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Decoding face recognition abilities in the human brain

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Significance

The ability to robustly recognise faces is crucial to our success as social beings. Yet, we still know very little about the brain mechanisms allowing some individuals to excel at face recognition. This study builds on a sizeable neural dataset measuring the brain activity of individuals with extraordinary face recognition abilities—super-recognisers—to tackle this challenge. Using state-of-the-art computational methods, we show robust prediction of face recognition abilities in single individuals from a mere second of brain activity, and reveal specific brain computations supporting individual differences in face recognition ability. Doing so, we provide direct empirical evidence for an association between semantic computations and face recognition abilities in the human brain—a key component of prominent face recognition models.

Abstract

Why are some individuals better at recognising faces? Uncovering the neural mechanisms supporting face recognition ability has proven elusive. To tackle this challenge, we used a multi-modal data-driven approach combining neuroimaging, computational modelling, and behavioural tests. We recorded the high-density electroencephalographic brain activity of individuals with extraordinary face recognition abilities—super-recognisers—and typical recognisers in response to diverse visual stimuli. Using multivariate pattern analyses, we

1 decoded face recognition abilities from 1 second of brain activity with up to 80% accuracy. To
2 better understand the mechanisms subtending this decoding, we compared representations in
3 the brains of our participants with those in artificial neural network models of vision and
4 semantics, as well as with those involved in human judgments of shape and meaning
5 similarity. Compared to typical recognisers, we found stronger associations between early
6 brain representations of super-recognisers and mid-level representations of vision models as
7 well as shape similarity judgments. Moreover, we found stronger associations between late
8 brain representations of super-recognisers and representations of the artificial semantic model
9 as well as meaning similarity judgments. Overall, these results indicate that important
10 individual variations in brain processing, including neural computations extending beyond
11 purely visual processes, support differences in face recognition abilities. They provide the first
12 empirical evidence for an association between semantic computations and face recognition
13 abilities. We believe that such multi-modal data-driven approaches will likely play a critical role
14 in further revealing the complex nature of idiosyncratic face recognition in the human brain.

16 Introduction

18 The ability to robustly recognise the faces of our colleagues, friends and family members is
19 paramount to our success as social beings. Our brains complete this feat with apparent ease
20 and speed, in a series of computations unfolding within tens of milliseconds in a wide brain
21 network comprising the inferior occipital gyrus, the fusiform gyrus, the superior temporal
22 sulcus, and more anterior areas such as the anterior temporal lobe (1–3). Accumulating
23 neuropsychological and behavioural evidence indicates that not all individuals, however, are
24 equally competent at recognising faces in their surroundings (4). Developmental
25 prosopagnosics show a great difficulty at this task despite an absence of brain injury (5). In
26 contrast, super-recognisers exhibit remarkable abilities for processing facial identity, and can
27 recognize individuals even after little exposure several years before (6–8). The specific nature
28 of the neural processes responsible for these individual differences remains largely unknown.
29 So far, individual differences studies have used univariate techniques to investigate face-
30 specific aspects of brain processing. This revealed that contrasts between responses to faces
31 compared to non-faces, measured by the N170 event-related potential component or by the
32 blood oxygen level dependent signals in regions of interest, are modulated by ability (9–15).
33 However, univariate and contrast approaches are limited in their capacity to reveal the precise
34 nature of the underlying brain computations (16–19).

35 Here, we tackled this challenge with a data-driven approach. We examined the functional
36 differences between the brains of super-recognisers and typical recognisers using decoding
37 and representational similarity analyses (RSA; (18, 20–23)) applied to high-density
38 electrophysiological (EEG) signals and artificial neural network models. We recruited 33
39 participants, including 16 super-recognisers, i.e., individuals better than the 98th percentile on
40 a battery of face recognition tests (8); **Fig. 1a**). We measured EEG in more than 100,000 trials
41 while participants performed a one-back task. The objects depicted in the stimuli belonged to

1 multiple visual categories including face images of different sexes, emotions, and identities, as
 2 well as images of man-made and non-face natural objects (e.g., a computer, a plant), animals
 3 (e.g., a giraffe, a monkey), and scenes (e.g., a city, a dining room; **Fig. 1b**).

5 Results

6 Behavioural results

7
 8 All participants' face recognition ability was assessed using the Cambridge Face Memory Test
 9 long-form (CFMT+, (8). Scores on the CFMT+ ranged from 50 to 85 in the typical recognisers
 10 group ($M_{TRs}=70.00$; $SD=9.09$), and from 92 to 100 in the experimental super-recogniser group
 11 ($M_{SRs}=95.38$, $SD=2.68$; difference between groups : $t(31)=10.6958$, $p<.00001$ see Fig. 1a).
 12 The main experimental task was a one-back task (Fig. 1b). Accuracy was significantly greater
 13 for the super-recognisers ($M_{SRs}=.8649$, $SD=.0626$) than for the typical recognisers
 14 ($M_{TRs}=.7591$, $SD=.096$; $t(30)=3.6131$, $p=.0011$). This was also true when analysing separately
 15 face ($M_{SRs}=.8677$, $SD=.0590$; $M_{TRs}=.7385$, $SD=.1048$; $t(30)=4.2180$, $p=.00020$) and non-face
 16 trials ($M_{SRs}=.8619$, $SD=.0750$; $M_{TRs}=.7798$, $SD=.1000$; $t(30)=2.6000$, $p=.0143$). Furthermore,
 17 accuracy in the one-back task was positively correlated with scores on the CFMT+ ($r=.68$,
 18 $p<.001$; RT was marginally associated with CFMT+, $r=.37$, $p=.04$). We observed a significant
 19 difference in response times between the two groups for face stimuli ($M_{SRs}=0.6222$ ms,
 20 $SD=.1386$ ms; $M_{TRs}=0.6817$ ms, $SD=.0660$ ms; $p=0.0258$) but not for non-face stimuli
 21 ($M_{SRs}=0.6262$ ms, $SD=.1401$ ms; $M_{TRs}=0.6739$ ms, $SD=.0643$ ms; $p=.0801$).

23 Discriminating super-recognisers and typical recognisers from 1 second of brain 24 activity

25 With this sizable and category-rich dataset, we first attempted to classify a participant as either
 26 a super- or a typical recogniser based solely on their brain activity. More specifically, we
 27 trained Fisher linear discriminants to predict group membership from single, 1-second trials of
 28 EEG patterns (in a moving searchlight of five neighbouring electrodes; **Fig. 2b**). We observed
 29 up to ~80% cross-validated decoding performance, peaking over electrodes in the right
 30 hemisphere. This performance is impressive given that the noise ceiling imposed on our
 31 classification by the test-retest reliability of the CFMT+ (8, 24), the gold-standard test used to
 32 identify super-recogniser individuals, is ~93% ($SD=2.28\%$; see Supplementary material). To
 33 reveal the time course of these functional differences, we applied the same decoding
 34 procedure to each 4-ms interval of EEG recordings. Group-membership predictions attained
 35 statistical significance ($p<.001$, permutation tests, **Fig. 2a**) from about 65 ms to at least 1 s
 36 after stimulus onset, peaking around 135 ms, within the N170 window (25, 26).

37 Notably, similar results were obtained following the presentation of both face *and* non-
 38 face visual stimuli (**Fig. 2a**; see also **Figure S1**). This did not result from face representations
 39 stored in short-term memory from one-back trials. Indeed, we repeated our decoding analysis
 40 for non-face trials either preceded by face trials or by non-face trials, and found significant

1 decoding of group membership in both cases (**Figure S1**). In addition, we successfully cross-
2 decoded group membership from a model trained on face EEG activity and applied to non-face
3 EEG activity (**see Figure S2**). The decoding of group-membership could be based on various
4 features. Some of these features are directly related to brain representations for object and
5 face recognition, and these aspects are further explored in subsequent sections of this article.
6 On the other hand, there could be additional contributing features that are not directly linked to
7 object and face recognition. For instance, differences in motor responses between the two
8 subject groups might explain these results to some extent. However, excluding the 10% of
9 trials with a motor response did not affect decoding accuracy (**Figure S2**). Additionally, the
10 decoding model might have relied on potential noise differences between the two subject
11 groups. Nevertheless, our analysis did not reveal any evidence supporting such differences in
12 the cross-participant similarity of the Representational Dissimilarity Matrices (RDMs) for both
13 groups (see section Linking neural representations with computational models of vision;
14 **Figure S3**).

16 **Predicting individual recognition ability from 1 second of brain activity**

17 An ongoing debate in individual differences research is whether the observed effects emerge
18 from qualitative or quantitative changes in the supporting brain mechanisms (27–35). The
19 decoding results presented up to this point might give the impression that face recognition
20 ability is supported by qualitative differences in brain mechanisms. However, these results
21 were obtained with dichotomous classification models applied, by design, to the brains of
22 individuals from a bimodal distribution of ability scores (e.g. (32)).

23 To better assess the nature of the relationship between neural representations and ability in
24 the general population, we thus performed a new decoding analysis on the typical recognisers
25 only, using a continuous regression model. Specifically, we used cross-validated fractional
26 ridge regression (36) to predict *individual* CFMT+ face recognition ability scores from single-
27 trial EEG data. This showed essentially similar results to the previous dichotomic decoding
28 results: performance was above statistical threshold ($p < .01$, FDR-corrected) from about 80 ms
29 to at least 1 s, peaking around 135 ms following stimulus onset for both face and non-face
30 stimuli (**Fig. 2c**, $\text{peak-}r_{\text{face}} = .4149$ at 133 ms, $\text{peak-}r_{\text{non-face}} = .4899$ at 141 ms). This accurate
31 decoding of individual scores from EEG patterns is compatible with a quantitative account of
32 variations in brain mechanisms across individuals differing in face recognition abilities.
33 Altogether, these decoding results provide evidence for important, quantitative and temporally
34 extended variations in the brain activity supporting face recognition abilities. This extended
35 decoding suggests effects of individual ability across multiple successive processing stages.

37 **Linking neural representations with computational models of vision**

38
39 Decoding time courses, however, offer limited insights on the level of brain computations (37,
40 38). To better characterise the visual brain computations covarying with face recognition
41 ability, we compared, using representational similarity analysis (20–22, 39), the brain

1 representations of our participants to that of convolutional neural networks (CNNs) trained to
2 categorise objects (40–42). These CNNs process visual features of gradually higher
3 complexity and abstraction along their layers (42), from low-level (e.g., orientation, edges) to
4 high-level features (e.g., objects and object parts).

5 The brain representations were characterised by computing representational dissimilarity
6 matrices (RDMs) for each participant and for each 4-ms time interval. These brain RDMs were
7 derived using the cross-validated decoding performance of a linear discriminant model, where
8 brain activity was decoded for every pair of stimuli at a given time interval (43, 44); see **Figure**
9 **S4** for the group-average RDMs and time course of key categorical distinctions). The visual
10 model representations were characterised by computing RDMs from the layers of the CNNs,
11 using Pearson correlations of the unit activations across all pairs of stimuli. Compared to
12 typical participants, we found that the brain RDMs of super-recognisers showed larger mutual
13 information (45) with the layer RDMs of CNNs that represent mid-level features (e.g.,
14 combinations of edges, contour, shape, texture; (42, 46) between 133 and 165 ms (**Fig. 3a**,
15 $p < .05$, cluster-test; see also **Figure S5** for similar results with unconstrained analyses;
16 supplementary analyses on specific category conditions in the RDMs are shown on **Figure**
17 **S6**). These results indicate that mid-level representations of an object-trained CNN matched
18 the representations of super-recognisers more closely than those of typical participants. We
19 replicated these results using a face-trained CNN (e.g., (47–49), VGGface (50), which possess
20 mid-level representations similar to those of object-trained CNN (see **Figure S7**; $p < .05$,
21 cluster-test). The stronger association between brain representational geometries of the super-
22 recognisers with computational models of vision could be explained by a marked difference in
23 signal to noise between the two groups of participants. To control for this potential confound,
24 we computed the cross-participant similarity of the RDMs in both groups (see **Figure S3**). If
25 the signal to noise was larger in the super-recognisers, we would expect larger cross-
26 participant similarity of the RDMs, however, we observed no significant difference between the
27 two groups.

28 **Linking neural representations with computational model of semantics**

29
30
31 The finding that ability decoding was significant as late as 1 s after stimulus onset hints
32 that brain computations beyond what is typically construed as pure visual processing also
33 differ as a function of face recognition ability. To test this hypothesis, we asked five new
34 participants to write captions describing the images presented during our experiment (e.g., “A
35 city seen through a forest.”), and used a deep averaging network (Google Universal Sentence
36 Encoder, GUSE; (51) to transform these captions into embeddings (points in a caption space).
37 GUSE has been trained to predict semantic textual similarity from human judgments, and its
38 embeddings generalise to an array of other semantic judgement tasks (51). We then compared
39 the RDMs computed from this semantic model to the brain RDMs of both typical- and super-
40 recognisers. Importantly, both this comparison, and the one comparing brain and visual
41 models, excluded the information shared between the semantic and visual models (but see

1 **Figure S8** for similar results with unconstrained analyses). We found larger mutual information
2 with these semantic representations in the brains of super-recognisers than in those of typical
3 recognisers in a late window between 598 and 727 ms (**Fig. 3b**, $p < .05$, cluster-test).
4 Supplementary analyses on specific stimulus categories of the RDMs (**Figure S9**) suggest that
5 these results emerged mainly from the face-vs-face and face-vs-non-face stimuli pair
6 conditions.

8 **Linking neural representations with behavioural representations for shape and** 9 **semantic similarity judgements**

10
11 Our findings so far suggest that mid-level visual and semantic brain processes both support
12 individual differences in face recognition abilities. We looked for further support for these
13 conclusions using RDMs derived from a behavioural experiment. A group of 32 new human
14 participants were submitted to two multiple arrangement tasks (52–54) in which they were
15 asked to evaluate the shape similarities of all pairs of the 49 visual stimuli used in the main
16 experiment, and the meaning similarities of all pairs of the 49 mean sentence captions
17 produced by five human participants to describe these images and used for the semantic
18 model (see section Linking neural representations with computational model of semantics).
19 More specifically, participants arranged the images/sentences inside a white circular arena
20 according to the task instructions using simple drag and drop operations (see **Fig. 4**). We
21 computed the mutual information between the mean RDMs extracted from each of these tasks
22 and the time-resolved brain RDMs of super- and typical recognisers as well as the same while
23 excluding the information shared with the other task. Results indicated only a small trend for
24 shape representations being enhanced around mid-latencies in super-recognisers relative to
25 typical recognisers which did not survive cluster correction ($p < .01$, uncorrected; $p_{MI} = .1259$;
26 $p_{CMI} = .2098$; cluster-corrected; see **Fig. 4**). Meaning representations were enhanced in late
27 latencies in super-recognisers compared to typical recognisers (sentence meaning : 635-787
28 ms $p < .05$, cluster-corrected; see **Fig. 4**). These results confirm that semantic representations
29 at relatively late latencies and, to a lesser degree, shape representations at mid latencies are
30 enhanced in the brains of super-recognisers.

32 **Discussion**

33
34 Using a data-driven approach combining neuroimaging, computational models, and
35 behavioural tests, we characterised the computations modulated by variations in face
36 recognition ability in the human brain. We recorded high-density electroencephalographic
37 (EEG) responses to face and non-face stimuli in super-recognisers and typical recognisers.
38 Using multivariate analysis, we reliably decoded group membership as well as recognition
39 abilities of single individuals from a single second of brain activity. We then characterised the
40 neural computations underlying these individual differences by comparing human brain activity
41 with representations from artificial neural network models of vision and semantics using

1 representational similarity analysis. Furthermore, we compared the brain activity with similarity
2 judgments derived from additional human participants engaged in two tasks. In the first task,
3 participants judged our visual stimuli on the similarity of their shape, while in the second task,
4 participants judged sentence captions describing these stimuli on the similarity of their
5 meaning. These sets of comparisons revealed two main findings. First, we found higher
6 similarity between early brain representations of super-recognisers and mid-level
7 representations of vision models as well as, to a lesser degree, shape similarity judgments.
8 Second, this approach revealed higher similarity between late brain representations of super-
9 recognisers and representations of an artificial semantic model as well as sentence caption
10 similarity judgments. To our knowledge, this is the first demonstration of a link between face
11 recognition ability and brain computations beyond high-level vision. Overall, these findings
12 revealed specific computations supporting our individual ability to recognise faces, and
13 suggest widespread variations in brain processes related to this crucial ability.
14 We achieved robust decoding of face recognition ability when examining EEG responses to
15 face *and* non-face stimuli. This is consistent with several neuropsychological (30, 55–59) and
16 brain imaging findings (12, 29, 60, 61) showing face and non-face processing effects in
17 individuals across the spectrum of face recognition ability ((19, 62); but see (13, 63–65)).
18 The decoding we observed for face and non-face stimuli peaked at right occipito-temporal
19 electrodes, in the temporal window around the N170 component (25). At that time, the
20 representations in the brains of our participants differed most with respect to the mid-layer
21 representations of artificial models of vision. These layers have been previously linked to
22 processing in human infero-temporal cortex (hIT; (42, 66–68) and functionally to mid-level
23 feature representations such as combinations of edges and parts of objects (42, 46). Such
24 associations with the N170, however, do not mean that this component is exclusively involved
25 in these mid-level processes. Rather, it suggests that other visual computations, including the
26 high-level visual computations usually associated with the N170, do not differ substantially
27 between super-recognisers and typical recognisers. The fact that these mid-level features are
28 mostly shared between face and non-face stimuli could explain at least partly the high
29 decoding performance observed for both classes of stimuli. They suggest that a mid-level
30 visual processing is enhanced in SRs leading to improved processing of faces and objects.
31 Crucially, we found that face recognition ability is also associated with semantic computations
32 that extend beyond basic-level visual categorisation in a late time-window around the P600
33 component (69–71). Recent studies using computational techniques have shown that word
34 representations derived from models of natural language processing explain significant
35 variance in the visual ventral stream (18, 72–74). The current study goes beyond this recent
36 work in two ways. First, our use of human sentence description and sentence encoders to
37 characterise semantic (caption-level) computations provides a more abstract description of
38 brain representations. Second, and most importantly, our work revealed a link between
39 semantic brain computations and individual differences in face recognition ability. An
40 association between semantic processes and face recognition ability had been posited in
41 models of face recognition (1, 75) but, to our knowledge, it had never been shown empirically

1 before.

2 Overall, thus, our findings suggest important differences in perceptual and semantic
3 representations in individuals with outstanding ability to recognise faces. The higher similarity
4 with computational models of vision indicate that super-recognisers have more efficient mid-
5 level representations. These enhanced representations suggest that part-based information
6 about faces and objects, putatively emerging from mid-level occipito-temporal regions (76), is
7 richer in individuals with strong face recognition abilities (77). Furthermore, our findings show
8 that the more similar the brain representations of an individual are to task-optimised
9 computational models of semantics, the better they are at recognising faces. These enhanced
10 late semantic representations, for example, might emerge from enhanced subordinate-level
11 information about objects and faces (78, 79).

12 Our approach of decoding group membership to reveal electrophysiological differences
13 between super-recognisers and typical recognisers, followed by representational similarity
14 analysis with computational models of vision and language, enabled revealing potential
15 mechanisms underlying enhanced recognition ability. Other possible differences between our
16 participants might also contribute to our ability to decode their brain signals. Differences in top-
17 down (i.e. attention) mechanisms, better ability to memorise images more generally, or both,
18 could also lead to enhanced representations. Interestingly, we could decode from both face
19 *and* nonface categories, and across categories (training with face trials and testing on non-face
20 trials) suggesting that the mechanisms subtending the enhanced abilities of super-recognisers
21 are not restricted to faces (4), (56).

22 Furthermore, while our decoding approach indicates that important differences in brain
23 processing emerge from early (80 ms) to late (~1s) processing windows, our RSA modelling
24 approach only explained part of these processing windows. Specifically, while broad visual
25 (~150 ms), face-specific (~430 ms), and semantic representations (~600 ms) were found to
26 differ in super-recognisers using this computational approach, it still remains to be shown what
27 specific representations are critical in differentiating the best face recognisers during early
28 (<150 ms) and very late (>800 ms) windows of processing.

29 In conclusion, our results offer a stepping stone for a better understanding of face recognition
30 idiosyncrasies in the human brain. Indeed, with the development of novel and better artificial
31 models simulating an increasing variety of cognitive processes, and with the technological
32 advances allowing the processing of increasingly larger neuroimaging datasets, the approach
33 described here provides a new and promising way to tackle the link between individual
34 differences in human behaviour and specific computations in the brain. In addition, this
35 decoding approach may provide quick and accurate alternatives to standardised behavioural
36 tests assessing face recognition ability, for example in the context of security settings that
37 benefit from strong face processing skills among their personnel (such as police agencies,
38 border patrol, etc.). It could also be used in a closed-loop training procedure designed to
39 improve face recognition ability (80).

40 **Methods**

41 **Participants**

42 A total of 33 participants were recruited for this study. The first group consisted of 16
43 individuals with exceptional ability in face recognition — super-recognisers. The second group
44 was composed of 17 neurotypical controls. These sample sizes were chosen according to the

1 effect sizes described in previous multivariate object recognition studies (43, 44, 54). The data
2 from one super-recogniser was excluded due to faulty EEG recordings. No participant had a
3 history of psychiatric diagnostic or neurological disorder. All had normal or corrected to normal
4 vision. This study was approved by the Ethics and Research Committee of the University of
5 Birmingham, and informed consent was obtained from all participants.

6 Sixteen previously known super-recognisers were tested in the current study (30-44 years old,
7 10 female). Eight of these (SR1-SR8) were identified by Prof. Josh Davis from the University of
8 Greenwich using an online test battery comprising a total of six face cognition tasks (6) and
9 tested at the University of Birmingham. The remaining eight (SR-9 to SR-16) were identified
10 using three challenging face cognition tests (7) and were tested at the University of Fribourg.
11 The behavioural test scores for all participants are provided in **Tables S1 and S2**. Across SR
12 cohorts, the Cambridge Face Memory Test long-form (CFMT+; (8) was used as the measure
13 of face identity processing ability. A score greater than 90 (i.e., 2 SD above average) is
14 typically considered the threshold for super-recognition (8, 56, 81). Our 16 super-recognisers
15 all scored above 92 ($M=95.31$; $SD=2.68$). A score of 92 corresponds to the 99th percentile
16 according to our estimation from a group of 332 participants from the general population
17 recruited in three independent studies (77, 82, 83).

18 An additional 17 typical recognisers (20-37 years old, 11 female) were recruited and tested on
19 campus at the University of Fribourg ($n=10$) and the University of Birmingham ($n=7$). Their
20 CFMT+ scores ranged from 50 to 85 ($M=70.00$; $SD=9.08$). Neither the average nor the
21 distribution of this sample differed significantly from those of the 332 participants from the
22 general population mentioned above (see **Fig. 1a**; $t(346)=1.3065$, $p=0.1922$; two-sample
23 Kolmogorov-Smirnov test; $D(346)=0.2545$, $p=0.2372$).

24 Tasks

25 CFMT+

26 All participants were administered the CFMT long-form, or CFMT+ (8). In the CFMT+,
27 participants are required to memorise a series of face identities, and to subsequently identify
28 the newly learned faces among three faces. It includes a total of 102 trials of increasing
29 difficulty. The duration of this test is about 15 minutes. EEG was not recorded while
30 participants completed this test.

31 One-back task

32 **Stimuli.** The stimuli used in this study consisted of 49 images of faces, animals (e.g., giraffe,
33 monkey, puppy), plants, objects (e.g., car, computer monitor, flower, banana), and scenes
34 (e.g., city landscape, kitchen, bedroom). The 24 faces (13 identities, 8 males, and 8 neutral, 8
35 happy, 8 fearful expressions) were sampled from the Radboud Face dataset (84). The main
36 facial features were aligned across faces using Procrustes transformations. Each face image
37 was revealed through an ellipsoid mask that excluded non-facial cues. The non-face images
38 were sampled from the stimulus set of Kiani et al. (85). All stimuli were converted to 250 x 250
39 pixels (8x8 deg of visual angle) greyscale images. The mean luminance and the luminance
40 standard deviation of these stimuli were equalised using the SHINE toolbox (86).

1 **Procedure.** We measured high-density electroencephalographic (EEG; sampling rate = 1024
2 Hz; 128-channel BioSemi ActiveTwo headset) activity while participants performed ~3200 trials
3 of a one-back task in two recording sessions separated by at least one day and by a maximum
4 of two weeks (**Fig. 1b**). Participants were asked to press a computer keyboard key on trials
5 where the current image was identical to the previous one. Repetitions occurred with a 0.1
6 probability. They were asked to respond as quickly and accurately as possible. Feedback was
7 done in the form of a change in colour of the fixation point (red or green) after a repetition trial
8 (which happened on a .1 probability basis). This was done to help participants pay attention
9 during the task. Target trials were not excluded from the analyses. A trial unravelled as follows:
10 a white fixation point was presented on a grey background for 500 ms (with a jitter of ± 50 ms);
11 followed by a stimulus presented on a grey background for 600 ms; and, finally, by a white
12 fixation point on a grey background for 500 ms. Participants had a maximum of 1100 ms
13 following stimulus onset to respond. This interval, as well as the 200 ms preceding stimulus
14 onset, constituted the epoch selected for our EEG analyses. In total, our participants
15 completed 105,600 one-back trials which constituted ~32 hours of EEG epochs.

16 **Shape and sentence meaning multiple arrangements tasks.** Thirty two new neurotypical
17 participants took part in two multiple arrangements tasks (22, 87) in counterbalanced orders. In
18 two of the tasks, they were asked to evaluate the shape or function similarities of the 49 stimuli
19 used in the main experiment while, in the other task, they were instructed to judge the meaning
20 similarities of sentence captions describing these stimuli (see Semantic Caption-level Deep
21 Averaging Neural Network RDM for more information about these sentence captions).

22
23 More specifically, participants were asked to arrange stimuli or sentence captions on a
24 computer screen inside a white circular arena by using computer mouse drag and drop
25 operations. During the shape/function (vs. meaning) multiple arrangement task, they were
26 instructed to place the displayed visual stimuli (vs. sentence captions) in such a way that their
27 pairwise distances match their shape/function (vs. meaning) similarities as much as possible
28 (**Fig. 4**). On the first trial of each task, participants arranged all 49 items. On subsequent trials,
29 a subset of these items was selected based on an adaptive procedure aimed at minimising
30 uncertainty for all possible pairs of items (e.g. items that initially were placed very close to each
31 other) and at better approximating the high-dimensional perceptual representational space
32 (87). This procedure was repeated until the task timed out (20 min).

33
34 We computed one RDM per task per participant. Three participants were excluded from the
35 final sample because their RDMs differed from the mean RDMs by more than two standard
36 deviations. Finally, we averaged the remaining individual RDMs within each task.

37 **Analyses**

38 All reported analyses were performed independently for each EEG recording session and then
39 averaged. Analyses were completed using custom code written in MATLAB (MathWorks) and
40 Python.

41 **EEG preprocessing**

42 EEG data was preprocessed using FieldTrip (88): continuous raw data was first re-referenced

1 relative to Cz, filtered with a band-pass filter [0.01-80 Hz], segmented into trial epochs from -
2 200 ms to 1100 ms relative to stimulus onset, and down-sampled at 256 Hz.

3 Decoding analyses

4 **Whole-brain analyses.** To predict group-membership from EEG brain activity, we trained
5 Fisher linear discriminant classifiers to predict participants' group membership based on raw
6 EEG topographies, using all 128 channels of single-trial EEG data as features. Notably, here,
7 the decoding is made on an *across-participants* basis. This was done across all trials of either
8 face or non-face condition, for each of the two sessions separately (~26,000 observations per
9 condition, per session, 5-fold cross-validation, 5 repetitions; (89, 90). The number of trials were
10 matched across participants. This process was repeated over all EEG time samples
11 separately, starting from -200 ms and ending 1100 ms after stimulus onset, creating decoding
12 accuracy time courses. The Area Under the Curve (AUC) was used to assess sensitivity.
13 Decoding time courses were averaged across the two EEG sessions. The resulting evidence
14 indicates when super-recognisers can be categorised from brain activity when processing
15 faces (blue) and non-face stimuli (grey), as shown in **Figure 2a**. Additional control decoding
16 analyses investigating effects of one-back trials on the predictions are shown in **Figure S1**.
17 These trials required that our participant compared their representations of the presented
18 image and the one stored in short-term memory. This showed similar findings, with one
19 notable difference being that the face-face discrimination condition was the one that obtained
20 peak decoding accuracy.

21 **Searchlight analysis.** We conducted a searchlight analysis decoding EEG signals from all
22 subsets of five neighbouring channels to characterise the scalp topographies of group-
23 membership AUC. This searchlight analysis was done either using the entire EEG time series
24 of a trial (0-1100 ms; **Fig. 2b**, leftmost topographies), or using 60 ms temporal windows
25 (centred on 135 ms, 350 ms, 560 ms, and 775 ms; **Fig. 2b** rightmost topographies). We ran
26 additional control searchlight decoding procedures investigating the effect of one-back trials
27 (**Figure S1**).

28 **Regression analysis.** We used fractional ridge regression models (36) to predict individual
29 face recognition ability scores (CFMT+) among the typical recognisers from EEG patterns
30 across time. We trained our model on subsets of 60% of the EEG patterns. We chose the
31 alpha hyperparameter with the best coefficient of determination among 20 alpha
32 hyperparameters ranging linearly from 0.001 to 0.99 applied on a 30% validation set. The
33 decoding performance was assessed using the Spearman correlation between the CFMT+
34 scores and predictions from the overall best model (applied on the remaining 10% of EEG
35 patterns). This process was repeated 10 times and the Spearman correlations were averaged.
36 Significance was assessed using a permutation test (see *Group comparisons and inferential*
37 *statistics* section).

38 Representational Similarity Analysis of brain and computational models

39 We compared our participants' brain representations to those from visual and semantic
40 (caption-level) artificial neural networks using Representational Similarity Analysis (RSA; (20-
41 22, 39).

1 **Brain Representational Dissimilarity Matrices.** For every participant, we trained a Fisher
 2 linear discriminant to distinguish pairs of stimuli from every 4-ms intervals of EEG response (on
 3 all 128 channels) to these stimuli from -200 to 1100 ms after stimulus onset (91, 92). Cross-
 4 validated AUC served as pairwise classification dissimilarity metric. By repeating this process
 5 for all possible pairs (1176 for our 49 stimuli), we obtained a representational dissimilarity
 6 matrix (RDM). RDMs are shown for selected time points in **Figure S4**.

7
 8 **Visual Convolutional Neural Networks RDMs.** We used a pre-trained AlexNet (40) as one
 9 model of the visual computations along the ventral stream (42). Our 49 stimuli were input to
 10 AlexNet. Layer-wise RDMs were constructed comparing the unit activation patterns for each
 11 pair of images using Pearson correlations. Similarly, we computed layer-wise RDMs from
 12 another well-known CNN, VGG-16 (see **Figure S5**). Following previous studies using this
 13 model (93, 94), we averaged the convolutional layer RDMs situated between each max pooling
 14 layers and the layers' input into five aggregated convolutional RDMs (e.g. conv1-1 & conv1-2
 15 into RDM-conv1); this facilitated the comparison of our results with the five convolutional layers
 16 of AlexNet.

17
 18 **Semantic Caption-level Deep Averaging Neural Network RDM.** We asked five new
 19 participants to provide a sentence caption describing each stimulus (e.g., "a city seen from the
 20 other side of the forest", see **Fig. 1d**) using the Meadows online platform (www.meadows-
 21 research.com). The sentence captions were input in Google's universal sentence encoder
 22 (GUSE; (51) resulting in 512 dimensional sentence embeddings for each stimulus. We then
 23 computed the dissimilarities (cosine distances) between the sentence embeddings across all
 24 pairs of captions, resulting in a semantic caption-level RDM for each participant. The average
 25 RDM was used for further analyses.

26 Comparing brain representations with computational models

27
 28 We compared our participants' brain RDMs to those from the vision (Fig. 3a) and semantic
 29 (Fig. 3b) models described in the previous section using Conditional Mutual Information (45),
 30 which measures the statistical dependence between two variables (e.g. mutual information
 31 $I(x;y)$), removing the effect from a third variable (i.e. $I(x;y|z)$). Additional comparisons using
 32 unconstrained Mutual Information between brain RDMs and both models are shown in **Figure**
 33 **S5 and S8**.

34 Group comparison and inferential statistics

35
 36 **Comparison of Conditional Mutual Information time courses.** Time courses of CMI were
 37 compared between the super-recognisers and typical recognisers using independent samples
 38 t-tests and a Monte Carlo procedure at a *p-value* of .05, as implemented in the Fieldtrip
 39 Toolbox (88). Family-wise errors were controlled for using cluster-based corrections, with
 40 maximum cluster size as cluster-level statistic and an arbitrary *t* threshold for cluster statistic of
 41 [-1.96, 1.96] for the comparison of brain and semantic (excluding CNN) and for the comparison
 42 of brain and CNN (excluding semantic) time courses. The standard error is shown for all
 43 curves as colour-shaded areas (**Fig. 3**). Analyses with MI (brain; CNN) and MI (brain;
 44 semantic) were completed in an identical manner.

1 **Time course of group-membership decoding.** Significance was assessed using non-
2 parametric permutation tests. We simulated the null hypothesis by training the linear classifier
3 to identify shuffled group-membership labels from the experimental EEG patterns. This
4 process was repeated 1000 times for each time point and each one of the two sessions. We
5 then compared the real, experimental decoding value at each time point to its corresponding
6 null distribution, and rejected the null hypothesis if the decoding value was greater than the
7 prescribed critical value at a $p < .001$ level.

8
9 **Time course of individual ability decoding using ridge regression.** Significance was again
10 assessed using non-parametric permutation testing. The ridge regression analysis predicted
11 cross-validated CFMT+ scores from single trial EEG patterns, and goodness of fit is reported
12 using Spearman's correlation between the predicted and observed CFMT+ scores. Under the
13 null hypothesis that all participants elicited comparable EEG response patterns, irrespective of
14 their CFMT+ score, the face recognition ability scores are exchangeable. We simulated this
15 null hypothesis by repeating the ridge regression model training using randomly shuffled
16 CFMT+ scores. The predicted CFMT+ scores were then correlated to the empirical, observed
17 CFMT+ scores using Spearman's correlation, and this was repeated 1000 times for each time
18 point. We finally compared the real, experimental correlation value with its corresponding null
19 distribution at each time point, and rejected the null hypothesis if the correlation value was
20 greater than the prescribed critical value at a $p < .01$ level.

21 22 **Data availability**

23
24 High-density EEG data associated with this article is available on The Open Science
25 Framework (<https://osf.io/pky28/>).

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39 40 41 **Author contributions** 42 **(CRediT standardised author statement)**

43
44 **S.F.-S.:** Conceptualisation, methodology, software, formal analysis, investigation, data curation,
45 writing - original draft, visualisation, supervision, project administration, funding acquisition.

46 **M.R.:** Investigation, resources, project administration, writing - review and editing. **E.B.:**

1 investigation, project administration. **M.Z.:** investigation. **J.W.:** funding acquisition, writing -
 2 review and editing. **A-R.R.:** Investigation. **R.C.:** Resources. **F.G.:** Methodology, writing -
 3 original draft, supervision, funding acquisition. **I.C.:** Supervision, methodology, software,
 4 resources, formal analysis, writing - original draft, project administration, funding acquisition.
 5

6 **Competing interests**

7
 8 The authors declare no competing interests.
 9

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26 27 **Figure captions**

28
29 **Figure 1. Experimental procedure. a)** The histogram shows the Cambridge Face Memory Test long-
30 form (CFMT+, (8)) scores of super-recognisers (yellow bars), typical recognisers (black bars), and an
31 additional 332 neurotypical observers from three independent studies for comparison (77, 82, 83). **b)**
32 Participants engaged in a one-back task while their brain activity was recorded with high-density
33 electroencephalography. The objects depicted in the stimuli belonged to various categories, such as
34 faces, objects, and scenes. Note that the face drawings shown here are an anonymised substitute to
35 the experimental face stimuli presented to our participants.

36
37 **Figure 2. Decoding interindividual recognition ability variations from EEG activity. a)** Trial-by-trial
38 group-membership predictions (super-recogniser or typical recogniser) were computed from EEG

1 patterns, for each 4-ms interval, while participants processed face (blue trace) or non-face stimuli (grey
 2 trace). Significant decoding performance occurred as early as 65 ms, peaked in the N170 window, and
 3 lasted for the remainder of the EEG epochs ($p < .001$). **b**) Topographies were obtained using searchlight
 4 decoding analyses, either concatenating all time points (left topographies) or for selected time-windows
 5 (right topographies). Concatenating all time points resulted in peak classification performance of 77.3%
 6 over right occipito-temporal electrodes for face and 77.5% over right occipito-temporal electrodes for
 7 non-face conditions. In the N170 window, we observed a peak classification performance of 74.8% over
 8 right-temporal electrodes for face, and 72.1% over left-temporal electrodes for non-face conditions. **c**)
 9 We decoded the CFMT+ scores of the typical recognisers using fractional ridge regression. This
 10 yielded similar results with significant decoding as early as 75 ms, peaking around the N170 time
 11 window (peak- $\rho_{\text{face}} = .4149$, peak- $\rho_{\text{non-face}} = .4899$), and lasted for the remainder of the EEG epochs
 12 ($p < .01$, 1K permutations, 10 repetitions).

13
 14 **Figure 3. Comparison of super- and typical-recogniser brain representations with those of**
 15 **artificial neural networks of visual and semantic processing.** **a**) Representational dissimilarity
 16 matrices (RDM) were computed from convolutional neural networks (CNN; (40, 41) of vision, human
 17 brain activity, and a deep neural network of caption classification and sentence semantics (51). To
 18 characterise the CNN RDMs, we computed the pairwise similarity between unit activation patterns for
 19 each image independently in each CNN layer. The caption-level RDMs were derived from human
 20 caption descriptions of the images transformed into sentence embeddings. Brain RDMs were computed
 21 using cross-validated decoding performance between the EEG topographies from each pair of stimuli at
 22 every 4 ms time-point. Mutual information (45) between the model RDMs and the brain RDMs was
 23 assessed, for every participant, at each 4 ms step from stimulus onset. **b**) Mutual information between
 24 brain RDMs and AlexNet RDMs (removing shared mutual information between brain and semantic
 25 model) is shown for typical- (grey solid curve) and super-recognisers (pink solid curve). We found
 26 greater similarity with mid-level visual representations (layer 4 and 5 shown, but similar results were
 27 found for mid-layers of VGG16, another popular CNN model; see **Figure S5**) in the brains of super-
 28 recognisers (black line indicates significant contrasts, $p < .05$, cluster-corrected) between 133 ms and
 29 165 ms. Similar results were observed when comparing brains and CNN models without removing the
 30 shared mutual information between brains and the semantic (caption-level) model (**Figure S5**). **c**)
 31 Mutual Information with the semantic model (excluding shared mutual information between brain and
 32 AlexNet) differed for typical- and super-recognisers in a later time window centred around 650 ms (cyan
 33 curve; super > typical, $p < .05$, cluster-corrected). Again, similar results were observed when comparing
 34 brains and the semantic model without removing the shared mutual information between the brain and
 35 CNN model (see **Figure S8**).

36 **Figure 4. Linking neural representations with behavioural representations for shape, function,**
 37 **and semantic similarity judgements.** **a**) Mutual information between brain RDMs and the mean RDM
 38 built from shape similarity judgements (first column) and sentence meaning similarity judgements
 39 (second column) is shown for typical- (grey curves) and super-recognisers (coloured curves). Greater
 40 similarity with shape information in the brains of super-recognisers ($p < .01$, uncorrected; $p\text{-corrected}_{MI} =$
 41 $.1259$) and greater similarity with sentence meaning information for super-recognisers ($p < .01$,
 42 uncorrected; $p\text{-corrected}_{MI} = 0.0819$) only reached significance before cluster corrections. The shaded
 43 areas of all curves represent the standard error. **b**) Conditional Mutual information between brain RDMs
 44 and the mean RDM built from similarity judgements of shape & of sentence captions meaning
 45 (removing shared mutual information between brain and sentence caption meaning RDM for shape
 46 similarity, and vice versa) is shown in typical- and super-recognisers. We found greater similarity with
 47 sentence meaning in the brains of super-recognisers between 635 ms and 787 ms (black line indicates
 48 significant contrasts, $p < .05$, cluster-corrected), in agreement with our comparisons with the artificial

1 semantic model (fig. 3b). Greater similarity with shape information in the brains of super-recognisers
 2 only reached significance before cluster corrections ($p < 0.01$, uncorrected; $p_{corrected_{CMI}} = .2098$).
 3

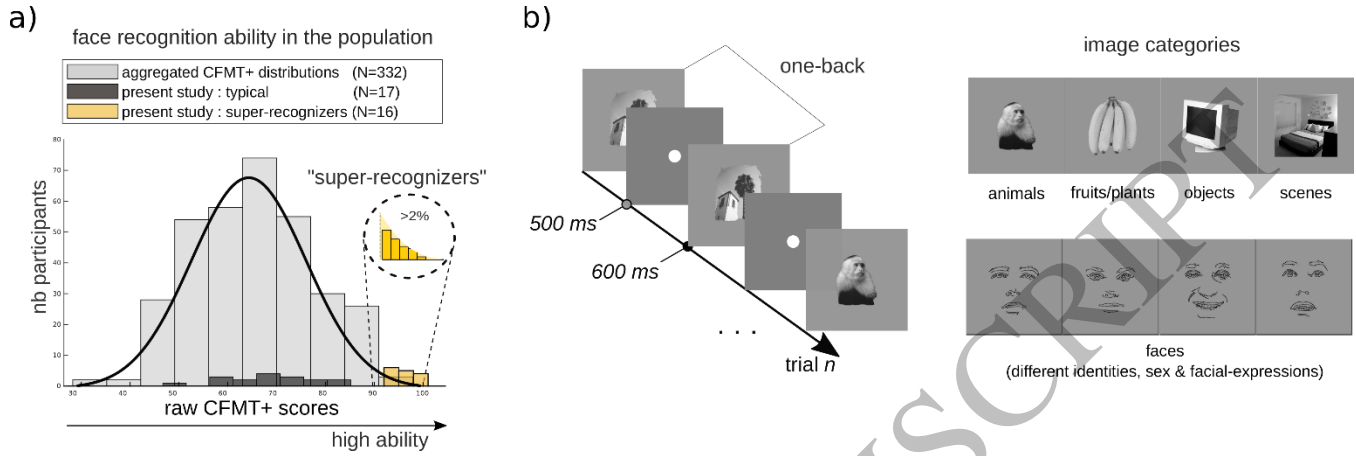


Figure 1
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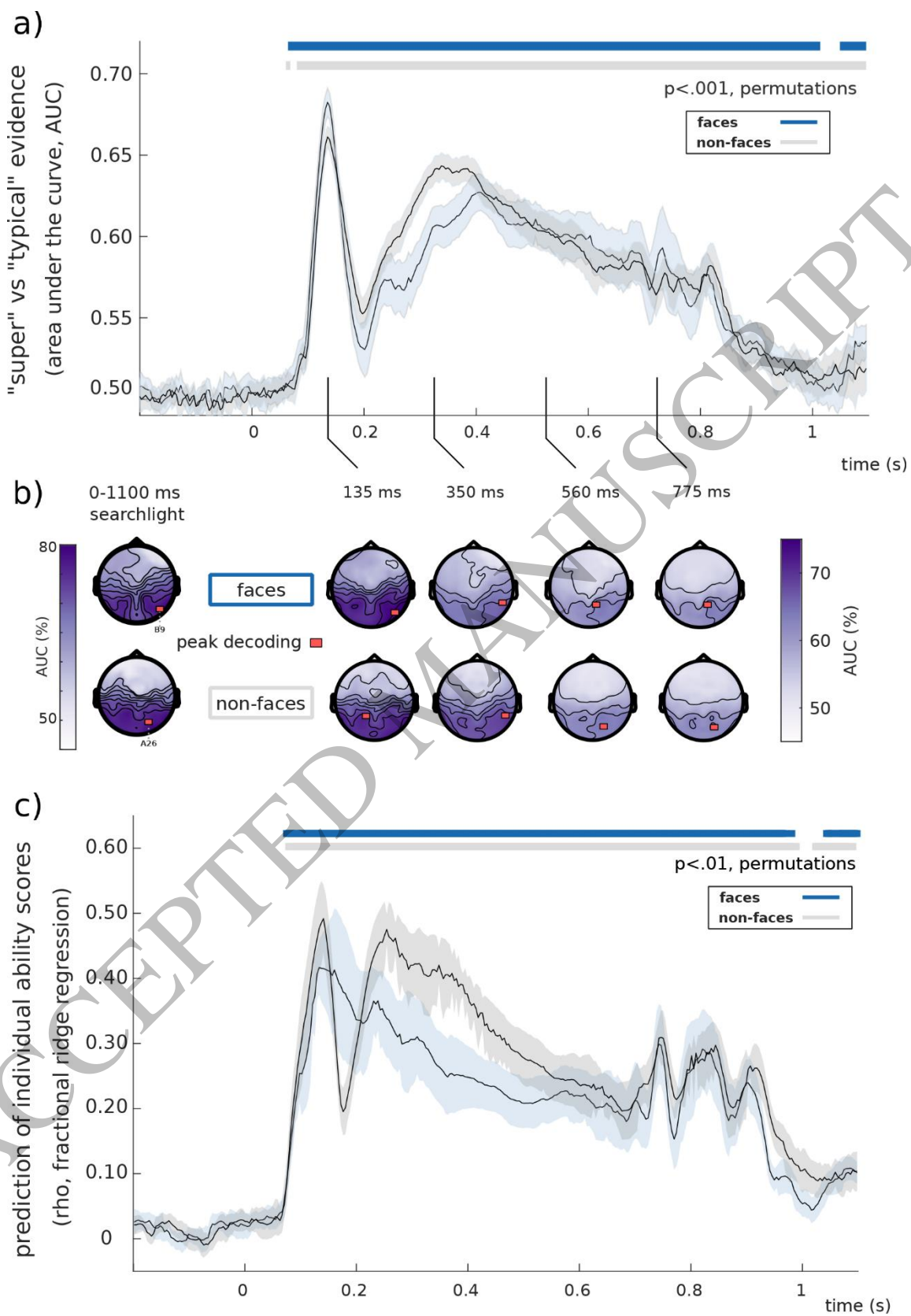


Figure 2
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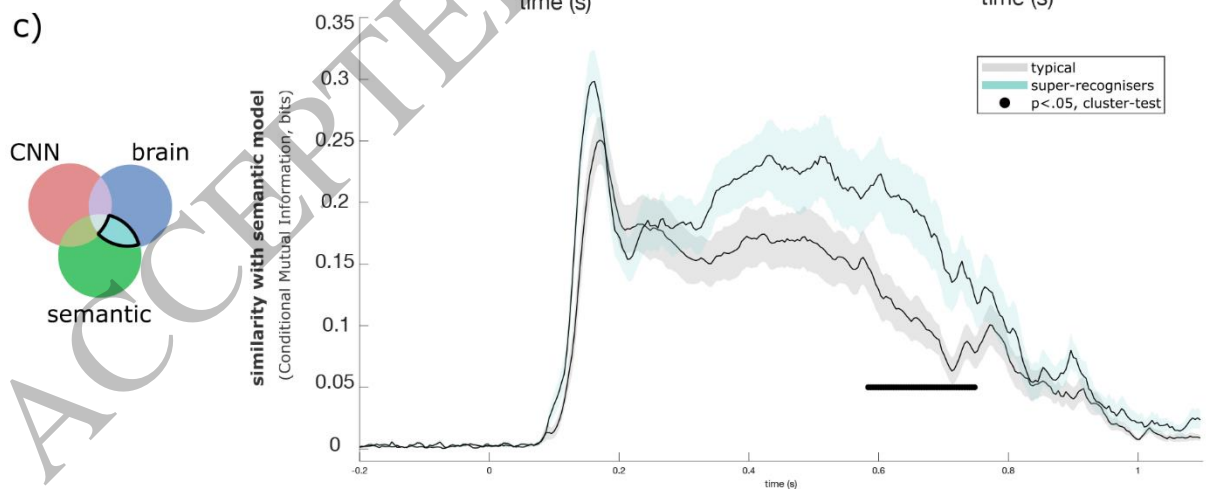
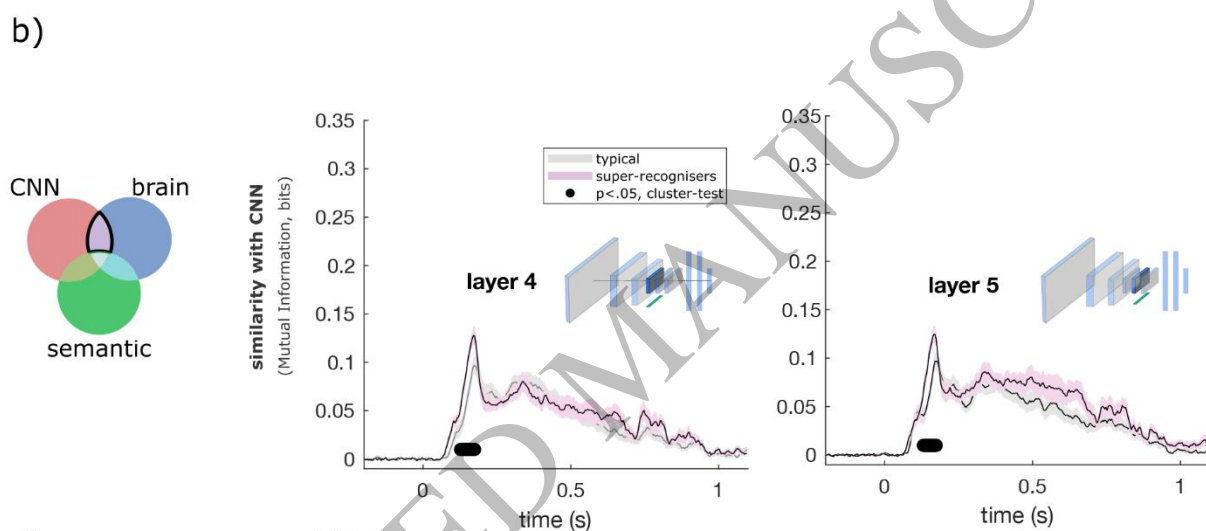
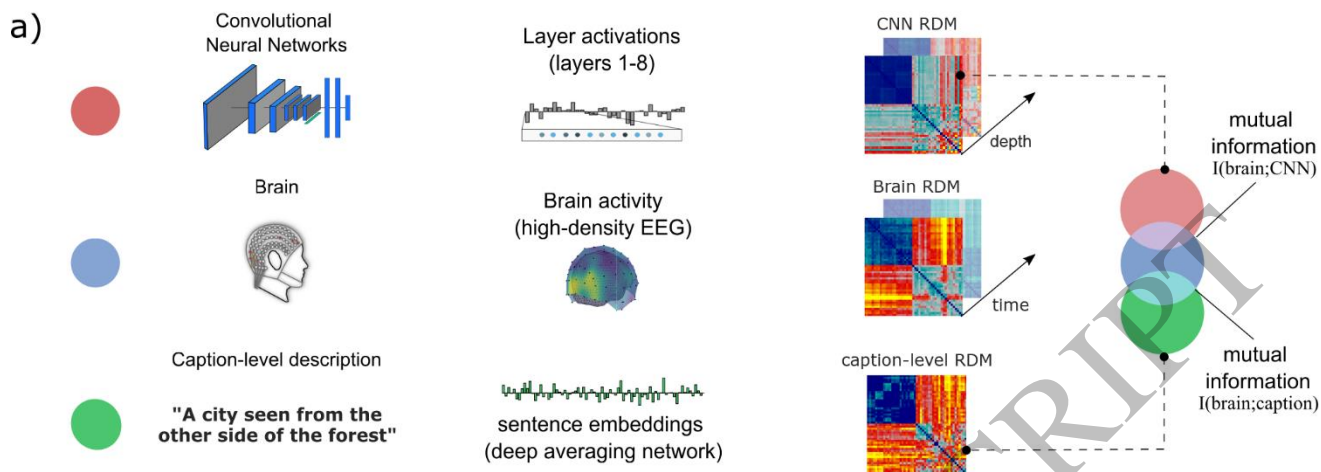


Figure 3
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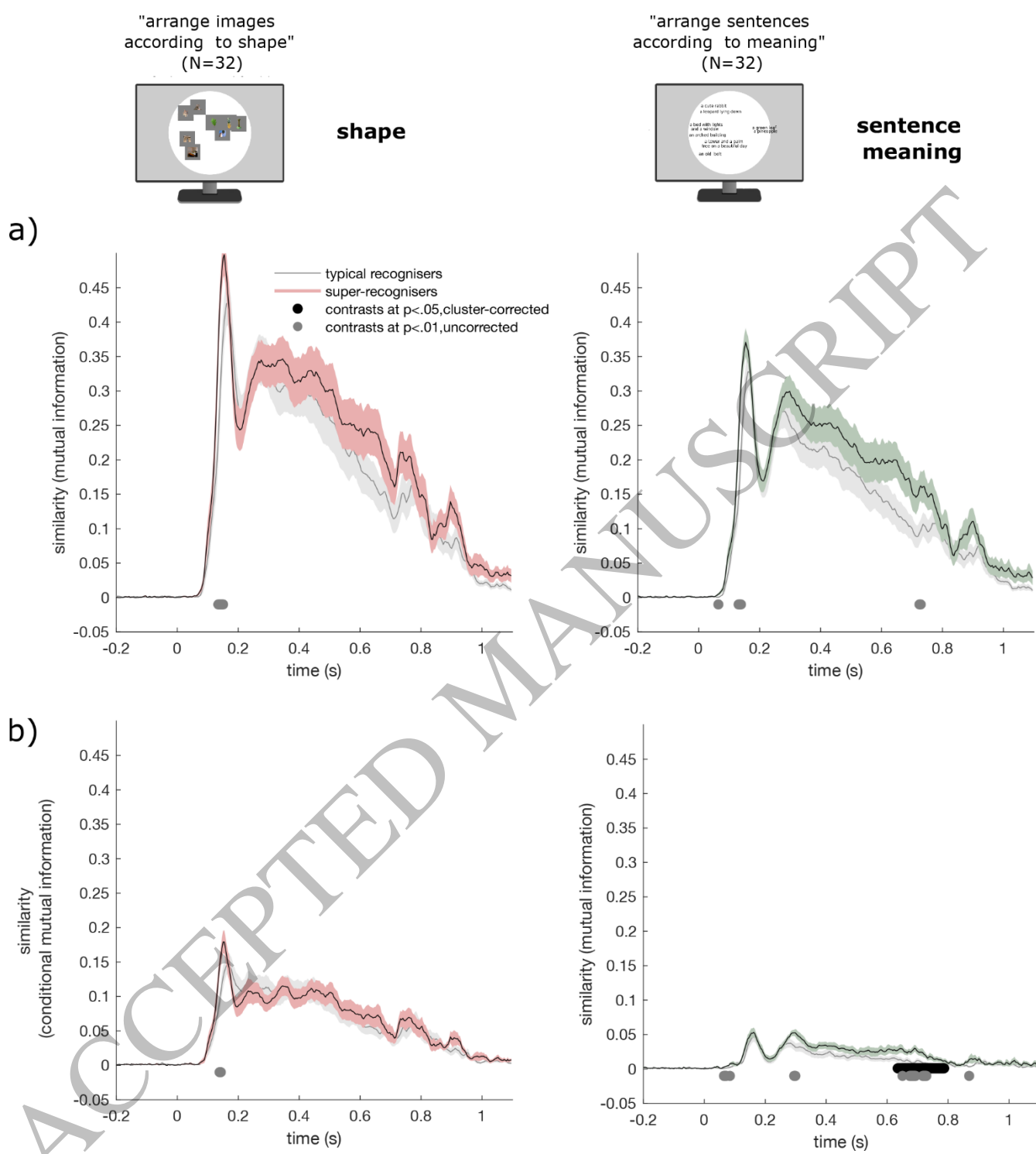


Figure 4
176x194 mm (x DPI)

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