
IPC / TPJ	PFm R	52	-50	24	20	-0.00035
IPC / TPJ	PGs L	-34	-76	40	14	-0.00044
PCC	31a L	-2	-42	42	20	-0.00054
IPC / TPJ	PFm R	52	-44	48	28	-0.00064

Note. Significant positive and negative weights contributing to the Self-Referential Signature (Self-RS). FDR-corrected $p < 0.05$ with cluster size $k > 10$ across the masked whole-brain. Cortical atlas regions are labeled based on a combination of parcellations available on GitHub: https://github.com/canlab/Neuroimaging_Pattern_Masks/tree/master/Atlases_and_parcellations/2018_Wager_combined_atlas. L refers the left hemisphere, and R refers to the right hemisphere.

Table S3

Significant clusters of the Other-RS

Labeled Name	Atlas region (see note)	x	y	z	Voxel number	Max(z)
Superior temporal sulcus (STS)	STSda L	-56	-16	-12	174	0.00053
dlPFC	a9 46v L	-38	50	2	90	0.00085
PCC/Precuneus	Multiple regions	4	-60	34	733	0.00081
IPC / TPJ	PGi L	-52	-60	26	245	0.00048
IPC / TPJ	PGi R	52	-58	30	339	0.00058
Retrosplenial cortex	RSC L	-4	-28	28	15	0.00039
IPC / TPJ	PGs L	-36	-76	42	14	0.00048
IPC / TPJ	PFm L	-42	-58	42	38	0.00034
Anterior insula (AI)	AAIC R	30	12	-10	15	-0.00034
vACC/vmPFC	Multiple regions	-2	40	2	498	-0.00058
Caudate nucleus	Caudate Ca R	20	8	-6	20	-0.00032
Thalamus	Bstem Midbd R	12	-30	-2	24	-0.00049
Anterior insula (AI)	AAIC L	-34	10	-6	13	-0.00027
Ventral striatum	V Striatum L	-2	16	-2	13	-0.00045
Thalamus	Multiple regions	0	-10	10	314	-0.00059
Caudate nucleus	Caudate Ca L	-12	14	6	24	-0.00036
Ventral striatum	Cau R	0	24	8	13	-0.00035
Middle temporal complex (MT+)	LO3 L	-44	-80	12	17	-0.00026
IPC	IP2 L	-46	-40	42	10	-0.00036
Somatosensory cortex	2 L	-30	-44	54	19	-0.00033

Note. Significant positive and negative weights contributing to the Self-Referential Signature (Self-RS). FDR-corrected p< 0.05 with cluster size k>10 across the masked whole-brain. Cortical atlas regions are labeled based on a combination of parcellations available on GitHub: https://github.com/canlab/Neuroimaging_Pattern_Masks/tree/master/Atlases_and_parcellations/2018_Wager_combined_atlas. L refers the left hemisphere, and R refers to the right hemisphere.

Table S4

Significant clusters of the MS

Labeled Name	Atlas region (see note)	x	y	z	Voxel number	Max(z)
Cerebellum	Cblm IX R	2	-54	-44	109	0.00016
Cerebellum	Cblm CrusI R	28	-82	-32	597	0.00040
Cerebellum	Cblm CrusI L	-24	-80	-34	373	0.00028
STS/IFG (incl. vlPFC, AI, STG, temporal pole)	Multiple regions	-48	18	-10	2536	0.00038
Temporal pole	TGd R	50	16	-30	114	0.00014
Orbitofrontal cortex (OFC)	10v R	0	38	-20	15	0.00012
IFG/ventrolateral PFC (vlPFC)	45 R	44	24	-10	195	0.00014
Amygdala	Bstem Ponscd	-24	-12	-10	68	0.00010
Dorsal anterior cingulate cortex (dACC)/vACC (incl. dmPFC, vmPFC, dlPFC, frontal eye fields)	Multiple regions	-6	42	36	3532	0.00036
STS	STSdp R	46	-28	0	20	0.00010
Putamen	Putamen Pa R	30	12	0	13	0.00007
Thalamus	Bstem_SC R	4	-28	2	10	0.00015
Caudate nucleus	Caudate Ca R	16	10	10	107	0.00012
Thalamus	Thal MD	-2	-16	10	96	0.00025
IPC / TPJ	PGi L	-48	-62	26	512	0.00023
Posterior opercular cortex	OP1 L	-50	-24	18	12	0.00008
IPC / TPJ	PGi R	52	-58	30	48	0.00012
PCC	Multiple regions	-2	-50	32	544	0.00023
dlPFC	9p R	18	40	36	42	0.00010
Supplementary motor area (SMA)	8Av L	-36	12	46	68	0.00012
dlPFC	8BL R	14	26	52	19	0.00008
Perirhinal ectorhinal cortex	PeEc L	-34	0	-38	17	-0.00010
Amygdala	Amygdala LB	26	0	-26	13	-0.00012
Cerebellum	Cblm VI L	-36	-42	-24	21	-0.00011
Middle temporal gyrus (MTG) posterior	TE1p R	54	-52	-14	215	-0.00024
MTG anterior	TE2a R	48	-18	-22	27	-0.00012
Hippocampus	H R	20	-16	-20	29	-0.00020
Entorhinal cortex/amygdala	Pir R	36	2	-18	29	-0.00014
Parahippocampal gyrus	PHA3 L	-32	-32	-20	10	-0.00010
Amygdala	Amygdala LB	18	4	-18	29	-0.00015
Posterior temporal cortex/MT+	PH L	-52	-58	-10	419	-0.00029
OFC	11l R	20	54	-14	34	-0.00019
MTG medial	TE1m R	60	-26	-16	12	-0.00011

Posterior temporal cortex	PH R	50	-70	-8	43	-0.00017
Auditory association cortex	A5 R	60	-6	-2	54	-0.00020
STS	STSvp R	56	-40	-4	12	-0.00012
Middle Insula	MI L	-34	14	0	18	-0.00010
Inferior frontal sulcus	IFSa R	48	38	6	57	-0.00016
Extrastriate cortex/MTG	TPOJ2 R	48	-64	12	327	-0.00013
Premotor cortex/Inferior frontal sulcus	6r L	-46	6	26	333	-0.00023
dlPFC	a9 46v L	-36	48	10	17	-0.00016
Extrastriate cortex	V3CD R	36	-84	12	32	-0.00011
IPC	PGp L	-44	-80	16	38	-0.00009
Superior temporal gyrus (STG)	STV R	58	-42	18	35	-0.00012
Supramarginal gyrus/IPC	PF L	-44	-42	44	629	-0.00029
TPJ/Angular gyrus (AG)	PSL R	60	-30	18	18	-0.00011
dlPFC	p9 46v L	-40	30	22	10	-0.00010
Premotor cortex	6v R	50	14	28	32	-0.00015
IPC	IP1 R	30	-64	42	151	-0.00016
IPC/TPJ	PFm R	46	-42	48	576	-0.00033
PCC	5mv L	-10	-38	46	121	-0.00019
Superior parietal cortex/medial intraparietal sulcus	MIP L	-24	-62	50	75	-0.00018
MCC	24dd R	10	-16	42	14	-0.00006
SMA	SCEF R	0	4	52	284	-0.00018
Premotor cortex/SMA	55b R	50	-4	44	31	-0.00013
SMA	6a L	-28	0	50	20	-0.00010
SMA	8Av R	32	30	50	13	-0.00021
SMA	6a L	-24	8	54	23	-0.00012
Primary sensory cortex	1 R	46	-28	62	35	-0.00036

Note. Significant positive and negative weights contributing to the Self-Referential Signature (Self-RS). FDR-corrected p< 0.05 with cluster size k>10 across the masked whole-brain. Cortical atlas regions are labeled based on a combination of parcellations available on GitHub: https://github.com/canlab/Neuroimaging_Pattern_Masks/tree/master/Atlases_and_parcellations/2018_Wager_combined_atlas. L refers the left hemisphere, and R refers to the right hemisphere.

Table S5

Prediction results of the mentalizing signatures across training and validation datasets

Self-Referential Signature (Self-RS)					
Dataset	**Study**	**Sample**	**n**	**Classification Task**	**Prediction Outcome**
Training	Study 1	Healthy adult	21	Self vs Other	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.61
				Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.74
Validation	Study 2	Adolescent	44	Self vs Other	acc.=0.77(+/-0.06), P=0.0004***, sens.=0.77, spec.=0.77, AUC=0.88, *d*=1.13
				Self vs Control	acc.=0.98(+/-0.02), *P*<0.0001***, sens.=0.98, spec.=0.98, AUC=1.00, *d*=2.60
Validation	Study 3	Adolescent	61	Self vs Other	acc.=0.75(+/-0.06), *P*<0.0001***, sens.=0.75, spec.=0.75, AUC=0.84, *d*=0.95
				Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.52
Validation	Study 4a	Healthy adult	33	Self vs Other	acc.=0.91(+/-0.05), *P*<0.0001***, sens.=0.91, spec.=0.91, AUC=0.98, *d*=1.83
				Self vs Control	acc.=0.82(+/-0.07), *P*=0.0003***, sens.=0.82, spec.=0.82, AUC=0.93, *d*=1.51
Validation	Study 4b	Schizophrenia patient	23	Self vs Other	acc.=0.78(+/-0.09), *P*=0.0106***, sens.=0.78, spec.=0.78, AUC=0.71, *d*=0.50
				Self vs Control	acc.=0.83(+/-0.08), *P*=0.0026***, sens.=0.83, spec.=0.83, AUC=0.87, *d*=1.01
Validation	Study 5a	Healthy adult	15	Self vs Other	acc.=0.47(+/-0.13), *P*>0.20, sens.=0.47, spec.=0.47, AUC=0.71, *d*=0.61
				Self vs Control	acc.=0.53(+/-0.13), *P*>0.20, sens.=0.53, spec.=0.53, AUC=0.60, *d*=0.31
Validation	Study 5b	Schizophrenia patient	17	Self vs Other	acc.=0.76(+/-0.10), *P*=0.0490***, sens.=0.76, spec.=0.76, AUC=0.78, *d*=0.60
				Self vs Control	acc.=0.71(+/-0.11), *P*=0.1435, sens.=0.71, spec.=0.71, AUC=0.70, *d*=0.39
Validation	Study 5c	Bipolar patient	18	Self vs Other	acc.=0.78(+/-0.10), *P*=0.0309***, sens.=0.78, spec.=0.78, AUC=0.74, *d*=0.58
				Self vs Control	acc.=0.67(+/-0.11), *P*>0.20, sens.=0.67, spec.=0.67, AUC=0.71, *d*=0.35
Other-Referential Signature (Other-RS)					
Signature	Dataset	Sample	n	Classification Task	Prediction Outcome
Training	Study 1	Healthy adult	21	Other vs Self	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.36
				Other vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.53
Validation	Study 2	Adolescent	44	Other vs Self	acc.=0.70(+/-0.07), *P*=0.0096***, sens.=0.70, spec.=0.70, AUC=0.83, *d*=0.90
				Other vs Control	acc.=0.95(+/-0.03), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=0.97, *d*=0.99
Validation	Study 3	Adolescent	61	Other vs Self	acc.=0.75(+/-0.06), *P*<0.0001***, sens.=0.75, spec.=0.75, AUC=0.80, *d*=0.81
				Other vs Control	acc.=0.38(+/-0.06), *P*>0.20, sens.=0.38, spec.=0.38, AUC=0.39, *d*=0.39
Validation	Study 4a	Healthy adult	33	Other vs Self	acc.=0.94(+/-0.04), *P*<0.0001***, sens.=0.94, spec.=0.94, AUC=0.99, *d*=2.15
				Other vs Control	acc.=0.88(+/-0.06), *P*<0.0001***, sens.=0.88, spec.=0.88, AUC=0.95, *d*=1.55

Validation	Study 4b	Schizophrenia patient	23	Other vs Self	acc.=0.70(+/-0.10), *P*=0.0931, sens.=0.70, spec.=0.70, AUC=0.81, *d*=0.83
				Other vs Control	acc.=0.83(+/-0.08), *P*=0.0026***, sens.=0.83, spec.=0.83, AUC=0.90, *d*=1.21
Validation	Study 5a	Healthy adult	15	Other vs Self	acc.=0.87(+/-0.09), *P*=0.0074***, sens.=0.87, spec.=0.87, AUC=0.97, *d*=1.65
				Other vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.73
Validation	Study 5b	Schizophrenia patient	17	Other vs Self	acc.=0.76(+/-0.10), *P*=0.0490***, sens.=0.76, spec.=0.76, AUC=0.93 , *d*=1.34
				Other vs Control	acc.=0.94(+/-0.06), *P*=0.0003***, sens.=0.94, spec.=0.94, AUC=0.99, *d*=1.89
Validation	Study 5c	Bipolar patient	18	Other vs Self	acc.=0.83(+/-0.09), *P*=0.0075***, sens.=0.83, spec.=0.83, AUC=0.86, *d*=1.02
				Other vs Control	acc.=0.94(+/-0.05), *P*=0.0002***, sens.=0.94, spec.=0.94, AUC=0.96, *d*=1.79

Mentalizing Signature (MS)

Signature	Dataset	Sample	n	Classification Task	Prediction Outcome
Training	Study 1	Healthy adult	21	Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=5.12
				Other vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=4.72
Validation	Study 2	Adolescent	44	Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=4.84
				Other vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=4.99
Validation	Study 3	Adolescent	61	Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.76
				Other vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.98
Validation	Study 4a	Healthy adult	33	Self vs Control	acc.=0.97(+/-0.03), *P*<0.0001***, sens.=0.97, spec.=0.97, AUC=1.00, *d*=2.13
				Other vs Control	acc.=0.97(+/-0.03), *P*<0.0001***, sens.=0.97, spec.=0.97, AUC=0.98, *d*=1.87
Validation	Study 4b	Schizophrenia patient	23	Self vs Control	acc.=0.91(+/-0.06), *P*<0.0001***, sens.=0.91, spec.=0.91, AUC=0.99, *d*=1.61
				Other vs Control	acc.=0.96(+/-0.04), *P*<0.0001***, sens.=0.96, spec.=0.96, AUC=0.98, *d*=1.74
Validation	Study 5a	Healthy adult	15	Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.47
				Other vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.36
Validation	Study 5b	Schizophrenia patient	17	Self vs Control	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec=1.00, AUC=1.00, *d*=1.95
				Other vs Control	acc.=0.94(+/-0.06), *P*=0.0003***, sens.=0.94, spec.=0.94, AUC=0.98, *d*=1.91
Validation	Study 5c	Bipolar patient	18	Self vs Control	acc.=0.89(+/-0.07), *P*=0.0013***, sens.=0.89, spec.=0.89, AUC=0.97, *d*=1.61
				Other vs Control	acc.=0.94(+/-0.05), *P*=0.0002***, sens.=0.94, spec.=0.94, AUC=0.99, *d*=2.19

Note. The predictions of signatures were assigned using paired observations with a forced-choice principle. acc. = accuracy; sens. = sensitivity; spec. = specificity, AUC = area under the curve. *d* refers to the estimated *Cohen's d* calculated as the mean difference of true and false paired predictions divided by the pooled standard deviation of differences (where difference = input_values[binary_class]- input_values[~binary_class]). Asterisks (***) mark the significant classification accuracies with *p*<.05.

Supplementary Table S6

Prediction results of the ROI classifiers across training and validation datasets

ROI 1: mPFC

Trained for	Task	Sample	Prediction Outcome
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=1.00, *d* =2.17
		Validation (n=211)	acc.=0.66(+/-0.03), *P*<0.0001***, sens.=0.66, spec.=0.66, AUC=0.69, *d*=0.37
	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.29
		Validation (n=211)	acc.=0.79(+/-0.03), *P*<0.0001***, sens.=0.79, spec.=0.79, AUC=0.88, *d*=0.96
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.23
		Validation (n=211)	acc.=0.63(+/-0.03), *P*=0.0002***, sens.=0.63, spec.=0.63, AUC=0.66, *d*=0.36
	Other vs Control	Training (n=21)	acc.=0.86(+/-0.08), *P*=0.0015***, sens.=0.86, spec.=0.86, AUC=0.97, *d*=1.68
		Validation (n=211)	acc.=0.78(+/-0.03), *P*<0.0001***, sens.=0.78, spec.=0.78, AUC=0.85, *d*=0.86
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=5.63
		Validation (n=211)	acc.=0.97(+/-0.01), *P*<0.0001***, sens.=0.97, spec.=0.97, AUC=0.99, *d*=1,64
	Other vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=6.01
		Validation (n=211)	acc.=0.97(+/-0.01), *P*<0.0001***, sens.=0.97, spec.=0.97, AUC=0.99, *d*=1.69
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=1.00, *d*=2.10
		Validation (n=211)	acc.=0.68(+/-0.03), *P*<0.0001***, sens.=0.68, spec.=0.68, AUC=0.68, *d*=0.36

ROI 2: Precuneus/PCC

Trained for	Task	Sample	Prediction Outcome
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.81(+/-0.09), *P*=0.0072***, sens.=0.81, spec.=0.81, AUC=0.90, *d*=1.20
		Validation (n=211)	acc.=0.70(+/-0.03), *P*<0.0001***, sens.=0.70, spec.=0.70, AUC=0.74, *d*=0.57
	Self vs Control	Training (n=21)	acc.=0.90(+/-0.06), *P*=0.0002***, sens.=0.90, spec.=0.90, AUC=0.96, *d*=1.52
		Validation (n=211)	acc.=0.68(+/-0.03), *P*<0.0001***, sens.=0.68, spec.=0.68, AUC=0.73, *d*=0.59
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.10
		Validation (n=211)	acc.=0.81(+/-0.03), *P*<0.0001***, sens.=0.81, spec.=0.81, AUC=0.84, *d*=0.85
	Other vs Control	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=1.00, *d*=2.72
		Validation (n=211)	acc.=0.91(+/-0.02), *P*<0.0001***, sens.=0.91, spec.=0.91, AUC=0.96, *d*=1.45
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.11
		Validation (n=211)	acc.=0.91(+/-0.02), *P*<0.0001***, sens.=0.91, spec.=0.91, AUC=0.96, *d*=1.29
	Other vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.42

		Validation (n=211)	acc.=0.91(+/-0.02), P<0.0001***, sens.=0.91, spec.=0.91, AUC=0.97, d=1.40
Differentiating „self" vs „other" conditions	Self vs Other	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=2.07
		Validation (n=211)	acc.=0.75(+/-0.03), P<0.0001***, sens.=0.75, spec.=0.75, AUC=0.82, d=0.78

ROI 3: TPJ right

Trained for	**Task**	**Sample**	**Prediction Outcome**
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.81(+/-0.09), P=0.0072***,sens.=0.81, spec.=0.81, AUC=0.84, d=0.69
		Validation (n=211)	acc.=0.47(+/-0.03), P>0.20, sens.=0.47, spec.=0.47, AUC=0.49, d=0.05
	Self vs Control	Training (n=21)	acc.=0.76(+/-0.09), P=0.0266***, sens.=0.76, spec.=0.76, AUC=0.88, d=1.03
		Validation (n=211)	acc.=0.63(+/-0.03), P=0.0003***, sens.=0.63, spec.=0.63, AUC=0.69, d=0.45
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.76(+/-0.09), P=0.0266***, sens.=0.76, spec.=0.76, AUC=0.86, d=0.90
		Validation (n=211)	acc.=0.69(+/-0.03), P<0.0001***, sens.=0.69, spec.=0.69, AUC=0.74, d=0.49
	Other vs Control	Training (n=21)	acc.=0.81(+/-0.09), P=0.0072***, sens.=0.81, spec.=0.81, AUC=0.92, d=1.12
		Validation (n=211)	acc.=0.69(+/-0.03), P<0.0001***, sens.=0.69, spec.=0.69, AUC=0.74, d=0.60
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=3.32
		Validation (n=211)	acc.=0.80(+/-0.03), P<0.0001***, sens.=0.80, spec.=0.80, AUC=0.90, d=1.07
	Other vs Control	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=2.55
		Validation (n=211)	acc.=0.86(+/-0.02), P<0.0001***, sens.=0.86, spec.=0.86, AUC=0.93, d=1.15
Differentiating „self" vs „other" conditions	Self vs Other	Training (n=21)	acc.=0.76(+/-0.09), P=0.0266***, sens.=0.76, spec.=0.76, AUC=0.84, d=0.82
		Validation (n=211)	acc.=0.65(+/-0.03), P<0.0001***, sens.=0.65, spec.=0.65, AUC=0.71, d=0.45

ROI 4: TPJ left

Trained for	**Task**	**Sample**	**Prediction Outcome**
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.57(+/-0.11), P>0.20, sens.=0.57, spec.=0.57, AUC=0.64, d=0.23
		Validation (n=211)	acc.=0.56(+/-0.03), P=0.0983, sens.=0.56, spec.=0.56, AUC=0.60, d=0.24
	Self vs Control	Training (n=21)	acc.=0.81(+/-0.09), P=0.0072***, sens.=0.81, spec.=0.81, AUC=0.75, d=0.57
		Validation (n=211)	acc.=0.69(+/-0.03), P<0.0001***, sens.=0.69, spec.=0.69, AUC=0.80, d=0.74
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.81(+/-0.09), P=0.0072***, sens.=0.81, spec.=0.81, AUC=0.87, d=0.95
		Validation (n=211)	acc.=0.71(+/-0.03), P<0.0001***, sens.=0.71, spec.=0.71, AUC=0.72, d=0.44
	Other vs Control	Training (n=21)	acc.=0.90(+/-0.06), P=0.0002***, sens.=0.90, spec.=0.90, AUC=0.98, d=1.81
		Validation (n=211)	acc.=0.81(+/-0.03), P<0.0001***, sens.=0.81, spec.=0.81, AUC=0.90, d=1.07
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=3.04
		Validation (n=211)	acc.=0.89(+/-0.02), P<0.0001***, sens.=0.89, spec.=0.89, AUC=0.96, d=1.19

	Other vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.70
		Validation (n=211)	acc.=0.92(+/-0.02), *P*<0.0001***, sens.=0.92, spec.=0.92, AUC=0.98, *d*=1.23
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.86(+/-0.08), *P*=0.0015***, sens.=0.86, spec.=0.86, AUC=0.88, *d*=1.04
		Validation (n=211)	acc.=0.68(+/-0.03), *P*<0.0001***, sens.=0.68, spec.=0.68, AUC=0.72, *d*=0.45

ROI 5: aMTG right

Trained for	**Task**	**Sample**	**Prediction Outcome**
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.67(+/-0.10), *P*=0.1893, sens.=0.67, spec.=0.67, AUC=0.74, *d*=0.51
		Validation (n=211)	acc.=0.64(+/-0.03), *P*<0.0001***, sens.=0.64, spec.=0.64, AUC=0.69, *d*=0.47
	Self vs Control	Training (n=21)	acc.=0.67(+/-0.10), *P*=0.1893, sens.=0.67, spec.=0.67, AUC=0.75, *d*=0.59
		Validation (n=211)	acc.=0.41(+/-0.03), *P*>0.20, sens.=0.41, spec.=0.41, AUC=0.36, *d*=-0.37
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.81(+/-0.09), *P*=0.0072***, sens.=0.81, spec.=0.81, AUC=0.86, *d*=1.11
		Validation (n=211)	acc.=0.66(+/-0.03), *P*<0.0001***, sens.=0.66, spec.=0.66, AUC=0.69, *d*=0.46
	Other vs Control	Training (n=21)	acc.=0.81(+/-0.09), *P*=0.0072***, sens.=0.81, spec.=0.81, AUC=0.94, *d*=1.35
		Validation (n=211)	acc.=0.84(+/-0.03), *P*<0.0001***, sens.=0.84, spec.=0.84, AUC=0.92, *d*=1.13
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=0.76(+/-0.09), *P*=0.0266***, sens.=0.76, spec.=0.76, AUC=0.92, *d*=1.25
		Validation (n=211)	acc.=0.80(+/-0.03), *P*<0.0001***, sens.=0.80, spec.=0.80, AUC=0.87, *d*=1.00
	Other vs Control	Training (n=21)	acc.=0.86(+/-0.08), *P*=0.0015***, sens.=0.86, spec.=0.86, AUC=0.95, *d*=1.39
		Validation (n=211)	acc.=0.83(+/-0.03), *P*<0.0001***, sens.=0.83, spec.=0.83, AUC=0.89, *d*=1.00
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.81(+/-0.09), *P*=0.0072***, sens.=0.81, spec.=0.81, AUC=0.84, *d*=0.90
		Validation (n=211)	acc.=0.65(+/-0.03), *P*<0.0001***, sens.=0.65, spec.=0.65, AUC=0.71, *d*=0.51

ROI 6: aMTG left

Trained for	**Task**	**Sample**	**Prediction Outcome**
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=0.98, *d*=1.83
		Validation (n=211)	acc.=0.57(+/-0.03), *P*=0.0386***, sens.=0.57, spec.=0.57, AUC=0.63, *d*=0.35
	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.53
		Validation (n=211)	acc.=0.75(+/-0.03), *P*<0.0001***, sens.=0.75, spec.=0.75, AUC=0.81, *d*=0.87
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.86(+/-0.08), *P*=0.0015***, sens.=0.86, spec.=0.86, AUC=0.96, *d*=1.69
		Validation (n=211)	acc.=0.71(+/-0.03), *P*<0.0001***, sens.=0.71, spec.=0.71, AUC=0.80, *d*=0.81
	Other vs Control	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=0.97, *d*=1.71
		Validation (n=211)	acc.=0.73(+/-0.03), *P*<0.0001***, sens.=0.73, spec.=0.73, AUC=0.80, *d*=0.74
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=4.43

		Validation (n=211)	acc.=0.92(+/-0.02), *P*<0.0001***, sens.=0.92, spec.=0.92, AUC=0.97, *d*=1.30
	Other vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=3.49
		Validation (n=211)	acc.=0.94(+/-0.02), *P*<0.0001***, sens.=0.94, spec.=0.94, AUC=0.98, *d*=1.47
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=0.99, *d*=1.91
		Validation (n=211)	acc.=0.64(+/-0.03), *P*<0.0001***, sens.=0.64, spec.=0.64, AUC=0.69, *d*=0.49

ROI 7: SMA left

Trained for	**Task**	**Sample**	**Prediction Outcome**
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.67(+/-0.10), *P*=0.1893, sens.=0.67, spec.=0.67, AUC=0.70, *d*=0.23
		Validation (n=211)	acc.=0.52(+/-0.03), *P*>0.20, sens.=0.52, spec.=0.52, AUC=0.51, *d*=-0.02
	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=2.44
		Validation (n=211)	acc.=0.48(+/-0.03), *P*>0.20, sens.=0.48, spec.=0.48, AUC=0.53, *d*=0.12
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.43(+/-0.11), *P*>0.20, sens.=0.43, spec.=0.43, AUC=0.51, *d*=-0.02
		Validation (n=211)	acc.=0.50(+/-0.03), *P*>0.20, sens.=0.50, spec.=0.50, AUC=0.51, *d*=-0.08
	Other vs Control	Training (n=21)	acc.=0.62(+/-0.11), *P*>0.20, sens.=0.62, spec.=0.62, AUC=0.81, *d*=0.87
		Validation (n=211)	acc.=0.71(+/-0.03), *P*<0.0001***, sens.=0.71, spec.=0.71, AUC=0.75, *d*=0.60
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), *P*<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, *d*=4.30
		Validation (n=211)	acc.=0.85(+/-0.02), *P*<0.0001***, sens.=0.85, spec.=0.85, AUC=0.94, *d*=1.20
	Other vs Control	Training (n=21)	acc.=0.95(+/-0.05), *P*<0.0001***, sens.=0.95, spec.=0.95, AUC=1.00, *d*=3.05
		Validation (n=211)	acc.=0.86(+/-0.02), *P*<0.0001***, sens.=0.86, spec.=0.86, AUC=0.93, *d*=1.20
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.62(+/-0.11), *P*>0.20, sens.=0.62, spec.=0.62, AUC=0.69, *d*=0.20
		Validation (n=211)	acc.=0.50(+/-0.03), *P*>0.20, sens.=0.50, spec.=0.50, AUC=0.50, *d*=-0.03

ROI 8: Cerebellum bilateral

Trained for	**Task**	**Sample**	**Prediction Outcome**
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.62(+/-0.11), *P*>0.20, sens.=0.62, spec.=0.62, AUC=0.65, *d*=0.29
		Validation (n=211)	acc.=0.52(+/-0.03), *P*>0.20, sens.=0.52, spec=0.52, AUC=0.56, *d*=0.10
	Self vs Control	Training (n=21)	acc.=0.86(+/-0.08), *P*=0.0015***, sens.=0.86, spec.=0.86, AUC=0.94, *d*=1.48
		Validation (n=211)	acc.=0.67(+/-0.03), *P*<0.0001***, sens.=0.67, spec.=0.67, AUC=0.71, *d*=0.39
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.48(+/-0.11), *P*>0.20, sens.=0.48, spec.=0.48, AUC=0.54, *d*=0.06
		Validation (n=211)	acc.=0.54(+/-0.03), *P*>0.20, sens.=0.54, spec.=0.54, AUC=0.55, *d*=0.05
	Other vs Control	Training (n=21)	acc.=0.76(+/-0.09), *P*=0.0266***, sens.=0.76, spec.=0.76, AUC=0.85, *d*=0.81
		Validation (n=211)	acc.=0.45(+/-0.03), *P*>0.20, sens.=0.45, spec.=0.45, AUC=0.46, *d*=-0.10

Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=2.70
		Validation (n=211)	acc.=0.69(+/-0.03), P<0.0001***, sens.=0.69, spec.=0.69, AUC=0.76, d=0.61
	Other vs Control	Training (n=21)	acc.=0.95(+/-0.05), P<0.0001***, sens.=0.95, spec.=0.95, AUC=1.00, d=2.61
		Validation (n=211)	acc.=0.73(+/-0.03), P<0.0001***, sens.=0.73, spec.=0.73, AUC=0.77, d=0.68
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.62(+/-0.11), P>0.20, sens.=0.62, spec.=0.62, AUC=0.64, d=0.26
		Validation (n=211)	acc.=0.54(+/-0.03), P>0.20, sens.=0.54, spec.=0.54, AUC=0.56, d=0.07

ROI 9: Cerebellum right

Trained for	Task	Sample	Prediction Outcome
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.48(+/-0.11), P>0.20, sens.=0.48, spec.=0.48, AUC=0.46, d=-0.31
		Validation (n=211)	acc.=0.40(+/-0.03), P>0.20, sens.=0.40, spec.=0.40, AUC=0.37, d=-0.34
	Self vs Control	Training (n=21)	acc.=0.76(+/-0.09), P=0.0266***, sens.=0.76, spec.=0.76, AUC=0.84, d=0.95
		Validation (n=211)	acc.=0.73(+/-0.03), P<0.0001***, sens.=0.73, spec.=0.73, AUC=0.81, d=0.79
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.67(+/-0.10), P=0.1893, sens.=0.67, spec.=0.67, AUC=0.62, d=0.21
		Validation (n=211)	acc.=0.49(+/-0.03), P>0.20, sens.=0.49, spec.=0.49, AUC=0.47, d=-0.10
	Other vs Control	Training (n=21)	acc.=0.90(+/-0.06), P=0.0002***, sens.=0.90, spec.=0.90, AUC=0.95, d=1.31
		Validation (n=211)	acc.=0.60(+/-0.03), P=0.0058***, sens.=0.60, spec.=0.60, AUC=0.64, d=0.38
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=3.52
		Validation (n=211)	acc.=0.88(+/-0.02), P<0.0001***, sens.=0.88, spec.=0.88, AUC=0.96, d=1.32
	Other vs Control	Training (n=21)	acc.=1.00(+/-0.00), P<0.0001***, sens.=1.00, spec.=1.00, AUC=1.00, d=3.61
		Validation (n=211)	acc.=0.88(+/-0.02), P<0.0001***, sens.=0.88, spec.=0.88, AUC=0.95, d=1.36
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.57(+/-0.11), P>0.20, sens.=0.57, spec.=0.57, AUC=0.51, d=-0.14
		Validation (n=211)	acc.=0.43(+/-0.03), P>0.20, sens.=0.43, spec.=0.43, AUC=0.41, d=-0.24

ROI 10: Cerebellum left

Trained for	Task	Sample	Prediction Outcome
Predicting Self-mentalizing	Self vs Other	Training (n=21)	acc.=0.29(+/-0.10), P>0.20, sens.=0.29, spec.=0.29, AUC=0.45, d=-0.05
		Validation (n=211)	acc.=0.49(+/-0.03), P>0.20, sens.=0.49, spec.=0.49, AUC=0.50, d=-0.02
	Self vs Control	Training (n=21)	acc.=0.76(+/-0.09), P=0.0266***, sens.=0.76, spec.=0.76, AUC=0.90, d=0.94
		Validation (n=211)	acc.=0.71(+/-0.03), P<0.0001***, sens.=0.71, spec.=0.71, AUC=0.78, d=0.73
Predicting Other-mentalizing	Other vs Self	Training (n=21)	acc.=0.62(+/-0.11), P>0.20, sens.=0.62, spec.=0.62, AUC=0.63, d=0.12
		Validation (n=211)	acc.=0.52(+/-0.03), P>0.20, sens.=0.52, spec.=0.52, AUC=0.50, d=-0.02
	Other vs Control	Training (n=21)	acc.=0.81(+/-0.09), P=0.0072***, sens.=0.81, spec.=0.81, AUC=0.88, d=1.09

		Validation (n=211)	acc.=0.62(+/-0.03), *P*=0.0006***, sens.=0.62, spec.=0.62, AUC=0.64, *d*=0.35
Predicting mentalizing	Self vs Control	Training (n=21)	acc.=0.90(+/-0.06), *P*=0.0002***, sens.=0.90, spec.=0.90, AUC=0.99, *d*=2.26
		Validation (n=211)	acc.=0.85(+/-0.02), *P*<0.0001***, sens.=0.85, spec.=0.85, AUC=0.93, *d*=1.12
	Other vs Control	Training (n=21)	acc.=0.90(+/-0.06), *P*=0.0002***, sens.=0.90, spec.=0.90, AUC=0.99, *d*=2.10
		Validation (n=211)	acc.=0.86(+/-0.02), *P*<0.0001***, sens.=0.86, spec.=0.86, AUC=0.93, *d*=1.08
Differentiating „self“ vs „other“ conditions	Self vs Other	Training (n=21)	acc.=0.48(+/-0.11), *P*>0.20, sens.=0.48, spec.=0.48, AUC=0.58, *d*=0.11
		Validation (n=211)	acc.=0.48(+/-0.03), *P*>0.20, sens.=0.48, spec.=0.48, AUC=0.49, *d*=-0.04

Note. Each ROI was trained for four classification tasks and tested in validation datasets. acc. = accuracy; sens. = sensitivity, spec. = specificity, AUC = area under the curve. *d* refers to the estimated *Cohen's d* calculated as the mean difference of true and false paired predictions divided by the pooled standard deviation of differences (where difference = input_values[binary_class]- input_values[~binary_class]). Asterisks (***) mark the significant classification accuracies with *p*<.05.